Lille University of Science and Technology

Doctoral School of Engineering Science

Laboratory of Civil Engineering and geo-Environment

PhD Thesis

To obtain the grade of

DOCTOR FROM LILLE UNIVERSITY

Discipline: Civil Engineering

By

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A DATA-BASED MODEL FOR THE DOMESTIC WATER DEMAND IN PALESTINIAN TERRITORY

Defended on November 4, 2016 in front of the following dissertation committee

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Abstract

Water scarcity and increasing water demand especially for residential use are major challenges facing Palestine. The need to accurately forecast water consumption is useful for the planning and management of this natural resource. The main objective of this research is to (i) study the major factors influencing the water consumption in Palestine, (ii) understand the general pattern of Household water consumption, (iii) assess the possible changes in household water consumption and suggest appropriate remedies and (iv) develop prediction model based on the Artificial Neural Network to the water consumption in Palestinian cities.

The research is organized in four parts. The first part includes literature review of household water consumption studies. The second part concerns data collection methodology, conceptual frame work for the household water consumption surveys, survey descriptions and data processing methods. The third part presents descriptive statistics, multiple regression and analysis of the water consumption in the two Palestinian cities. The final part develops the use of Artificial Neural Network for modeling the water consumption in Palestinian cities.

Keywords

Water Management; Domestic water; Demand modeling; Consumption; ANN; Palestine.

Résumé

La pénurie d'eau et l'augmentation de la demande en eau, en particulier pour un usage résidentiel sont les principaux défis auxquels sont confrontés la Palestine. La nécessité de prévoir avec précision la consommation d'eau est utile pour la planification et la gestion de cette ressource naturelle. L'objectif principal de cette recherche est de (i) étudier les principaux facteurs qui influent la consommation d'eau en Palestine, (ii) de comprendre le schéma général de la consommation d'eau des ménages, (iii) d'évaluer les éventuels changements dans la consommation d'eau des ménages et de proposer des solutions appropriées et (iv) élaborer un modèle de prédiction de la consommation d'eau dans les villes palestiniennes basé sur le Réseau de Neurones Artificiels.

Le travail de recherche est organisé en 4 parties. La première partie comprend une analyse bibliographique des travaux réalisés sur la consommation d'eau des ménages. La deuxième partie concerne la collecte de données, la méthodologie, l'enquête sur la consommation d'eau des ménages et le traitement de données. La troisième partie présente une analyse statistique des données de consommation d'eau dans deux villes palestiniennes. La dernière partie développe la modélisation de la consommation d'eau dans les deux villes à l'aide des Réseaux de Neurones Artificiels.

Mots clés

Gestion de l'eau; Domestique; Prévision; Demande Modélisation; Consommation; ANN; Palestine.

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List of Abbreviations

ANNs	Artificial Neural Networks
CMWU	Coastal Municipalities Water Utility
FFNN	Feed Forward Neural Networks
GRNN	Generalized Regression Neural Networks
IPCC	Intergovernmental Panel on Climate Change
JWU	Jerusalem Water Undertaking
MCM	Million cubic meters
MDPS	Medium Term Development Palestinian government strategy
PC	Pearson correlation
PCBS	Palestinian Central Bureau of Statistics
PMA	Palestinian Meteorological Authority
PNA	Palestinian National Authority
PWA	Palestinian Water Authority
RBNN	Radial Basis Neural Networks
UN	United Nations
UNRWA	United Nations Relief and Works Agency
UPVC	Unplasticised Poly Vinyl Chloride
UWM	Urban Water Management
WB	World Bank
WBWD	West Bank Water Department
WHO	World Health Organization's
WSSA	Water Supply and Sewage Authority

General Introduction

As the world population becomes more urbanized, the social, economic, and environmental vitality of our growing cities are all dependent upon urban management of water. The water sector and the development community have a symbiotic relationship which usually goes unrecognized, and therefore, is not realized. Without adequate water resources and water infrastructure, urban development and redevelopment can be stymied. On the other hand, land use and development impact the use and the need for water. It takes more than turning on the tap to bring safe, reliable drinking water to an urban area. An approach which exploit the water managers is Urban Water Management (UWM), sometimes also called One Water. UWM principles recognize that water from all sources must be managed holistically and cooperatively to meet social, economic, and environmental needs.

Predicting and managing urban water demand is complicated by the tightly coupled relationship that exists between human and natural systems in urban areas. This relationship results from multiple interactions between microscale (individual, household, or parcel level) and macroscale (municipal or regional) processes and patterns. For example, in complex systems, local interactions among individuals cumulate over space and time, generating mesoscale and macroscale variables that in turn feedback to influence or constrain individual choices [Liu et al., 2007; Irwin et al., 2009].

This embedded nature of social and ecological systems in natural resource management poses a significant challenge to water managers. Separate analysis of these systems is not feasible; accounting for the complex and often unpredictable reactions to various shocks, policies, and interventions remains extremely difficult [Berkes and Folke, 2001; Irwin et al., 2009].

Analyzing and forecasting urban water demand is a complex yet imperative task, as it is essential that cities meet the water demands of their residents. The ability to estimate water demand under multiple climate, population growth, and conservation scenarios is intimately tied to urban hydrological processes and modeling. Peak water demand forecasts influence infrastructure expansion strategies. Many urban areas face similar stresses and will require expansion of water supply and distribution facilities. Ensuring a least cost and reliable infrastructure expansion strategy requires an accurate estimate of the required size and operation of reservoirs, pumping stations, and pipe capacities. The first step is to develop an accurate and a reliable water demand forecast models, especially for assessing peak demand. There are two types of demand forecasting. The first are short-term forecasts, which are used for operation and management. The second are the long-term forecasts, which are required for planning and infrastructure design [Bougadis et al., 2005]. Currently, water managers produce demand estimates using a long-term climate trends and the principle of stationarity (the idea that natural systems fluctuate within an unchanging envelope of variability) [Milly et al., 2008]. However, climate change introduces uncertainties that may limit the accuracy of this method, as historical trends will no longer be reliable for predicting future climate-sensitive water demand [Milly et al., 2008; Gober et al., 2010].

A transition in water demand modeling, forecasting, and management depends first on an understanding of the current and historical methods of acquiring and producing knowledge in the discipline. An understanding of the origin, structure, and limits of this knowledge is also required [Ward, 2007; van de Meene and Brown, 2009; Gober et al., 2010; van de Meene et al., 2010].

Water scarcity and increasing water demand especially for residential use are major challenges facing Palestine. The need to accurately forecast water consumption is useful for the planning and management of this natural resource.

Residential water use studies partially enabled by modern smart metering technologies such as those provide the opportunity to align disaggregated water use demand for households with an extensive database covering household demographic, socio-economic and water appliance stock efficiency information. Artificial Neural Networks (ANNs) provide the ideal technique for aligning these databases to extract the key determinants for each water use category, with the view to build a residential water end-use demand forecasting model.

This research aims at developing tools, understanding and strategy for the water policy in the urban area in Palestine. The use of water in urban area constitutes a strategic issue for the Palestinian Authority. In order to analyze this use and to understand its drivers as well as barriers, we conducted field studies in two cities in Palestine. The first city is Ramallah, which is located in the West Bank of Jordan and considered as the administrative center of the Palestinian authority. The second city is Khan Younis, which represents the Gaza strip, it is known for the high population density, poor economic and environmental conditions and lack of water resources.

Comprehensively understanding of water consumption behavior is necessary to design efficient and effective water strategy. Despite global efforts to identify the factors that affect domestic water consumption, those related to domestic water use in Palestine have not been sufficiently studied, particularly in districts that have developed access to improved water supply. To address this gap, this study will analyze the water use in 100 households in Ramallah city and 100 households in Khan Younis city.

Objective of Study

The main objective of this research is to:

- Study the major factors influencing the water consumption in Palestine.
- Understand the general pattern of Household water consumption in Palestine. Two case studies will be done - Ramallah at West Bank and Khan Younis in Gaza strip.
- Assess the possible changes in household water consumption and suggest appropriate remedies.
- Develop prediction model based on the Artificial Neural Network to the water consumption in Ramallah and Khan Younis.

Research layout

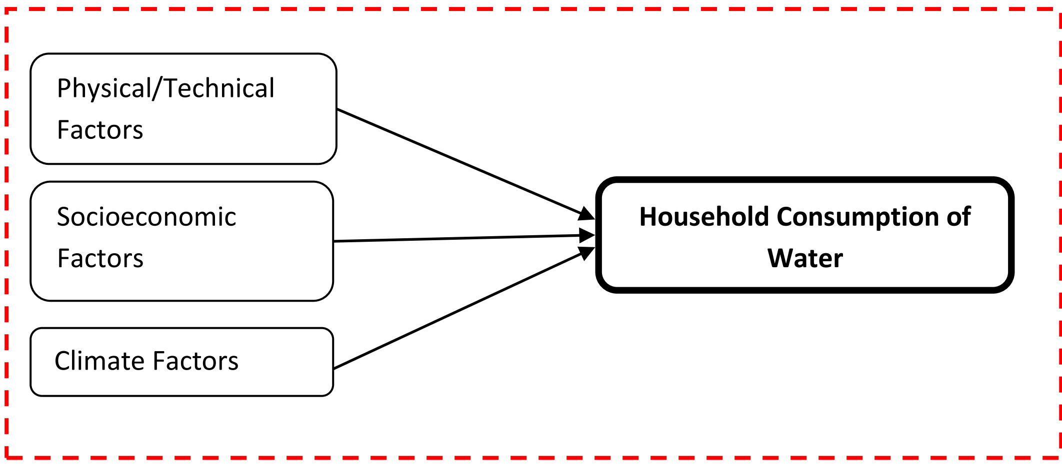
The study is organized as follow:

- Chapter 1 is devoted to literature review of household water consumption studies and water issues.
- Data collection, methodology, conceptual frame work for the household water consumption surveys, survey descriptions and data processing methods are presented in Chapter 2.

- Chapter 3 presents descriptive statistics, multiple regression and analysis of the water consumption in the two case studies.
- Chapter 4 develops the Artificial Neural Network modeling of the water consumption in Ramallah and Khan Younis.

Research Methodology

Conceptual framework was developed based on the literature review and a research model was recognized showing the relationship between input variables and water consumption and then artificial neural network model for prediction was developed.



1 Urban Water Management: Literature Review

1.1 Introduction

According to the U.N.'s Millennium Development Report (2010), the urban population was projected to exceed the rural population in developing regions of the world. Urban populations were growing at more than 3 percent per annum in 2012, three times faster than the populations in rural areas. More than one-third of city dwellers - almost 1 billion people - lived in conditions characterized by overcrowding and poor water services. For the urban poor residing, lack of water supply and sanitation services represents a frightening challenge and multiple strategically targeted initiatives will be required to meet the targets of reducing by half the proportion of people without sustainable access to safe drinking water and basic sanitation (U.N., 2010).

Urbanization is one of the most important demographic trends of our time. In 2008, the number of people living in urban areas has for the first time surpassed the number of people living in rural areas. It is estimated that by 2050, the percentage of urban population will reach nearly 70% (BIRCH et al. 2012).

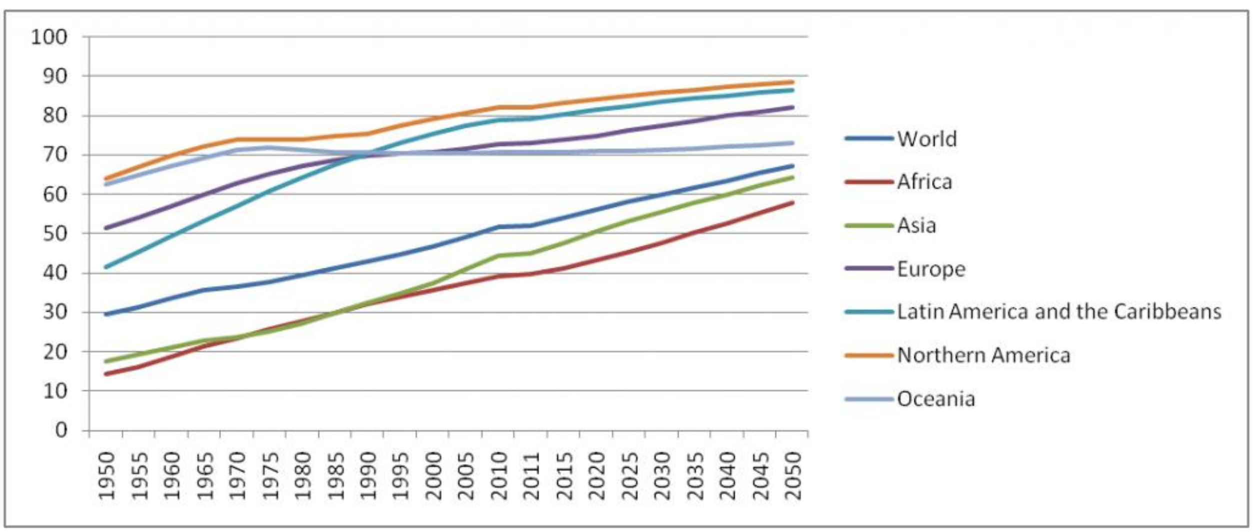


Figure 1.1 Urbanization trends and estimates in major regions of the world (in % from 1950 to 2050). Source: UN-DESA (2010) and UN-DESA (2011)

Many countries in both developed and developing world face significant problems in maintaining reliable water supplies; this is expected to continue in the coming years mainly due to the impact of global climate change, the rapid population growth and the limited cost-effective water supply augmentation options (Dharmaratna and Harris, 2010).

During the period 2010- 2014, the proportion of the population with access to an improved drinking water source in developing regions rose from 75% to 85%. However, nearly 1 billion people are still using water from unimproved sources such as shallow wells, rivers, streams, ponds and drainage ditches with their attendant health and safety risks. Large numbers of those who lack access to improved water supply infrastructure live in urban areas (World Bank, 2014).

As a result, reliable estimates of residential water consumption, water source choice decisions and the factors affecting it become critical for the water policy makers. On the one hand, there is a debate around whether policies aimed at reducing water consumption should use price or non-price methods. On the other hand, supply augmentation requires several years of planning and large amount of capital investments before the water is available. In light of these challenges, governments are seeking strategies that promote water conservation, particularly with residential consumers (Ibid, 2010).

Water consumption analysis is doomed at providing relevant information and awareness for designing an effective water demand policy in general and a policy that seeks the efficient use of water in particular. In this way, efficient use of water is defined as a pattern of use that maximizes the payback arising from the elimination of a given water resource (Tietenberg, 1991; Pearce, 1999).

As shown in Figure 1.2, global water usage continues to increase, it will be important to consider urban management as a means to deal with the problem. By reducing usage, we can mitigate the demand of water

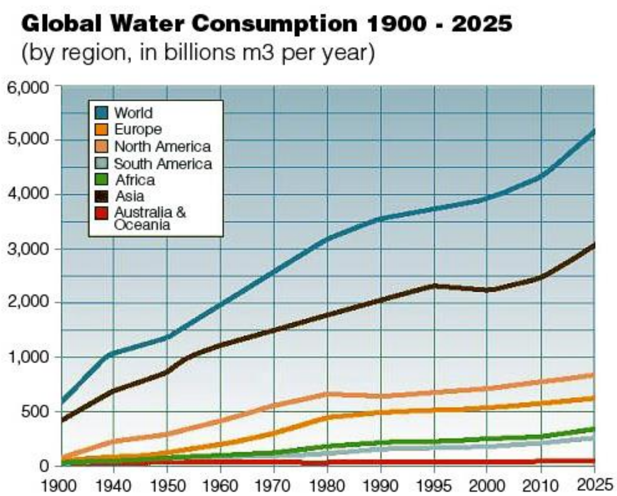


Figure 1.2 Global water consumption 1900 -2025

Source: [http://www.lowimpactliving.com/pages/your-impacts/water1]

1.2 Factors Affecting Urban Water Demand

1.2.1 Overview

Water management constitutes a vital alarm for both water supply companies and public administrations due to the magnitude of water for life and current lack in many areas.

Water demand management aims at motivating consumers and influencing their water use, through a range of social marketing, economic, and other management programs (Argues et al., 2003; Broody et al., 2005; Russell and Fielding, 2010). The most commonly used factors in urban water management are: number of connections or population, household size, number of households, income or factors of the standards of living, price of water, quality of water, educational level and climatic factors such as temperature and rainfall (Babel et al, 2007). Barkatullah (2002) used income and property values as indicators of the accessible resources for households. Höglund (1999) included the average gross household income; whileGunatilakeet et al. (2001) used the household income data from a survey. Household size was frequently used in the water consumption equation (Nieswiadomy et al, 1998) as having significant influence on water consumption.

Renwick and Green (1999) included seasons and climate. The climate variables found to affect the water consumption by shifting soil water accessibility and evaporation rate (Fox et al., 2009; Godchild, 2003), whilerainfall was found to reduce the need for watering and other outdoor activities resulting in brief reduction in water demand (Maidu, 1990). Price is also considered as an important factor that affect water consumption, as pricing can set off consumers to adjust the way they use water thus ensuring available capacity is used competently and investments are carried out only when extremely necessary (Stephenson, 1999), (Chestnut et al., 2007) found that tariffs can be based on water metering or on a non-volumetric tariff. In case of fixed tariffs, consumers are charged a fixed amount, regardless of how much water they use. This tariff system does not encourage efficient use of water since consumers do not have an encouragement to reduce water consumption.

When metering is introduced in establishing water tariffs, two schemes are usually employed in setting the tariff, the flat tariff and the blocked tariff, both have their own effects on water consumers and thus on the revenues generated by the public agency, the conservation wastage of water and the even distribution among affluent and relatively poorer users of water. Renwick and Green (1999) used median household income for each of the water agencies included based on aggregated water data.

Water use practices depend highly on the household income. To better serve the low income consumers, it is often suggested that high income households, who rely on private taps, cross-subsidize poor households because a significant number of these households is unwilling or unable to pay for the water from a public tap. However, as experiences have shown, a fee on public taps is advisable because water for free leads to less sustainability, does not give any incentive for the distributor to expand networks, and might therefore be a bad policy for the poor overall (Minten et al., 2002).

The challenges for understanding the dynamics of water management are complex and include the study of climate change, population growth, public attitude, urban planning and policy, and the impact on successful water management. Embedded in this complexity are the influencing residential water demands. Many studies were made in residential water demand has identified demands such as the presence of low flush toilets, dishwashers and washing machines as factors that influence water consumption (Malla and Gopglakrishnan 1997; Arubes et al. 2003; Domene and Sauri 2006).Furthermore, dwelling type, house size, and the number of members in the household also contribute significantly to the amount of water used (Domene and Sauri 2006; Wentz and Gober 2007). Socioeconomic factors that show a positive influence on water usage are average age of residents, educational level and household income (Chu et al. 2009; Guhathakurta and Gober 2007; Harlan et al. 2009; Kenney et al. 2008; Schleich and Hillenbrand 2009).

Studies have also shown that along with household demand, residential water usage can be characterized through seasonal changes and climate stressors. These water demands are largely for outdoor amenities, primarily pools, gardens, and irrigated landscaping (Domene and Sauri 2006; Fullerton and Nava 2003; Head and Muir 2007; Lee et al. 2008; Praskievicz and Chang 2009; Wentz and Gober 2007). Pools use a great deal of water due to evaporation but provide recreation, aesthetic value, and summer time relief to high temperature (Agthe and Billings 2002; Wentz and Gober 2007). Gardens and irrigated landscaping provide vegetation and some temperature relief through shade and evapotranspiration, but this landscaping style can be highly water intensive (Gober et al. 2010; Yabiku et al. 2008). Arbues et al. (2003) also mentioned the total size of the area to be irrigated, the presence of a garden, and whether there is a sprinkler system or not as major factors that increase outdoor residential water use.

Understanding the components of indoor and outdoor water demand is crucial, studies have shown that neighborhood characteristics, spatial organization of housing, and dwelling type influence water demand (Franczyk and Chang 2009; HousePeters et al. 2010; Wentz and Gober 2007), other studies showed that neighbors tend to have similar water consumption patterns even when other factors may be different (Chang et al. 2010; Fox et al. 2009). Moreover, there are others showed that water use can be predicted by dwelling type, such as detached single structures, semi-detached, and apartment complexes (Fox et al. 2009; Randolph and Troy 2008; Zhang and Brown 2005).

Incorporating spatial characteristics and dwelling types are important factors for urban planners to consider in policy development and the impact of climate change on water demand.

Researchers showed that domestic water consumption was significantly correlated with several factors such as water supply pattern and garden area, and significantly negatively correlated with family size and age of household head. Traditional hygiene habits and use of water appliances are dominant behaviors in the district with access to improved water supply.

Recent studies on domestic water consumption payed more attention to user lifestyles (water appliance usage habits, outdoor water use) and cultural backgrounds (age, education).

The main characteristics of the household head (age, gender, and educational level and socioeconomic situation (net family size, household income, vegetable garden and yard area, and possession of livestock, washing machines, and solar water heaters) also affected the water consumption.

The main domestic water consumption includes:

- Indoor consumption such as drinking, personal hygiene (i.e., washing face, hands, and feet), kitchen activities, showering and laundry.
- Outdoor consumption such as garden irrigation, livestock needs, house and yard cleaning.

The dominant water use behaviors include:

- Indoors factors such as frequency of laundry, frequency of personal hygiene activities, water appliance usage ratio;
- Outdoors factors such as frequency of vegetable garden watering, frequency of house and yard cleaning, swimming pool and car cleaning.

1.2.2 Lack of Data in Developing Countries

In most developing countries, the quality of datasets on residential water consumption often poses a problem for demand estimation, especially as metering is not common. In contrast to developed countries, where almost all households obtain water from the utility through a piped network, the market for residential water demand in many developing countries shows much more variation. Households may have a connection to the piped network and use water exclusively from their private tap, but they may also combine piped water with water collected from wells, public taps, or purchase water from vendors; or they may have no connection and rely exclusively on non-piped water. Little is known about households' behavior in developing countries regarding the factors driving their choices and in particular the substitution or complementary relationships between piped and non-piped water for piped households or the combination of non-piped water from different sources for non-piped households. As a result, policy decisions are often not very well informed; it is usually assumed that residential water demand in developing countries mirrors those of developed countries (Basania et al., 2008).

1.2.3 Household Demographic Indicators

Demographic factors are well known to influence the water demand (Arbués et al., 2003; Cavanagh et al., 2002; and Lyman, 2002), while aggregate data can be helpful in the investigation of this issue; customer data provide opportunities to aggregate water consumption is a function of the decisions of many individual water users, not all of whom are likely to respond to price, weather, and non-price policies equally. Not only the characteristics of these water users vary from community to community, but also they evolve within communities over longer time periods (a decade or more).

Data limitations are common impediment to assess the impact of demographic characteristics on household water demand. We rarely have data sets that allow going with household level consumption data with demographic data about the people and house associated with a household water account. However, previous studies showed that household water consumption is influenced by heterogeneity associated with differences in wealth (income), family size and age distribution, and household preference towards water use and conservation (Hankeand de Mare, 1982; Jones and Morris, 2004; Lyman, 2002; Renwick and Green, 2000; Syme et al., 2000; Cavanagh et al., 2002).

Other studies investigated the effect of HH demographics on water use revealed that HH size has a positive effect on water use. However, Arbués et al. (2000) found that water use is less than proportionate to the increase in HH size or population because of economies of scale in discretionary and nondiscretionary water usage, including cooking, cleaning, car washing and gardening as there is an optimum household size beyond which these economies of scale diminishes.

Families with children could be expected to use more water as children require frequent sanitations, outdoor uses by children and teenagers might be higher, young people might use water less carefully, have more showers and demand more frequent laundering, while retired people might have saving and disciplined water use behaviors (Nauges and Thomas, 2000). But, Lyman (2002) found that retired people tend to spend more time at home and do more gardening, which is associated with more water use.

1.2.4 House Hold Income

Some assess of wealth (e.g., income) is often included into water consumption studies, based on the assumption that greater wealth is likely to lead to an accumulation of water-using devices and, simultaneously, temper the influence of price in restricting water demand. Here it is worth reviewing the significance of personal wealth (income) independently as a key demographic factor in shaping demand, and consider the ways that this issue has been addressed in the literature.

The income is usually measured by the total money income for the area divided per household or per capita. In household-based studies, the variable assessed value of the property is occasionally used (Howe and Linaweaver, 2007; Hewitt and Hanemann, 2005; Dandy et al., 2007; Arbués et al., 2000). This variable could be introduced in addition to income, acting as a substitute for wealth and household preferences for home life-style. However, it is usually too correlated with income and other variables to be useful in practice (Lyman, 2002; Barkatullah, 2006).

Users with high income present a lower level of perception of the rate structure, since the total bill represents a lower proportion of their income. Thus, several studies (Hanke and de Maré, 2002; Agthe and Billings, 2007, 2007; Saleth and Dinar, 2000) analyzed these income effects, estimating different consumption functions for different income levels. Income (or expenditure) and education level (or the ability of head of household to read and write) have been found to be positively associated with household choice of improved water source (Madanat and Humplick 1993; Hindman Persson 2002; Briand and others, in press; Larson and others 2006; Nauges and Strand 2007; Basani and others 2008; Nauges and van den Berg, 2009).

Piper (2003) mentioned that, "Almost all of the demand models have estimated the elasticity price of demand to be negative and inelastic and the income elasticity to be positive and inelastic. This general result has occurred in spite of the region where the study was conducted or the modeling technique used." Cavanagh et al. (2002) reported that most income elasticity in the literature (2001 to 2011) generally fall in the range of 0.2 to 0.6. Representative studies included those by Jones and Morris (1984) (0.40 to 0.55 in Denver, depending on the price model), Cochran and Cotton (2005) (0.58 for Oklahoma City), Billings and Day (2009 in southern Arizona), Nieswiadomy (2002) (from 0.28 to 0.44 in the North Central, Northeast and South regions using the marginal price model), Renwick and Archibald (2008) (0.36, based on data from 119 single family households in two California cities over a 6-year period), and Renwick and Green (2000)(0.25 in 8 urban water agency service areas in California). Howe and Linaweaver (2007) showed a similar range over 39 areas spread across the U.S., as well as demonstrated higher income elasticity for outdoor water use than indoor use.

1.2.5 Household Size

Two related considerations regarding family demographics and water consumption are the size of the family (number of members) and their age distribution. Several studies confirmed the intuitive hypothesis that household water consumption increases as the number of members increases (Howe and Linaweaver, 2007; Foster and Beattie, 2009; Lyman, 2002; Nieswiadomy, 2002; Renwick and Archibald, 2008; Nauges and Thomas, 2000; Cavanagh et al., 2002; and Piper, 2003). For example, Cavanagh et al. (2002) used data from 1,082 single-family homes in the U.S. and Canada, it showed that each additional household resident increases daily consumption by 22%, the increase is not one-to-one due to economies of scale i.e., doubling household members does not double water consumption, as some major water uses (notably outdoor irrigation) is not family size dependent (Hoglund, 2009).

The significance of age distribution on water demand has been studied in two investigations: Hanke and de Mare's (2002) study of Sweden, and Lyman's (2002) study of Moscow, Idaho. Hanke and de Mare found that the elasticity of water consumption for adults (0.13) was more than twice that for children (0.05). On the other hand, Hanke and De Mare's study found that only distinguished between adults and children, Lyman considered adults, children and teenagers (actually ages 10 to 20), while both studies showed that adults use less water (per capita) than those under age 20, Lyman suggested that the highest users are actually children (those under age 10) and the lowest water users are teens (age 10 to 20). Lumping children and teens together, therefore, can hide an interesting water use dynamic. Lyman found that adding a child to a home increases the water usage by 2.5 times that of another teen and 1.4 times that of an adult.

Another interesting dynamic may occur as people enter retirement age. Billings and Day (2009) found the levels of water use are increased as individuals in Tucson, AZ are transitioned from the 55-64 age range to the "post-retirement" class, possibly as a stress on work gives way to time at home and activities such as gardening. A seemingly contradictory result is found in Martinez-Epineuria's (2002) study of northwestern Spanish cities, where per capita use is lower in cities with a high concentration of people over age 64.

Some researchers have tried to use number of bathrooms as a surrogate statistic for household size; for example, Hewitt and Hanemann's (2005) study of summer water use in Texas found the number of bathrooms has a significant effect on water consumption. However, this raised a variety of methodological questions, including the possibility that number of bathrooms is correlated with other factors, namely income.

1.2.6 Area of the Household

It is often assumed that the house size and lot size are positively correlated with indoor and outdoor water demand. Cavanagh et al. (2002), for example, found that every 1,000 square feet of house size in 11 urban areas in the U.S. and 39 in Canada increased water demand by 13-15%. Others, such as Hewitt and Hanemann (2005), found no significant relationship between house size and water demand in Denton, TX. A slightly different metric of house size, number of bathrooms, also produced inconsistent results. Cavanagh et al. (2002) found that each bathroom increased the demand by 6%; Hewitt and Hanemann (2005) also found that the number of bathrooms is important and positively correlated with the water demand. However, Lyman (2002) found that by using data from 30 households in Idaho, the total number of bathrooms was negatively related to the water usage, and it was correlated with other variables such as property value.

A different clearer picture exists regarding the lot size (or related measures of irrigable acreage). Studies by Lyman (2002), Renwick and Green (2000) and Cavanaghet al. (2002) found that the water demand increased with the lot size. Cavanagh et al. (2002) detected only a modest increase, concluding that each additional 1,000 square feet of lot area increased household demand by less than 1%, while Renwick and Green (2000) found that a 10% increase in lot size yielded a 2.7% increase in the water demand. However, as seen with many other household and house variables, many researchers, including Howe and Linaweaver (2007), eventually throw irrigable acreage out of their demand model, believing it to be too closely correlated with housing value.

1.2.7 Water Price

Water consumption studies overlooked the presence of block rates in general using the average price of water as the separate indicator of price (Billings and Agthe, 1980). However, as noted by Howe and Linaweaver (1967), such an approach ignored (a) the role that marginal prices play in the consumer demands and (b) a change in the marginal price of a particular block may affect in a quantity reduction demanded yet result in little to no change in the average price paid.

Water consumption in most cases is estimated as rather inelastic. This is because water has no substitutes for basic uses and because the customer exhibits a low level of perception of the rate structure, since water bills typically represent a small proportion of income (Chicoineand Ramamurthy, 1986; Arbués et al., 2000). However, prices can play a crucial role in the demand management as long as the softness is different from zero.

Under block rate tariffs, it is difficult to analyze the effect of changes in the intra marginal rates, that is, rates that do not correspond to the current level of consumption. As shown in Taylor (2007), who showed that the marginal price is not affected by a change in the intra-marginal rate, the latter will only affect demand through an income effect. This finding has led to different reactions, as the lack of consumer information about the tariff structure and then the fact that the difference erratic amounts to such a small fraction of the household income have been suggested as explanations (Nieswiadomy and Molina, 2000). While a perfectly informed consumer should respond to marginal price and the rate premium (Nordin, 2000), most consumers will not dedicate much time or effort to study the structure or changes in intra-marginal rates (Billings and Agthe, 2000; Bachrach and Vaughan, 2000) because of information costs. An alternative specification applied in several studies was the average price. Other authors applied both average and marginal price in the same or different models.

Some elasticity values show that the choice of variable did not greatly affect the results, while some proposed that consumption is more approachable to average price. Another potential outcome of the lack of information by the consumers was that these could react to lag rather current average prices. Since water bills are received after a period, the issue arises of whether to use a current or lagged price specification (Arbués et al., 2000). It has been shown that consumers are not always aware of current price schedule, although the choice of the appropriate price ruins controversial (Charney and Woodard, 2000; Opaluch, 1984; Nieswiadomy and Molina, 2001).

1.2.8 Climate Factors

Water use has progressively become a greater concern to urban water resource managers, it became as concern over climate variability and change is growing and urban areas have expanded in many parts of the world during the 20th and early 21st centuries. The recent Intergovernmental Panel on Climate Change (IPCC) report projected an increase in temperature, spatial and temporal variability of precipitation, which may increase water demand but reduce seasonal water supply (Cineros et al. 2014).

Climatic behavior prediction is one of the challenging tasks to meteorological society all over the world. Its variability directly influences many sectors such as agriculture, water etc. So it is necessary to determine the relationship among the climatic variables and its influence on these sectors. Climatic variables include rainfall, maximum-minimum temperature and humidity (Surendra H et al. 2014).

1.3 Urban Water Management in Palestine

1.3.1 History overview

Growing competition, conflicts, shortages, waste and degradation of water resources make it imperative to rethink about conventional concepts, in order to shift from an approach that attempts to manage separately the different aspects of urban water cycle to an integrated approach including all stakeholders (Global Water Partnership GWP, 2012).

The law proposes to establish four public water and wastewater management utilities in Palestine (water governance in Palestine report,2015). Until this can be realized, the current management systems, in which municipalities and village councils will continue to provide water and sanitation services. Most of these councils lack adequate infrastructures, technical skills, and human and financial resource capacity.

Current statistics show that 29% of the Palestinian communities (7% of population) are not connected to drinking water. In the areas connected to water supply, 15% of the population is not served. Around 23% of the total population is not supplied with water in the West Bank (PHG, 2003).

Despite the fact that the total renewable water resources in the West Bank and Gaza Strip is estimated at 722 Mcm (m^3) / year, in the form of groundwater resources (Palestinians are not allocated their rightful shares from surface water), Palestinians are allowed to use only 250 Mcm / year ; the rest is used by Israel.

1.3.2 Current Water Management Models in Palestine

In the West Bank, the private sector was not given the opportunity to interfere in the water supply sector, public water utilities; municipal and village councils own and operate the water supply. Water supply management can be grouped into two main categories:

- Delegated Public Management Model;
- Direct Public Management Model

1.3.2.1 *Delegated Public Management Model*

In the delegated public management model, the system is built up and operated by a water utility. The water utility also operates the infrastructure as a permanent concessionaire. In this model, water utilities are owned by group of municipalities (shareholders) and thus it is a public organization, although it may be operated on a commercial basis.

This model was developed in the West Bank during the time of Jordanian rule prior to 1967. Two major utilities have been established: (i) the Jerusalem Water Undertaking (JWU), which currently runs the water sector in Ramallah and part of Jerusalem Governorates (ii) the Water

Supply and Sewage Authority (WSSA), which runs the water supply and sanitation sector in the Bethlehem Governorate.

1.3.2.2 *Direct Public Management Model*

In the direct management model, municipalities or villages councils manage the water services. Municipalities are responsible for funding the current investment and capital cost, the capital investments are almost funded by external financial aids (national or international development agencies). Municipalities are the owners and operators of the infrastructure. Direct public management is the dominant management mode in Palestine.

Both public models are functional in Palestine but the first model is more efficient as it is able to provide better services (water governance in Palestine report,2015). The delegated public management is more autonomous; it has more technical capacity and runs on a cost recovery basis for the provided services.

Efficiency is lower with the direct public management model, the customer base is smaller in general, and most of the municipal and village councils do not have a separate division to run the water service. Budgets are not differentiated among the various provided services or the collected revenue. It is difficult for this management model to be run on a sustainable basis. Development in the infrastructure needs financial support from external sources; this is also the case in the first model, though to a lesser degree. Donor agencies provide funds as grants and loans, especially the World Bank and the European Investment Bank. Although such loans are soft and long term, they increase the national debt.

1.4 Use of Artificial Neural Networks in Urban Water Management

An Artificial Neural Network (ANN) constitutes a powerful tool for modeling complex processes. It establishes relations between the cause (input data) and the result (output data) of a process without a need for making assumptions considering the nature of the process. Applications of ANN are widespread and vary from optimization of measuring networks, operational water management, prediction of drinking water consumption, on-line steering of wastewater treatment plants and sewage systems. Where processes are complex, neural networks can open new possibilities for understanding and modelling these kinds of complex processes.

The use of ANN in water management increases rapidly, several applications of ANN in water resources engineering have been reported (Schulze FH et al, 2005). Various Artificial Neural Network techniques such as Generalized Regression Neural Networks (GRNN), Feed Forward Neural Networks (FFNN) and Radial Basis Neural Networks (RBNN) have been evaluated based on their performances in monthly forecasting of water consumptions from several factors (Seth and Indranil, 2015).

1.5 Conclusion

This chapter presented a literature survey of the urban water demand management; this issue is one of the main important concerns for policy makers in order to establish strategies for investment in water infrastructures, particularly for countries suffering from high water stress such as Palestine.

This review showed different studies were conducted on factors affecting the water consumption. The previous results discussed in this chapter will be used again in the following chapters in order to analyze the water demand management in Palestine throughout field studies in two cities in Palestine.

The previous studies showed that the water demand is influenced by several factors, such as the household size, the family income, the age of family members, the level of education, the area of the building and the climate factors. The influence of each factor on water consumption was analyzed. In some cases, the influence is clear and could be used for planning. In other cases, the influence is not clear, because it could be interconnected with other influencing factors.

The chapter presented also the water management in Palestine. This issue is complex, because of the high influence of the occupation on the water management, particularly for the water resources management. The situation is still critical and requires urgent intervention to prevent the catastrophic lack of water for the Palestinian population, in particular in Gaza.

The use of Artificial Neural Networks (ANN) in urban water management was presented; this powerful tool specialized in modeling complex phenomena will be used in this research for the water demand analysis in two Palestinian cities.

In the following chapters, the cities used in this research will be presented successively, the water demand analysis in these cities will be shown and finally the ANN will be used to model the water demand in these cities.

2 Description of the Cases Study Areas: Cities of Ramallah and Khan Younis

2.1 Introduction

This study aims at developing tools, understanding and strategy for the water policy in urban area in Palestine. The use of water in urban area constitutes a strategic issue for Palestinian Authority. In order to analyze this use and to understand its drivers as well as barriers, field studies were conducted in two cities in Palestine. The first city is Ramallah, which is located in the West Bank of Jordan and considered as the administrative center of the Palestinian authority. The second city is Khan Younis, which represents the Gaza strip, it is known for the high population density, the poor economical and environmental conditions and the lack of water resources.

In this chapter, a detailed presentation of these cities will be discussed, in particular the environmental conditions, the socio-economic context as well as the water resources and infrastructures.

2.2 Water issue in Palestine

2.2.1 Palestine's Profile

Palestine is located in Western Asia between the Mediterranean Sea and the Jordan River. The State of Palestine claims the West Bank and Gaza Strip, with eastern Jerusalem as the designated capital with total area of 6,220 km². Since 1994, the Palestinian Authority assumes a partial control of these areas. The Palestinian Authority applied for United Nations (UN) membership in 2011. In 2012 it was granted a non-member observer state status. Situated at a strategic location, the region has a long and tumultuous history as a crossroads for religion, culture, commerce and politics (UN Report 2014).

Figure 2.1 State of Palestine location globally

According to Palestinian Central Bureau of Statistics (PCBS) in 2014, the West Bank has around 2.7 million I habitants, while the Gaza Strip has around 1.8 million inhabitants. Gaza's population is expected to increase to 2.1 million in 2020, leading to a density exceeding 5,800 inhabitants per square kilometer. Table 2.1 presents the annual growth rates in Palestine, 2013-2015. It shows that the annual growth in the West Bank is equal to 2.7%, while in Gaza Strip, it is around 3.4%.

Table 2.1: Annual Growth Rates in Palestine, 2013-2015 (PCBS report 2015)

Year	Palestine	Region	
		West Bank	Gaza Strip
2013	3	2.7	3.5
2014	2.9	2.7	3.4
2015	2.9	2.7	3.4

2.2.2 Climate

According to the Palestinian Meteorological Authority (PMA), for most parts of the year the Palestine Climate remains enjoyable, the winter season includes three months while the hottest months are July and August.

The temperature in summer reaches 35° C, while in winter; it could fall down to zero (Table 2.2). Rainfall occurs mainly from November to February (PMA report 2015).

Table 2.2: Climate indicators of Palestine in 2015 (PMA report 2015)

Indicator	Year	Value
Maximum Temperature C	2015	35
Minimum Temperature C	2015	0
Maximum Relative Humidity (%)	2015	73.0
Minimum Relative Humidity (%)	2015	50.0
Maximum Quantity of Rainfall (mm)	2015	476.4
Minimum Quantity of Rainfall(mm)	2015	79.9

2.2.3 Water in Palestine

According to the "Medium Term Development Palestinian government strategy "2010-2015", the target is to extend the water service to 85% (95% in urban and 65% rural) of the population in 2015, compared to 75% (85% in urban and 55% in rural) in 2010 (MDPS, 2010-2015) (Palestinian Government Report 2015).

According to the Palestinian Water Authority (PWA), the policy target of "National Drinking Water Policy, 2014" states to supply potable and stable water for the whole population by 2020 and to decrease the water losses (PWA report, 2015).

Currently, 87% of the Palestine's urban population and 61% of the rural population have access to public water supply. In-house connections are more widely available in urban area (80%); with a large portion of this water supplied through pipelines (73%), but 76% of the rural households depend on an outside source of water (PWA report, 2015).

According to the World Bank (WB), 60% of Palestinian's population had access to an "improved water source "during the period 2000–2005 (77% urban and 52% rural in 2005). According to the discordance between government department and independent sources, the water stakeholders should consider more carefully users claims and establish indicators to help transparency and answerability (WB report, 2000).

Around 60% of the urban households and 40% of rural households suffer from water supply shortage. Meanwhile, the huge majority of households (92%) think that the government should ensure the water supply (WB report, 2000).

Table 2.3: Percentages of Households in Palestine by the Main Mean of Obtaining Water, 2015

(PWA report, 2015)

Region	Mean of obtaining water					
	Public Water Network	Water Tanks	Domestic Well	Public Tap	Mineral Water and Gallons	Other
Palestine	**93.3**	**38.4**	**18.1**	**0.1**	**13.0**	**4.1**
West Bank	93.4	24.3	27.6	0.0	6.7	0.5
Gaza Strip	93.0	65.4	0.0	0.1	24.9	*11.0

The augmentation of the water supply capacity is required, because of the population increase in Palestine. The service ratio of the potable water is 57%. In addition the time of water supply is less than one hour/day in many locations (PWA report, 2015).

The Improvement of the water supply requires engineering solutions. The lack of metering in most households constitutes a major barrier in the water management, in particular in the identification of the water supply defaults. Where meters were installed, many were damaged.

Table 2.4: Data concerning water resources in Palestine

(Water Statistics in Palestine, 2012-2014)

Indicator	2012	2013	2014
Quantity of Water Available Annually	349.2	365.7	342.7
Quantity Pumped Annually from Groundwater Wells	253.3	262.9	246.3
Quantity of Spring Water Discharged Annually	39.3	39.5	28.2
Quantity of Water Purchased Annually from Israeli Water Company (Mekorot) for Domestic Use	56.6	63.3	63.5
Quantity of Annual Water Supply for Domestic Sector in West Bank	93.9	100.9	102.8

Quantity in Million m3\ Year

2.3 Presentation of the City of Ramallah

2.3.1 Location

Ramallah is the third largest city in Palestine in terms of population and industrial development. It is located in the central West Bank at 10 km in the North of Jerusalem (Figure 2.2). Ramallah is considered as the administrative capital of the Palestinian National Authority (PNA).

The city is rapidly developing, which results in an increase in the pressure on urban infrastructures and services. The rapid expansion of the city is accelerated by the population movement, because of the centralization of the administrative activities in this City.

On the other hand, the city suffers from water shortage, because it is located in the Middle Coast of Palestine.

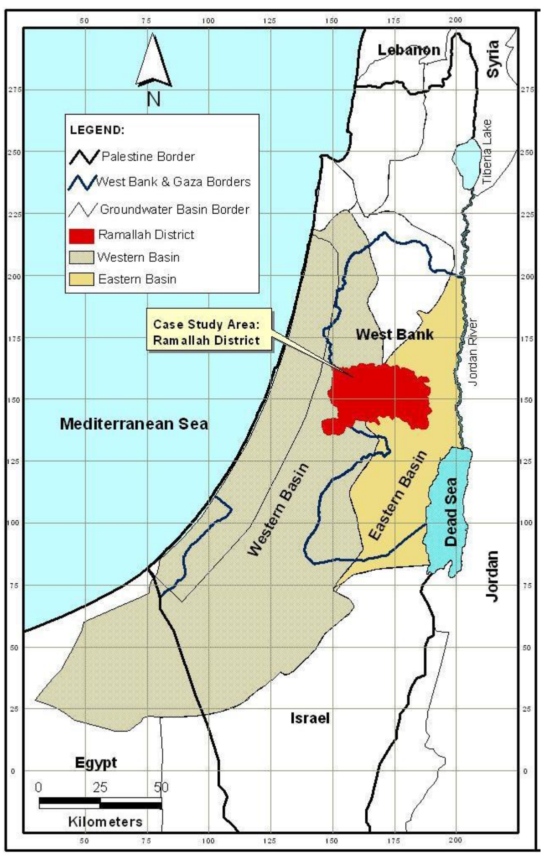


Figure 2.2 Location of the City of Ramallah

2.3.2 Land Use

The City of Ramallah lies on approximately 17,000 dunums (dunum = 1000 m2). According to a master plan developed in the 1960's, the old Ramallah occupies about 5,000 dunums of land. According to the estimates of municipal employees, the old Ramallah in 2015, divided into 30% roads, 40% residential and 30% commercial zones (Table 2.5). The city includes other zones such as a cemetery and public buildings.

Table 2.5: Land distribution in Ramallah (Municpality of Ramallah,2015)

Land distribution	Area (dunums)	Percentage (%)
Total residential area	6,707	39.3
Total commercial area	1,599	9.4
Total industrial zone and establishments	337	2.0
Total transportation: centers and roads (open and suggested)	3,737	21.9
Future development area	2,655	15.5
Agricultural land	814	4.8
Mixed zoning	563	3.3
Total public areas and buildings, and cemetery	650	3.8
Hotels	25	0.1
Total	17,087	100.0

2.3.3 Natural Environment

Ramallah's is about 780-880 m above the sea level. It is located on the edge of the western water divide, which runs from the North to the South of the West Bank.

The water drainage area is divided into two major areas: the first drains to the North and the Northwest, while the second drains to the South. In addition, the eastern side of Ramallah drains to the east towards al-Bireh city.

Ramallah did not have a weather station until 2004. The mean air temperature in Ramallah for that year was 16.8°C. Maximum and minimum temperatures were 21.4°C and 13.4°C, respectively. Absolute minimum and maximum temperatures were observed in February (0.0°C) and May (35.6°C), respectively.

The rainfall quantity in Ramallah in 2004 was 524 mm. This value was below the reported average (689mm) by the Jerusalem Water Undertaking (JWU). The number of rainy days in 2004 was 38 days, and the maximum daily rainfall was observed in November at 52.6 mm. The mean relative humidity in Ramallah is equal to 67%. The evaporation quantity is high, it reaches 2,108 mm. The mean recorded wind speed was between 6.4 and 13.0 km/hour, with some wind gust speed reaching 36 km/hour. The mean sunshine duration was between 4 and 12 hours a day. The lowest sunshine duration reported was in January, and the maximum in June.

2.3.4 Demographic and Socio-Economic data

Most of the data presented in this section come from Ramallah and Al-Bireh districts and the Palestinian Central Bureau of Statistics (PCBS) survey reports. Data were derived from municipal records or the 2014 PCBS census.

2.3.4.1 Demography

According to the 2014 PCBS census, the total population of Ramallah city was 108,017 persons.

The City hosts two refugees camps: Amari and Qaddura camps. Amari camp is located at its outskirts with basic services provided by the United Nations Relief and Works Agency (UNRWA).

Figure 2.3 shows the population distribution in Ramallah in 2015. It shows that 35% of the population is less than 15 years old, and 9% have more than 65%. The population of Ramallah is particularly young.

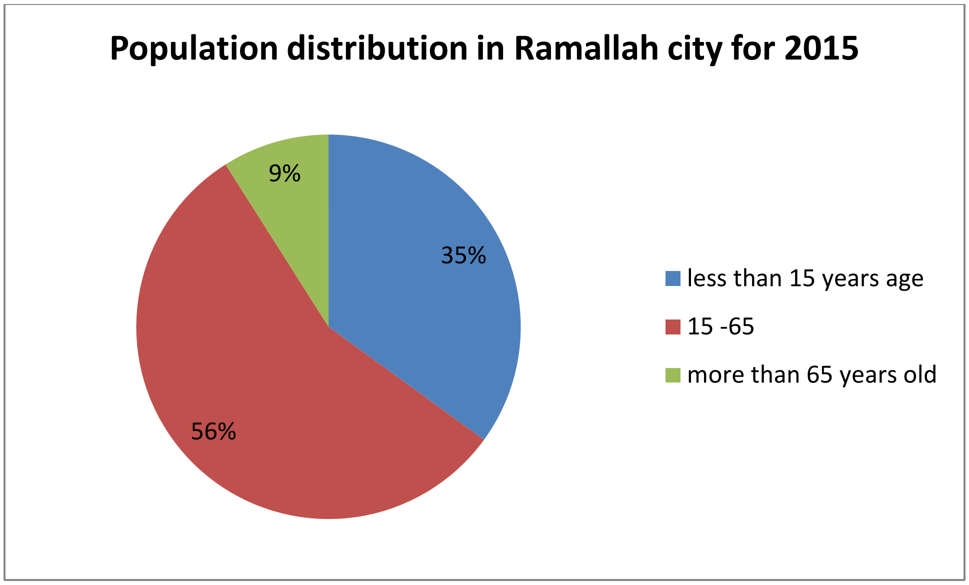


Figure 2.3: population distribution in Ramallah city for 2015 (PCBS report 2015)

The distribution of the population by sex indicates that 52% were females. The proportion of females to males is higher in the 15-30 years age group, at 46% males compared to 54% females, a possible indication of male out-migration for education or work.

60% of the City's population is composed of refugees from the 1948 and 1967 wars. Thus the city's population is heterogeneous and no longer composed primarily of its original inhabitants. This may also explain the City's relatively urbanized character compared to other cities in Palestine. The City's inhabitants are generally well educated. Around 37% are graduated from high schools. The percentage of illiterate population above 10 years old was 3.8%, and 7.9% among males and females, respectively.

Table 2.6: Population in Ramallah city (PCBS report 2012)

Year	Number of population surveyed (Ramallah city)	Number of population surveyed (camps)	Total
1997	39,852	1102	40,954
2004	74,857	2,520	77,377
2008	89,852	4,826	94,678
2012	108,017	7,986	116,003

Source: PCBS report 2012

2.3.4.2 Population Density

The population density of Ramallah is 1,598 inhabitants per square kilometer, based on the 2012 PCBS projections and the total land area of the City (17,087 dunums). Ramallah is thus not a very densely populated city, compared to other cities in the world.

2.3.4.3 Economic Base

According to the PCBS 2012 Census data, many of the establishments in Ramallah employed less than 4 employees per establishment. Nearly all the establishments employed less than 100 workers and hence are considered of small size according the World Bank standards.

In 2014, Ramallah's working population was composed of professionals, managers, legislators, technicians, and assistant professionals (37%); clerks, services and sales workers (30%); elementary workers (7%), while 25% of the working population were engaged in crafts and operating machinery (Figure 2.4). The services sector constitutes the main economic activity in Ramallah

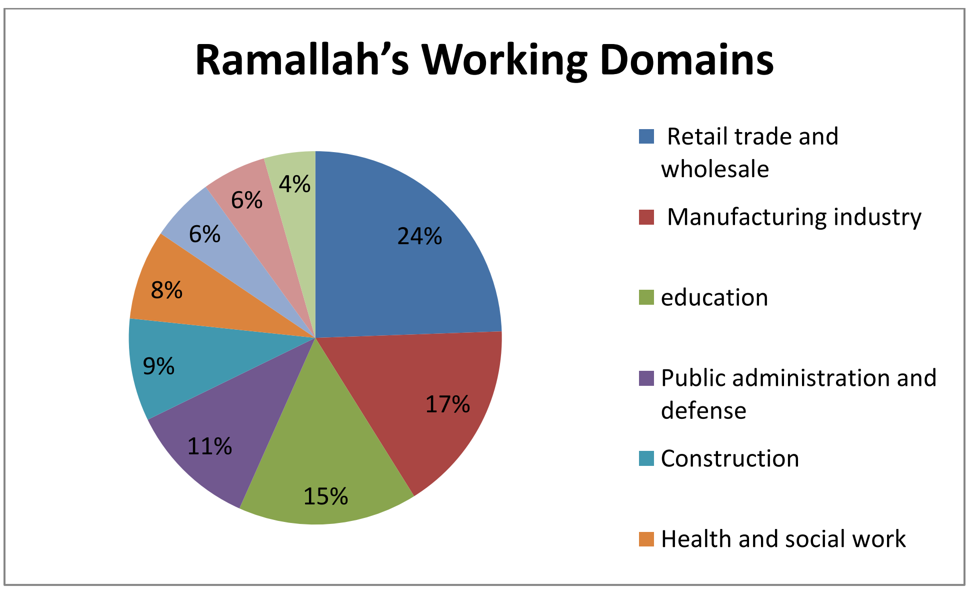


Figure 2.4: working domains in Ramallah city

2.3.5 Water in Ramallah

The evaluation of the water demand of Ramallah is based on the World Health Organization standard concerning the water domestic needs per capita: 150 l/c/d (WHO, 2008). According to the population consensus in 2013 (population of Ramallah =279,730 inhabitants), the domestic water demand is about 15.3 Mcm/yr. The Palestinian Central Bureau of Statistics calculated the per capita daily allocation of water for Ramallah- Al Bireh Governorate from the quantity of water supplied, which is about 13.70 Mcm, with a population of about 279,730, leading to a daily allocation per capita of 134.2 l/c/d. The Palestinians can supply only about 3.4 Mcm/yr from their own resources (PCBS, 2013c); the additional need is purchased from the Israeli water company (Mekorot). This issue is discussed further in the next section.

The main water resources in the West Bank, and region as a whole, are groundwater aquifers. Wells and springs constitute the main sources of water in the West Bank. Surface water and seasonal small rivers running in the Wadis can also be considered as additional water sources which are used mainly for agricultural.

In general, the supply of drinking water in the West Bank can be classified into two main sources: i) wells and springs managed by municipalities, village councils, or water distribution organizations; and ii) water purchased from the Israeli water company (Mekorot), which is distributed by the West Bank Water Department (PWA, 2013).

2.3.5.1 Domestic Water Resources

The renewable water resources in Ramallah and Al-Bireh Governorate consist primarily of groundwater resources, which are located in the Eastern aquifer system. In 2010, around 3.6 Mcm were produced from the Eastern Basin from the springs and wells located in Ramallah & Al-Bireh Governorate (PWA, 2012). The 31 major springs in the Governorate produced 0.7 Mcm in 2010 (PWA, 2012). Two are utilized for domestic purposes; four are utilized for both domestic and agriculture purposes, and the remainders are used for agricultural activities.

Wells produced 2.9 Mcm in 2010 and this water was used for domestic purposes in Ramallah & Al-Bireh Governorate (PWA, 2012).

Palestinians Owned Wells - Ein Samia Well Field: This well field is composed of 5 Palestinian wells owned by the Jerusalem Water Undertaking (JWU) for Ramallah and Al-Bireh Governorate. The JWU is responsible for the management, operation, and monitoring of these wells. Ein Samia wells are located in the eastern aquifer of the West Bank at a depth of 60 to 600 meters below the ground level. The annual extraction from the Ein Samia wells in 2007 was about 3.356 Mcm (PCBS, 2013*d*). The maximum annual extraction capacity of the wells in Ein Samiya is 3.5 Mcm, which is possible only with adequate rainfall during the winter season. A decrease in the productivity of the Ein Samia wells was reported (HWE, 2009).

Purchased Water Resources: These include water purchased from the West Bank Water Department and from the Israeli Water Company (Mekorot):

- West Bank Water Department (WBWD) Wells: These wells are originally Palestinian wells which were drilled during the Jordanian Mandate period, but were confiscated by the Israeli occupation authorities and managed by Mekorot. The WBWD holds the responsibility for the distribution of water to the Palestinian cities, villages and the Israeli settlements inside the West Bank. Four wells are located in the Shibtin area, west of Ramallah city, but only one of them is currently in operation, producing about 0.552 Mcm/yr, (PWA, 2013).

- Israeli Water Company (Mekorot): The sources of water for Mekorot are either from wells inside the green line or inside the West Bank, and recently also from desalination plants constructed inside Israel. The total amount of the purchased water from Mekorot in 2013 was about 10.875 Mcm (PCBS, 2013e) to supply the major parts of Ramallah and Al-Bireh Governorate. This includes the pumped water from the wells which are located in the Palestinian Territory and controlled by Mekorot.

The locations of the Ramallah water resources are shown in Figure 2.5.

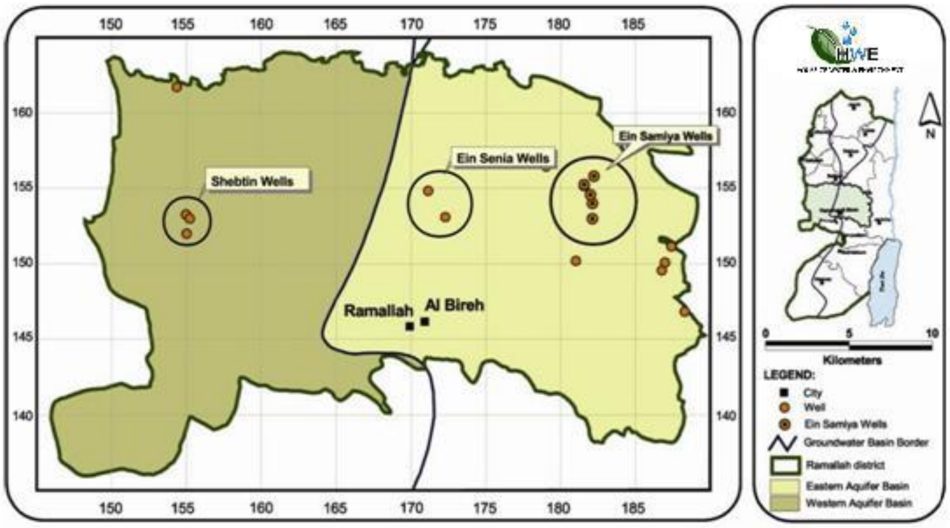


Figure 2.5: Palestinian wells in Ramallah and Al-Bireh Governorate (HWE, 2009)

Springs: There are a total of 31 springs in the governorate, with an annual discharge of 1.714 Mcm (PCBS, 2013). Only 6 of these springs are used for drinking water. The springs are located in villages within the governorate. A number of these springs, such as Ein Arik spring and Al‟Ajool spring are no longer used for drinking, because a water distribution networks have been installed to supply these areas (PWA, 2013).

2.3.5.2 Quantity of Water Supply

The quantity of water supplied for the domestic sector in Ramallah and Al-Bireh Governorate was 2.82 Mcm in 2013 (PCBS, 2013g). This represents the water quantities pumped from wells with domestic permits. No water quantities used for domestic use and pumped from agricultural wells with agricultural permits were recorded. No water quantity discharged from springs and used to supply localities through public networks was recorded. About 10.88 Mcm of water was purchased from Mekorot (which includes the pumped water from the wells which are located in the Palestinian Territory and controlled by Mekorot). Thus, the total quantity of water supplied for the domestic sector in Ramallah and Al-Bireh Governorate was about 13.70 Mcm in 2007 (PCBS, 2013g). It is important to note that in some areas there is a big difference between the water supply and the household use. By taking into consideration the commercial and public consumption and after deducting the loss rate, this difference is high.

In terms of domestic water availability, it is observed that the water deficit as the domestic water supply did not meet the needed quantity of water. Table 2.7 shows set of indicators related to the needed, available and consumed quantities and deficit of water in Ramallah and Al Bireh Governorate in 2010.

Table 2.7: Water indicators in Ramallah and Al Bireh Governorate, 2010

Governorate	Actual Deficit	Water Consumed	Deficit	Water Supply for Domestic Sector	Needed Quantities of Water(1)
	MCM/year	MCM/year	MCM/year	MCM/year	MCM/year
Ramallah & Al-Bireh	16.5	16.2	0.3	11.9	4.6
(1) Needed quantity of water is calculated based on a water supply of 150 l/c.d					

In 2010, the average per capita water consumption in Ramallah and Al-Bireh Governorate was 108 liter/capita/day, which was the second highest of the West Bank Governorates. This is also greater than the average per capita allocation in the West Bank, which is 73 liter/capita/day (PWA, 2012). However, the consumption rate varies from one locality to another in the Governorate. In some cases, this rate is less than 28 liter/capita/day and therefore well below the World Health Organization's (WHO) recommendation: 100 liter/capita/day.

2.3.5.3 Water and Sanitation Infrastructure

In Ramallah and Al-Bireh Governorate, there are two main institutions working in the water sector as suppliers: the Jerusalem Water Undertaking (JWU) and the West Bank Water Department. The served area of JWU extends over 600 km^2 and covers significant parts of Ramallah and Al-Bireh Governorate, which includes Ramallah and Al-Bireh twin cities, 10 other cities/towns, more than 43 villages and 5 refugee camps, and the northern part of Jerusalem. The number of subscriptions is about 51,567 serving a total estimated population of 280,000 people. The other localities in the Ramallah and Al-Bireh Governorate are either supplied by the West Bank Water Department or not yet served (JWU, 2007). About 92% of the governorate is served by a public network, 5% is served by a private system, and about 3% has no piped water supply (PCBS, 2013).

2.3.5.4 Water Tariffs

The Palestine Water Authority (PWA) is officially mandated to establish a unified tariff system and monitor its implementation for the water supply and wastewater utilities. The PWA, with the Ministry of Local Government and various municipalities and institutions, produced the "**Tariff Policy Guidelines**" which interprets the Water Law No. 3 / 2002, with the aim to promote water conservation and ideal consumption. The main goals of the guidelines are to: allow water departments to recover costs for water production and distribution; ensure social equality such that households with low income are able to pay for the tariffs on water consumed for basic needs; and to promote the water conservation such that the tariff increases with the increase in the water usage (PWA personal communication, 2010).

The tariff system classifies consumers according to water usage, and applies the water tariff accordingly (Table 2.8). The price of one cubic meter in level 1 is the same as that in level 2, thus they can be considered as one group. The value of 10 m^3 was selected for level 2, because it corresponds to the basic needs of Palestinian household.

Arguably, the water tariff should allow water suppliers to achieve financial sustainability and foster their ability to cover operational and service costs through the surveillance of the efficiency and quality of performance of public and private suppliers and distributors.

Water tariffs vary significantly between the various Palestinian areas; this discrepancy is due to the adoption of water suppliers, in many cases, to non-objective bases for the determination of prices, where covering the costs is the most important basis for price-setting strategies. Nevertheless, the majority of suppliers suffer from a financial deficit because of their inability to recover the costs. Other related factors, such as the lack of control of the costs and the weaknesses in obtaining receipts, contribute to the inability of suppliers to recover the costs of providing the locals with water. Additionally, other relevant factors were not considered such as the average income, the population size and their consumption abilities, and the marginal costs and utility of the water prices, which could have contributed to the principles of social justice and economic efficiency.

Table 2.8: Water tariff structure

Type of Use	**Levels of Consumption (m^3)**				
	Level 1	**Level 2**	**Level 3**	**Level 4**	**Level 5**
	<5	**5.1 – 10**	**10.1 – 20**	**20.1 – 30**	**>30**
Domestic	1.0	1.0	1.2 – 2.0	2.0 – 2.5	2.5 – 3.0
Public Institution	1.0	1.0	1.5 – 2.0	2.0 – 2.5	2.5 – 3.0
Commercial	2.0 – 3.0	2.0 – 3.0	2.5 – 4.0	2.5 – 4.0	2.5 – 4.0
Industrial	2.0 – 3.0	2.0 – 3.0	2.5 – 4.0	2.5 – 5.0	2.5 – 6.0

Source: PWA, personal communication.

2.4 Presentation of the City of Khan Younis

2.4.1 The Gaza Strip Background

The Gaza Strip (approximately 365 km^2) hosts more than 1.8 million people living in five governorates (Figure 2.6). The population is projected to grow rapidly; it could reach 3.7 million inhabitants by 2035. Currently, the Gaza Strip has the sixth highest population density in the world. The population is young, with about 50% of the population under 18 years. Over 74% of the population is registered by the United Nations Relief and Works Agency (UNRWA) as refugees.

The demography of the area is linked to the political conflict, which has limited the movement of goods and people in and out of Gaza, increasing the poverty and unemployment rates. This complex political and socio-economic context resulted in a significant pressure on the environmental resources and leaded to serious deterioration in both the water quality and quantity. We observe (i) severe water shortage, (ii) deterioration of the water quality due to the over-extraction of the coastal aquifer, (iii) increase in the salinity of the groundwater resources, because of the seawater intrusion and (iv) large pollution of the aquifer, because of the lack of sanitation network and high increase of the population. The United Nations report 2020 says that "Gaza will not be livable in just few years if the current situation continues".

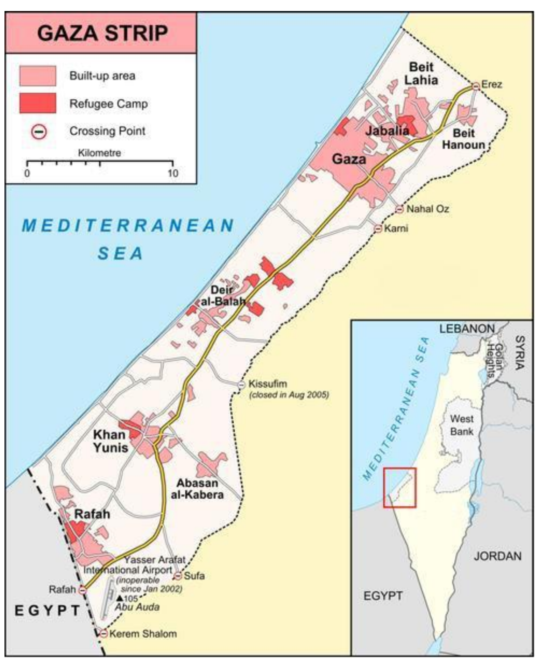


Figure 2.6: Governorates of the Gaza Strip Map

In addition to a lack of water, the situation is further exacerbated by damaged or destroyed infrastructure due to the ongoing conflict with Israel. For example, during the Operation Cast Lead in 2008/2009 at least 11 major wells and over 30 kilometers of water networks were destroyed.

The ongoing blockade of the Gaza Strip did not allow the materials supply for the reconstruction of damaged infrastructures. Other major factors affect the water quantity and quality in Gaza, in particular lack of electricity, lack of funding for large scale desalination plants, contamination of the aquifer, contamination of seawater, lack of experience and lack of economic resources. In addition, there is a significant tension between Israel and the Palestinians over ownership of the water rights and adherence to agreements over water management. These factors present tremendous challenges for the population to access to basic clean water service.

As a result of the growing population, the domestic water demand is projected to grow from 91 million m^3/year to 199 million m^3/year in 2035. In this context, the World Health Organization (WHO) has highlighted the gaps and needs for sufficient safe water, sanitation and reinforced hygiene, and has emphasized them as a priority for reducing morbidity and mortality in the Gaza Strip.

Table 2.9 illustrates the overall groundwater abstraction for each governorate in 2011 (CMWU, 2011).

Table 2.9: Amount of water uses in Gaza Strip (CMWU, 2011)

North Governorate (m^3)	22,030,009
Gaza Governorate (m^3)	33,226,214
Middle Governorate (m^3)	12,524,944
Khan younis Governorate (m^3)	13,677,696
Rafah Governorate (m^3)	7,866,840
Total (m^3)	89,325,703
Mekorot Water (m^3)	4,864,880
Water abstracted from the ground water (m^3)	84,460,823
UNRWA wells abstractions (m^3)	2,269,361
Agricultural wells abstractions (m^3)	80,000,000
Total water requirement from all sources (MCM)	~166.7

Gaza Strip is underlined by a shallow aquifer, which is contiguous with the Israeli Coastal Aquifer to the north. Gaza is the downstream user of the Coastal Aquifer system. The Gaza Aquifer has a natural recharge rate of approximately 95 million cubic meters (MCM) of water per year from rainfall, infiltrated irrigations, and lateral inflow of water (CAMP, 2000; Nasser, 2003).

Fresh water has become a scarce commodity due to the over exploitation and the pollution of water. The large increase in the population and domestic needs has led to the deterioration of surface and sub-surface water. The importance of groundwater for the existence of human society cannot be overemphasized. Besides, it is an important source of water for the domestic and industrial sector. Population growth and urban horizontal expansion after 2005 (Israeli withdrawal) have persistently raised the demand for water supply and consequently increased the exploitation of groundwater in the Gaza strip. Approximately 90% of the domestic water in the Gaza Strip comes from the shallow coastal aquifer via 10% licensed municipal wells. Most of the farmers use private unlicensed wells (Sharma, 2008; Al-Najar, 2010).

Underlying Gaza‘s geographical, political, social, and economical positions, there are different local, national and international factors that make it difficult to break the long poverty cycle. Gaza's residents have been using possible means of saving their food needs. Urban water management is one of the most persistent approaches for supplying water in the Gaza Strip. The quantity and quality of drinking water suffered from large deterioration in the past two decades due to the excessive use of domestic water especially in the semi urban areas (Mushtaha, 2006; Al-Najar, 2010).

2.4.2 Khan Younis City

Khan Younis is the second largest urban area in the Gaza Strip after Gaza. It is located in the southern part of Palestine, close to Egypt. The total area is about 117 km^2. This area includes the surrounding cities such as Qarara, Bani Suhaila and Abasan. The agricultural and agroindustry sectors constitute the main economic activity in Khan Younis. They are also responsible of the the overuse of ground water and the water pollution by fertilizers and pesticides.

In 2012 Khan Yunis had the highest unemployment rate in Palestine. Although Khan Younis lies only four kilometers (2.5 miles) east of the Mediterranean Sea, its climate is semi-arid with temperature of 30 degrees Celsius in summer and 10 degrees Celsius maximum in winter; the annual rainfall is approximately 260 mm (10.2 in).

Khan Younis governorate is composed of 7 administrative municipalities' districts including 54 different distribution zones. In 2013, the population of Khan Younis was about 369,048 inhabitants (PCBS, 2013).

2.4.3 Land Use

Figure 2.7 shows the satellite image of Khan Younes. The cultivated area in Khan Younis is about 37.3 km^2; 10.7 km^2 are cultivated via green houses, 13.7 km^2 are used to seasonal crops in grain open fields; 12.9 km^2 are dedicated to fructification cultivation. This means that 38% of Khan Younis municipals authorities areas are cultivated land and 32% of the total governorate areas are cultivated land. Besides, about 18.1 km^2 are arable lands. This means that 18.1 km^2 are considered agricultural and arable lands occupying about (15.6 %) of Khan Younis governorate lands. Khan Younis governorate master plan for 2013 identified a build area of (23,000) dounms, which represents 23% of the total master plan area, compared to 950 dounms which are dedicated for industrial and commercial activity (1% of the total area). Khan Younis is mainly an agricultural governorate.

Figure 2.7: Khan Younis governorate satellite image. (MOLG, 2012).

2.4.4 Demographic and social characteristics

In the census of 1997, Khan Younis Governorate population reached around 175,000 inhabitants, where as in 2007, Khan Younis Governorate population reached 270,979 inhabitants with a growth rate of 4.23%. It represents 19% of the Gaza Strip total population (PCBS, 2013). PCBS estimated the population of Khan Younis Governorate to 369,048 inhabitants.

2.4.5 Water sources, quality and access

Khan Younis has 295 wells. But only 38 wells are used for domestic supply with about 15,001,990 m^3 while the meter readings accounted for 9,989,310 m^3 in 2013. It is obvious that the unaccounted water is equal 33% (Khan Younis Governorate municipalities, 2013). According to Khan Younis water engineers, this low efficiency is due to: 1) The low efficiency of the water network, 2) The illegal connections to the water network.

2.4.5.1 Water from the coastal aquifer

Water resources in Gaza strip are essentially restricted to the coastal aquifer, which extends from Haifa in the North to Sinai desert in the South to Hebron Mountain in the East. Water from the aquifer is pumped from deep wells. The population of Khan Younis uses aquifer for domestic, agricultural and industrial needs. The aquifer is recharged by different water sources, such as rainfall (primary source), water network leakage, wastewater leakage, agricultural return flow and recharge storm water ponds. The extraction from the coastal aquifer is estimated to 170 million m^3/year (2010), whereas the annual sustainable yield of the aquifer within the geographical boundary of Gaza strip is widely quoted as 55 million m^3/year. The water level of the aquifer decreases by 20-30cm per year. The United Nations has warned that the aquifer might be unusable in 2016 and the damage will be irreversible by 2020.

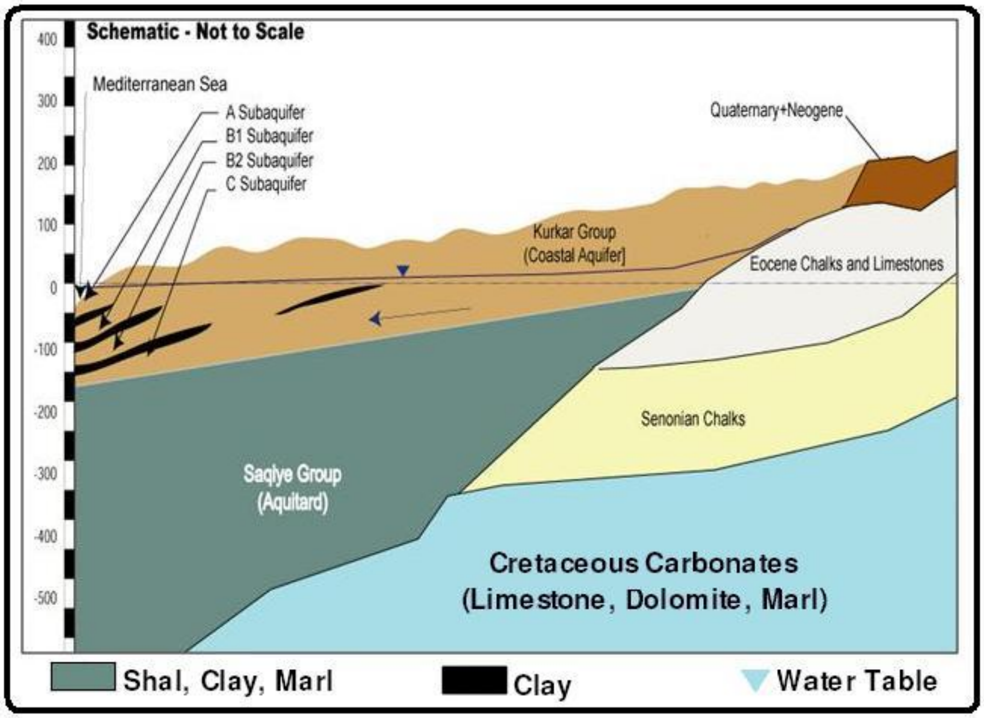


Figure 2.8: Schematic structure of aquifers in the Gaza Strip (Source: Dan, Greitzer 1967)

2.4.5.2 Desalinated water

In order to address the increasing salinity in the water supply, the Palestinian Authorities have pursued desalination for potable water. The prospects for seawater desalination capacity was estimated to 11 million m^3/year in 2012, increasing to 55 million m^3/year in 2017 and to 130 million m^3/year in 2035.

Water desalinated is obtained through different sources: there are seven public desalination facilities run by the CMWU. In addition there are at least 40 small scale private plants and more than 20,000 reverse osmosis (RO) housing units, which are often unregulated, from which most of the available desalinated drinking water is produced. Typically, the water feeding into these units is chlorinated piped water that is stored in rooftop storage tanks. The quality of water desalinated from these units varies. Domestic desalination units do not incorporate any treatment (such as mineralization or disinfection through UV or chlorination); filters must be regularly changed to reduce contamination. A substantial proportion of the Gaza population obtains drinking water from unregulated sellers of desalinated water.

Drinking water from desalination plants is distributed by cittern tracks. 83% of the population use water from citterns as the primary household water source. According to a water quality monitoring campaign conducted in 2009, the water from desalination plants is good in terms of chemical and microbiological content.

2.4.5.3 Bottled water

Bottled water available in Khan Younis is produced locally (using the aquifer as a source) or imported from the West Bank, Israel, Jordan, Turkey and Egypt. It is estimated that 80% of the total amount of bottled water consumed in Khan Younis is imported, according to information provided by managers of major stores in Khan Younis (personal communication). This percentage varies from 30 to 90% depending on the area and the economic status of the population. In theory, bottled water produced outside Gaza is tested and monitored before importation.

2.4.5.4 Rainwater Harvesting

The rainwater harvesting, commonly practiced in the West Bank, is not popular in Khan Younis. However, this could potentially be considered as a means of supplementing household water supplies. Rainwater is very low in mineral content, which may have a long-term health effect. There is also risk of water contamination during handling and storage of water in the households. A study conducted in 2008 concluded that residents of Khan Younis are willing to adopt on-site rooftop rainwater filtration where free land is available, but financial incentives from local authorities is necessary to make this alternative more attractive.

2.4.6 Water usage categories

Domestic water usage in Khan Younis can be divided into the following categories:

- Consumption (drinking and cooking)
- Hygiene (including basic needs for personal and domestic cleanliness)
- Amenity use (for instance car washing, lawn watering)
- Productive use (e.g. animal watering, construction and small-scale horticulture)

The two first categories have direct consequences for human health, both in relation to physiological needs and in the control of diverse infectious and non-infectious water-related disease. The third category is not directly affecting human health. Water used in production, however, may be critical for the urban poor sustaining livelihoods and therefore has considerable indirect influence on human health.

In addition to the proposed categories mentioned above, we have to add the agriculture activity, which consumes a large amount of water.

2.4.7 Khan Younis Water Distribution System Situation

The efficiency of the water distribution system in Khan Younis governorate is around 66%. This low efficiency is due to (i) the degradation of the water infrastructure and (ii) the high illegal connections to the water system. The Water distribution system in Khan Younis is composed of the main transmission pipes, distribution pipelines, ground water storage tanks, wells, booster pump stations and control valves. The supply scheme in Khan Younis is an intermittent water distribution system which is prevalent in Gaza Strip, where the water distribution cycle is completed every 48 hour to 72 hour in other areas; this is due to the insufficient water infrastructure and the scarce water sources. This system is controlled by manual operated valves located at the main feeders in the water network which may participate in the degradation of the network efficiency.

The quantity and quality are the main problems of drinking water in Khan Younis governorate. The shortage of water in Khan Younis municipalities are mainly caused by the distribution system losses which are estimated by (33 %) of the abstracted water quantities by municipalities. Over (99.7%) of Khan Younis governorate residents have access to water services, but unfortunately do not receive appropriate water quantities or qualities.

The water distribution system in new towns is in good conditions. It was installed 15-20 years ago. Most of the pipes in the network are made of steel, UPVC, and polyethylene. Unfortunately, the municipal water network services in Khan Younis city is in poor state. It was installed 25-45 years ago. The pipes in the network are made of spastoes, steel, UPVC and polyethylene.

2.5 Conclusion

This chapter presented the cities of Ramallah and Khan Younis, the two cities are used in this research in order to analyze the urban water demand in Palestine. For each city, the chapter presented different issues related to the water demand, such as land use, demography, social development climate, water management, water resource and water distribution system.

The City of Ramallah suffers from water shortage, which is mainly attributed to the Israeli control of the water resources in the West Bank; the City has to import around 65% of its water demand from Mekorot (Israeli Water Company). The City also suffers from population growth, an aged water infrastructures as well as a lack of water consumption metering.

The City of Khan Younis suffers from high water shortage, which is mainly attributed to the high pollution of the water resources, the high deterioration of the water infrastructure, due to the destructive war as well as the long Israeli blockade of the Gaza Strip. The City also suffers from a high population growth as well as a highly deteriorated social condition.

In the next chapter, an analysis of the water demand in these two cities will be discussed, which will be based on collected data from both cities in terms of water demand.

3 Data Collection and Global Analysis of Water Consumption

3.1 Introduction

A clear understanding of water use patterns and the factors that affect the water consumption is required for an effective management of the water supply and the establishment of the water public policies. Water use is influenced by different factors such as seasonal variability, water availability, supply restrictions, pricing, household characteristics and users attitudes regarding water conservation.

This chapter presents the data collection related to the municipal domestic water consumptions of Ramallah and Khan Younis, it provides a global analysis of technical, physical, socio-economic and climatic factors, and the data will then be analyzed using statistical tools.

A concrete understanding of the water consumption behavior is necessary to design efficient and effective water strategy. Despite global efforts to identify the factors that affect domestic water consumption, those related to the domestic water use in Palestine have not been sufficiently studied, particularly in districts that have developed access to improved water supply. To address this gap, this chapter analyzes the water use by 100 households in Ramallah and in Khan Younis.

3.2 Ramallah City

3.2.1 Global Overview of the Water Consumption

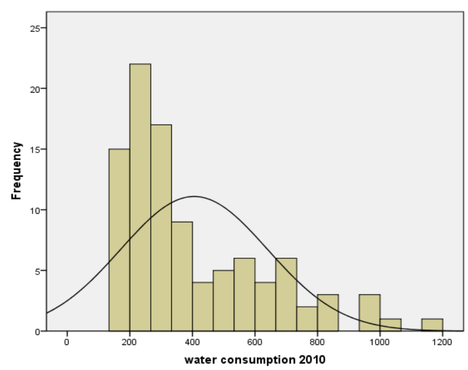
The data collected for Ramallah concerned the water consumption of 100 habitation units (houses or dwellings) in the period 2010 – 2013. It includes the monthly water consumption provided by the water authority. The yearly demographic data was obtained from the State Statistical Authority (PCBS) and then transformed into monthly basis.

Figure 3.1 shows for each year the distribution of the water consumption in the period (2010-2013). Table 3.1 summarizes the statistical characteristics: minimum, maximum, mean and standard deviation. We observe that the mean value of the water consumption varies between 409 and 434 m^3 /month, while the minimal consumption varies between 158 and 178 m^3

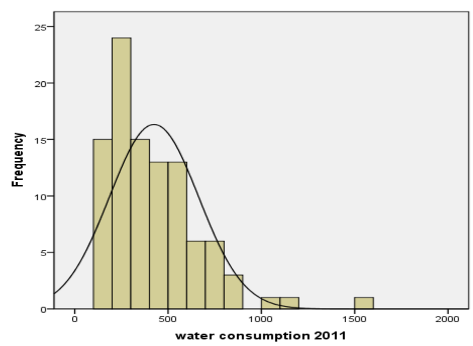
/month. The maximum consumption varies between 1106 and 1542 m^3/ month. We observe an important variation of the monthly consumption during the year. In 2012, it varies between 159 and 1542 m^3/month. This high amplitude of variation will be discussed later.

Table 3.1: the statistical parameters for yearly consumption water in Ramallah (m^3)

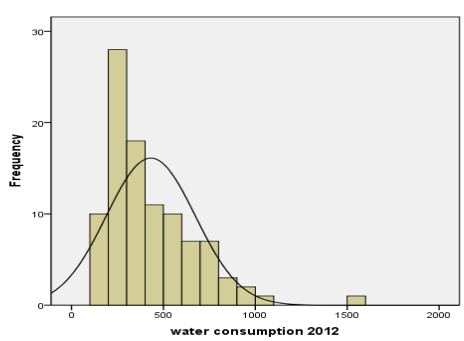
	Max	Min	Mean	Std. Deviation
2010	1184	160	409	233
2011	1508	158	427	238
2012	1542	159	434	242
2013	1016	178	420	185



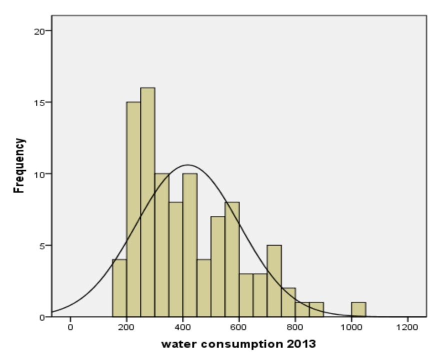
The distribution of water consumption m^3 in 2010



The distribution of water consumption m^3 in 2011



The distribution of water consumption m^3 in 2012



The distribution of water consumption m^3 in 2013

Figure 3.1: the distribution of water consumption during the period 2010-2013 (Ramallah)

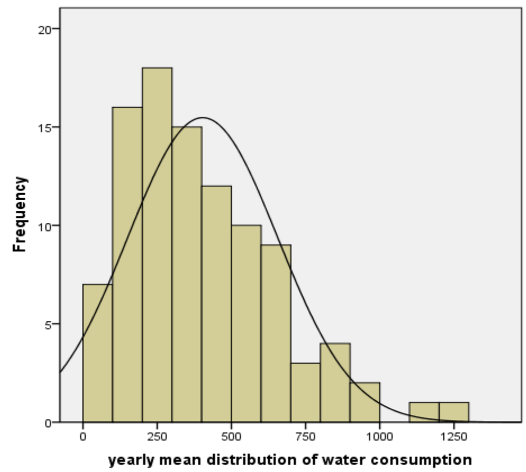


Figure 3.2 : The yearly mean distribution of water consumption during the period (2010-2013)

3.2.2 Physical Characteristics of housing units

In the following sections, an analysis will be presented of the physical characteristics of the housing units used in this study; the analysis concerns the following parameters:

1. Type of Building
2. Surface area
3. Garden area
4. Swimming pool volume

3.2.2.1 Type of Building

Figure 3.3 shows the repartition of habitation units into dwellings and houses units, it was observed that dwelling units represent 42% of the analyzed units, while houses represent 58%.

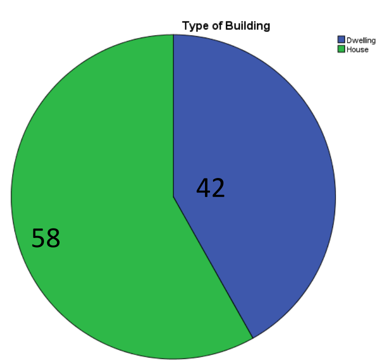


Figure 3.3:Type of building (percentage)

3.2.2.2 Surface area

Figure 3.4 illustrates the distribution of building units according to their surface area. The maximum surface area is equal to 720 m^2, while the minimum is equal to 90 m^2; the average is equal to 245 m^2 with a standard deviation of 134 m^2.

For dwelling units, the maximum surface area is equal to 290 m^2, while the minimum is equal to 90 m^2. For the houses units, the maximum surface area is equal to 720 m^2 and the minimum is equal to 160 m^2.

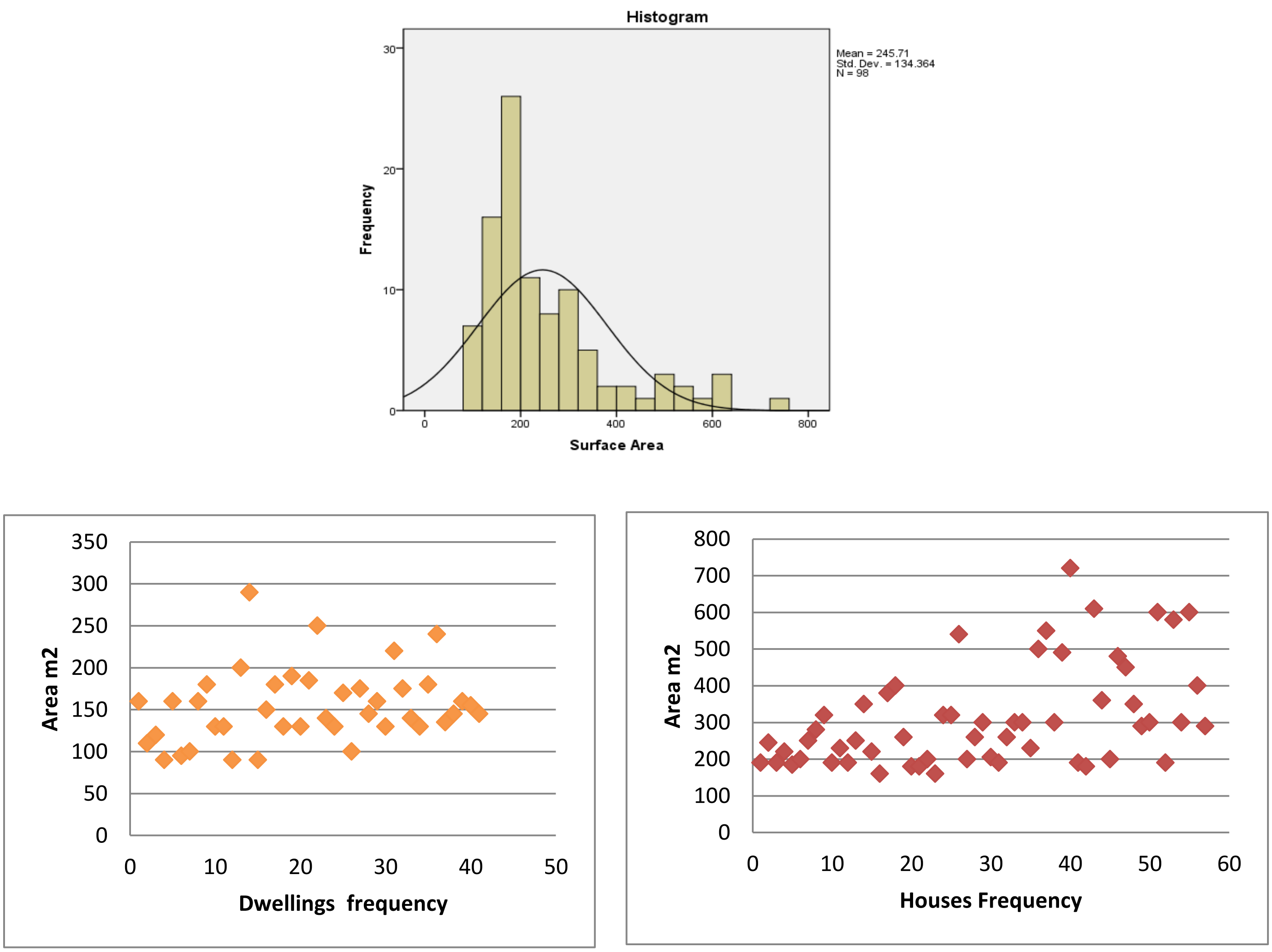


Figure 3.4 : Distribution of building according to their surface area

3.2.2.3 Garden area

The total number of buildings with garden is 24 (74 habitation units do not have gardens).

Figure 3.5 shows the distribution of buildings according to the garden area. The maximum garden area is equal to 250 m^2, the minimum is equal to $60m^2$ and the average is equal to 137 m^2 with a standard deviation of 73 m^2. The second part of figure shows the relationship between the surface area and garden area for dwellings and houses. A large dispersion was found in the relationship between the habitation unit surface and the surface of the garden, while no clear correlation was noticed between these parameters.

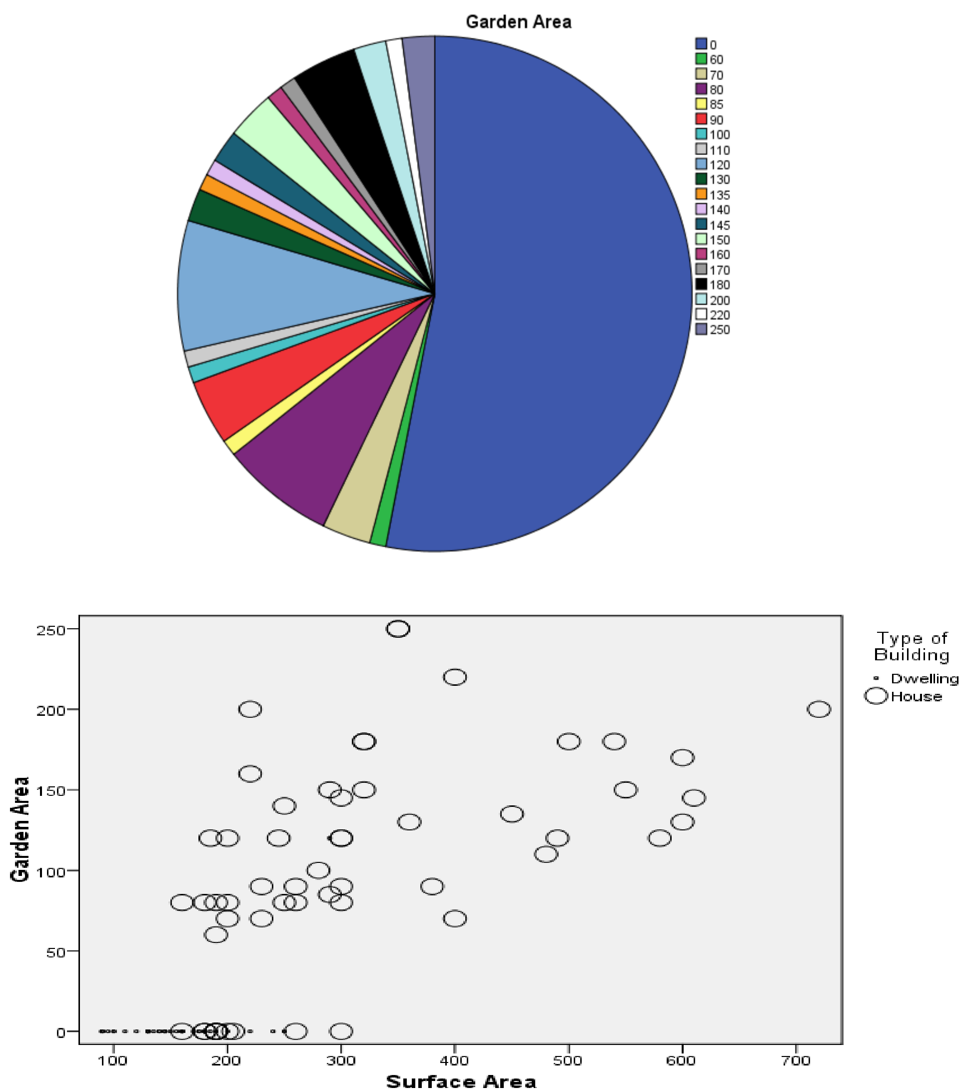


Figure 3.5 : Relationship between habitation units and the garden surface

3.2.2.4 Swimming Pool Volume

Only 8 houses have a swimming pool. Figure 3.6 shows the distribution of building according to their swimming pool volume, the maximum swimming pool volume is equal to 160 m^3, the minimum is equal to 60 m^3 and the average is equal to 115 m^3 with a standard deviation of 38 m^3.

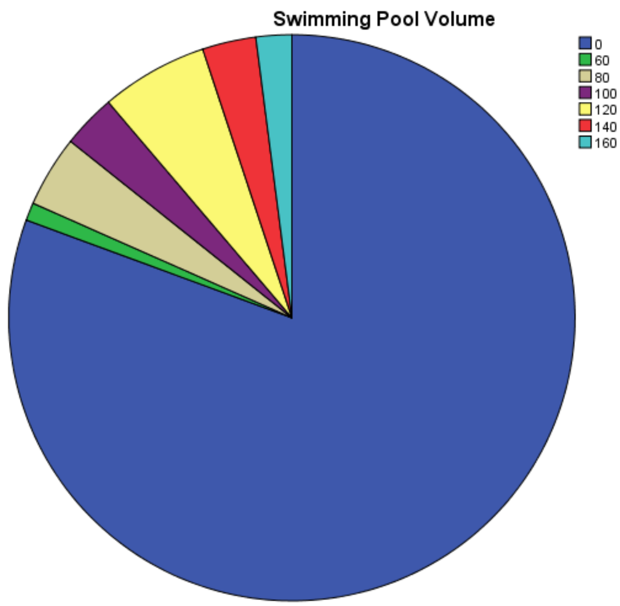


Figure 3.6 : Distribution of building according to their swimming pool volume

3.2.2.5 Correlation Analysis

The Pearson correlation Matrix has been used for the analysis of the relationship between the physical parameters of the habitation units used in this study. Table 3.2 presents the matrix of correlations between the following parameters: type of building, surface area, garden area and swimming pool volume, a significant positive correlation between the type of building, the habitation surface area, the garden area and the swimming pool volume was noticed, This indicates the increase in the habitation surface area is accompanied by an increase in the garden area and in the swimming pool volume.

Table 3.2: Pearson correlation Matrix between physical parameters of the habitation units

		Type of Building	Surface Area	Garden Area	Swimming Pool V.
Type of Building	Pearson Correlation	1	0.665**	0.472**	0.328**
	Sig. (2-tailed)		0.000	0.000	0.001
	N	98	98	98	98
Surface Area	Pearson Correlation	0.665**	1	0.655**	0.744**
	Sig. (2-tailed)	0.000		0.000	0.000
	N	98	98	98	98
Garden Area	Pearson Correlation	0.472**	0.655**	1	0.745**
	Sig. (2-tailed)	0.000	0.000		0.000
	N	98	98	98	98
Swimming Pool Volume	Pearson Correlation	0.328**	0.744**	0.745**	1
	Sig. (2-tailed)	0.001	0.000	0.000	
	N	98	98	98	98

**. Correlation is significant at the 0.01 level (2-tailed).

3.2.3 Socioeconomic indicators

For the study area, the following socioeconomic indicators were collected:

1. Number of people living in the habitation unit
2. Education level of household
3. Annual family income,
4. Numbers of cars per habitation unit.

3.2.3.1 Household size

The household size is a significant indicator for water consumption. Figure 3.7 shows the distribution of the buildings according to the household size. The maximum household size is equal to 29, while the minimum is equal to 4 and the average is equal to 10.5 with a standard deviation of 4.2. For dwelling units, the maximum household size is equal to 10; the minimum is equal to 4. For houses units, the maximum household size is equal to 29, while the minimum is equal to 6.

Figure 3.7 shows the repartition of the habitation units according to the household size. The following repartition was observed:

- 49 % are between 4 - 8 members
- 20 % are between 9 - 12 members
- 31 % are more than 12 members

Around half of household size is included in the range 4 to 8 members. In 2013, the average household size in the West Bank was equal to 5.9, while in Gaza strip, it was equal to 5.8.

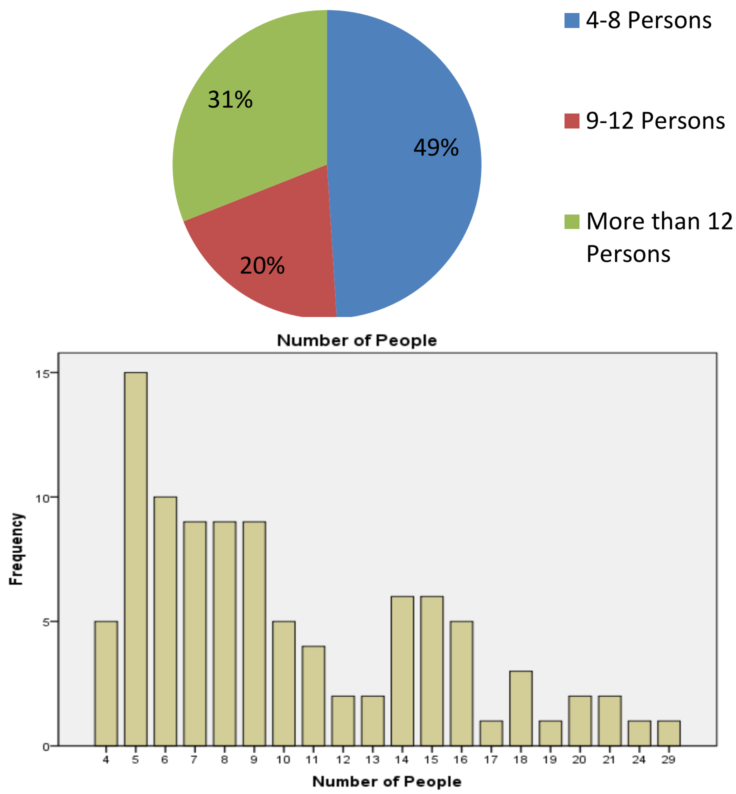


Figure 3.7 : Repartition of the habitation units according to household size

3.2.3.2 Educational Level

The repartition of the habitation households according to their education level is summarized in figure 3.8. The following repartition was observed:

- 30% without higher education certificate
- 40 % undergraduate level with BA degree
- 20% graduated level with Master and Doctorates degree

This reparation showed that around 60 % of households are graduated from the higher education.

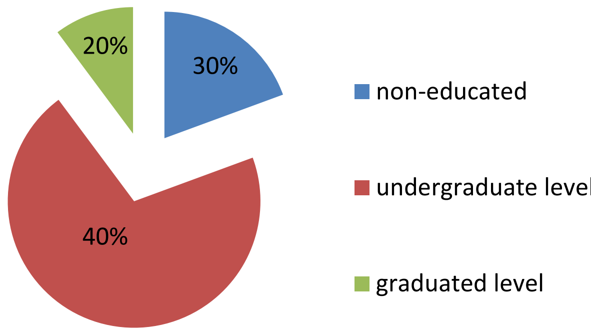


Figure 3.8 : Distribution of the households according to the education level

3.2.3.3 Family Income

Table 3.3 and figure 3.9 show the repartition of the households according to the family annual income. According to expert suggestion and the level of poverty in Palestine, the income level was organized into 5 categories: from low income (less than 10 000 $/year) to high income (more than 10 000 $/year). It was found that around42% of the household have a yearly income between 11 000 and 20 000 $, while around 14% have an income inferior to 10 000 $ and 17 % an income exceeding 31 000 $. The poverty line in Palestine is around 6 000 $ for a family composed of 2 adults and 3 children.

Table 3.3: Categories of households according to their income

[1]	Less than 10,000 $	14%
[2]	11,000 to 20,000 $	27%
[3]	21,000 to 30,000 $	42%
[4]	31,000 to 40,000 $	11%
[5]	More than 40,000 $	6%

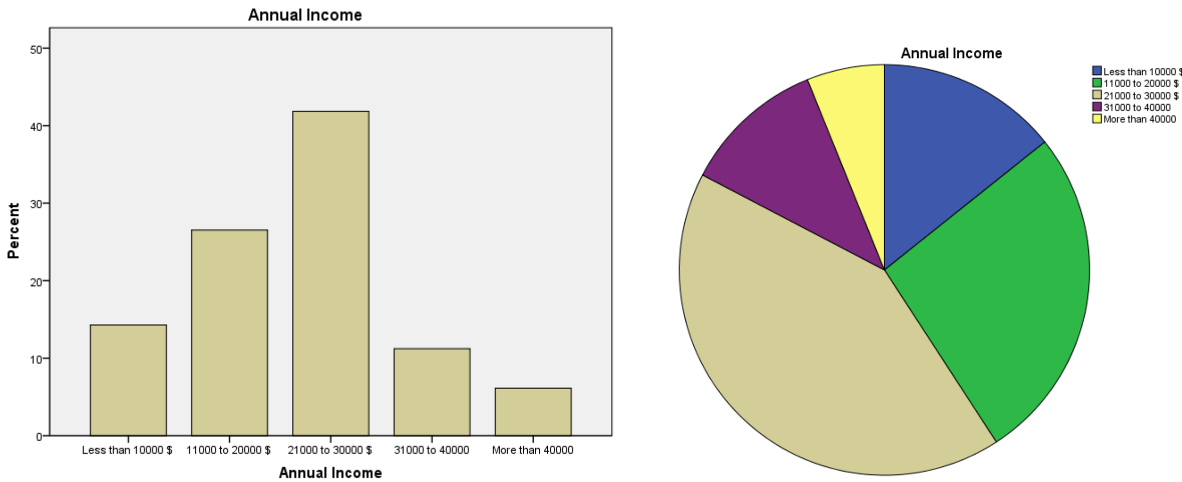


Figure 3.9: Distribution of households according to their Annual Income

3.2.3.4 Numbers of cars

Figure 3.10 illustrates the repartition of the cars number per household, the maximum number of cars was found 5, the minimum was equal to 0 and the average was equal to 1.0 with a standard deviation of 1.15. Around 32 of household do not have cars, while 38% have only one car. Only, 30% have a number of cars exceeding 2.

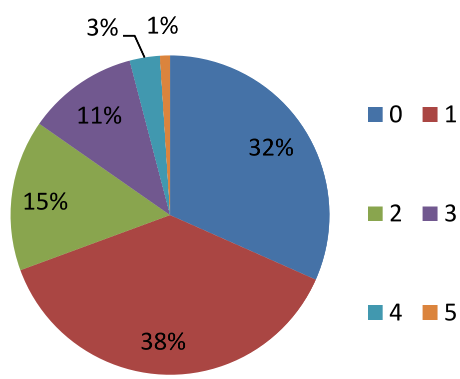


Figure 3.10 : Distribution of households according to cars number

3.2.3.5 Correlation Analysis between physical and socioeconomic parameters

Table 3.4 provides the correlation matrix of both physical and socioeconomic indicators. A significant positive correlation between the type of building and number of people and surface area was noticed, which shows the increase in the number of people is accompanied by an increase in the surface area. On the other hand, there was no significant correlation between number of cars, the education level and the annual income.

Table 3.4: Pearson correlation Matrix between physical and socioeconomic parameters

		Type of Building	Surface Area	Garden Area	Swimming Pool Volume	Number of People	Education Level	Annual Income	Number of Cars
Type of Building	P. C.	1	0.665**	0.472**	0.528**	0.962**	0.613	0.628	0.544
Surface Area	P. C.	0.665**	1	0.655**	0.744**	0.871**	0.834	0.647	0.683
Garden Area	P. C.	0.472**	0.655**	1	0.745**	0.305**	0.890	0.509*	0.396
Swimming Pool Volume	P. C.	0.528**	0.744**	0.745**	1	0.561	0.820	0.434	0.433
Number of People	P. C.	0.962**	0.871**	0.305**	0.561	1	0.194	0.490	0.676
Education Level	P. C.	0.720	0.834	0.890	0.820	0.194	1	0.936	0.478
Annual Income	P. C.	0.613	0.647	0.509*	0.434	0.490	0.936	1	0.366
Number of Cars	P. C.	0.628	0.683	0.369	0.433	0.676	0.478	0.366	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

3.2.4 Climate indicators

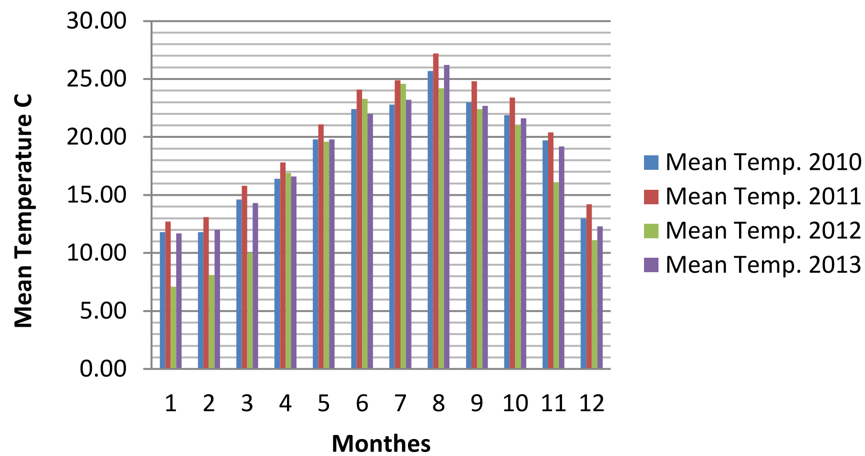
The climate effect was analyzed through the following parameters:

1. Mean Temperature
2. Mean Humidity Percentage
3. Mean Rainfall

3.2.4.1 Temperature

Figure 3.11 shows the variation of the monthly mean temperature in the period 2010 – 2013 in Ramallah. A good concordance in the temperature profile for the years 2010, 2011 and 2013 was found: the minimum was around 12°C, the maximum was around 26° C. The temperature in 2012 was lower: the minimum was around 7°C; the maximum was around 25°C.

The maximum mean temperature was equal to 27.2 in 2011, the minimum was equal to 7.1 C in 2012 and the average was equal to 18.51 C.



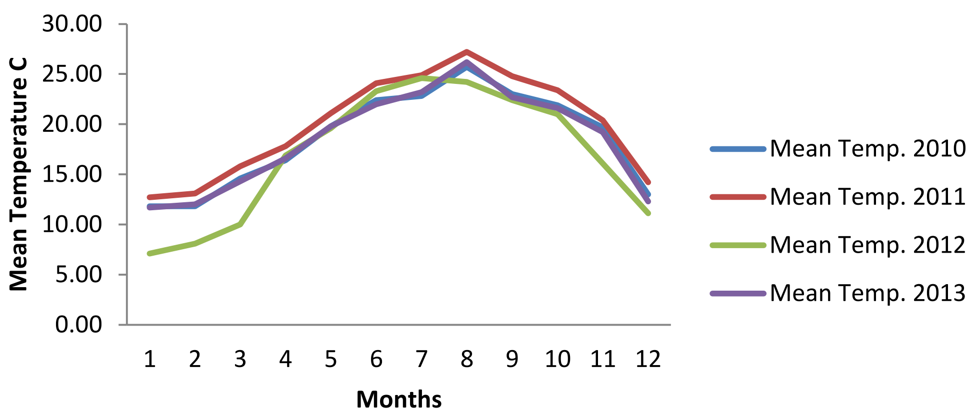


Figure 3.11: Monthly Mean temperatures in Ramallah (2010 – 2013)

3.2.4.2 Humidity

Figure 3.12 shows the variation of the mean humidity in the period 2010 – 2013. The maximum mean humidity was equal to 84% in 2013, the minimum was equal to 44% in 2012 and the average was equal to 66%. In 2012, the humidity level was lower than that in 2010, 2011 and 2013. This observation is coherent with the low level of temperature in this year.

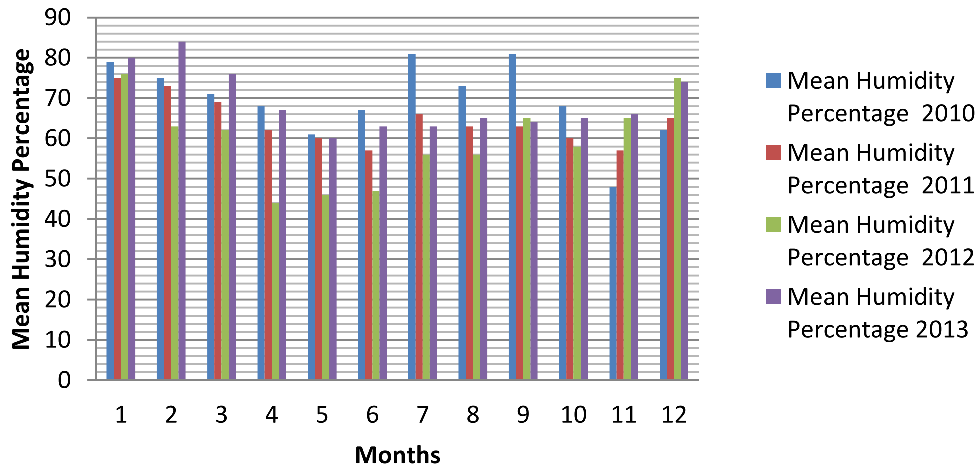


Figure 3.12: Variation of humidity in Ramallah

3.2.4.3 Rainfall

Figure 3.13 shows the variation of the rainfall in the period 2010 – 2013 in Ramallah. The rainfall concerns the period from November to March, low rainfall occurs in October, April and May, there is no rainfall in summer, the maximum rainfall occurred in 2010 and 2013 in February; it attained around 250 mm.

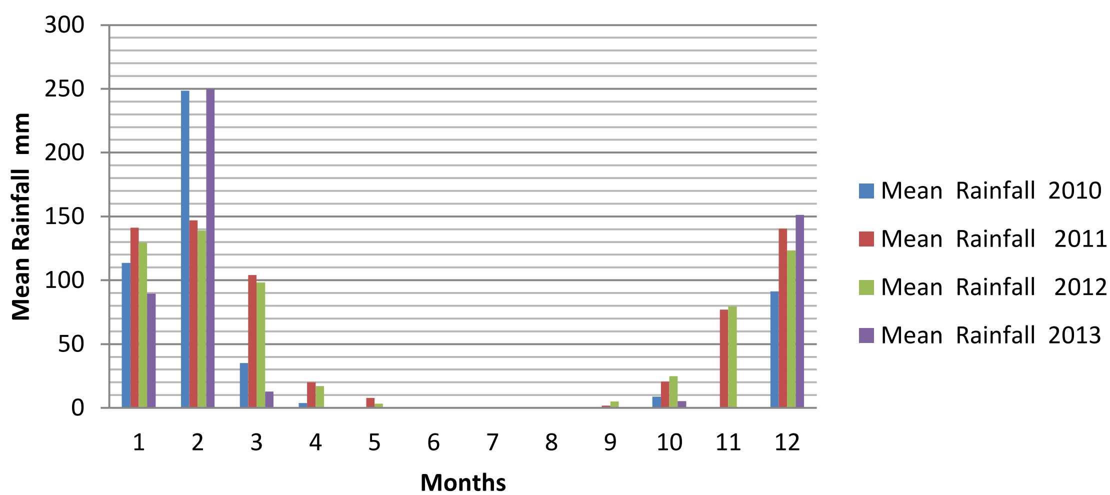


Figure 3.13: Monthly Rainfalls in Ramallah (2010 – 2013)

3.2.5 Analysis of the influence of physical and socio-economic parameters on water consumption

This section presents a statistical analysis of the physical influence (type of building, surface area, garden area, swimming pool volume) as well as the socio-economic (household size education level, family income and numbers of cars) and the climate indicators (temperature, mean humidity and rainfall) on domestic water consumptions in Ramallah.

3.2.5.1 Physical parameters of habitation units

3.2.5.1.1 Type of habitation unit

As explained earlier, the type of habitation unit is an important parameter that could affect the water consumption. Figures 3.14 and 3.15 shows the variation of the water consumption in the period from 2010 to 2013 with the type of building and the relationship between the water consumption and the type of building. For the dwelling habitation, a high variation was observed in the water consumption with a peak around 1692 m^3 and minimum around 780 m^3. In most cases, the water consumption varies between 800 m^3 and 1200 m^3. For the house habitation, a high variation was also noticed in the water consumption with a peak around 4860 m^3 and a minimum around 1225 m^3. In most cases, the water consumption varies between 1200 m^3 and 3200 m^3.

This high variation for each habitation type shows that the water consumption was not related only to the habitation type. In the following, the influence of other parameters on the water consumption will be analyzed.

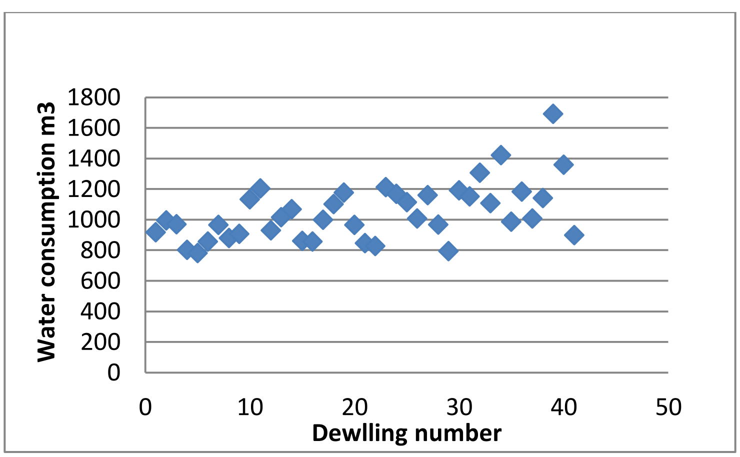


Figure 3.14: Variation of the water consumption in dwelling habitation

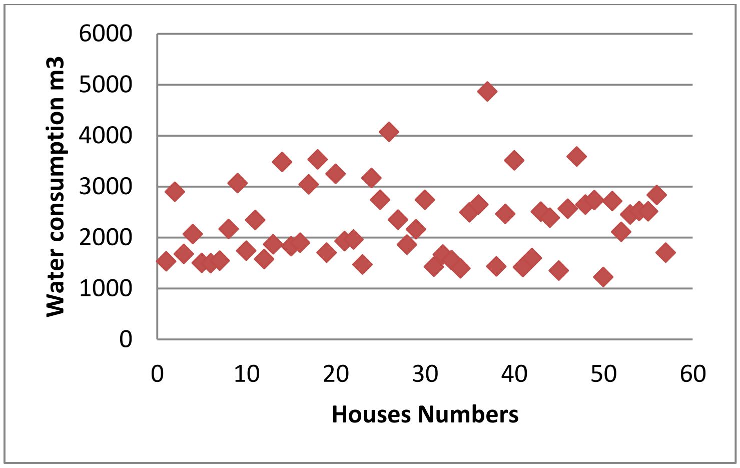


Figure 3.15: Variation of the water consumption in house habitation

3.2.5.1.2 Habitation surface area

Figure 3.16 illustrates the relationship between the water consumption and the habitation surface area. It shows that the increase in the habitation area globally led to an increase in the water consumption (Pearson correlation = 0.56).

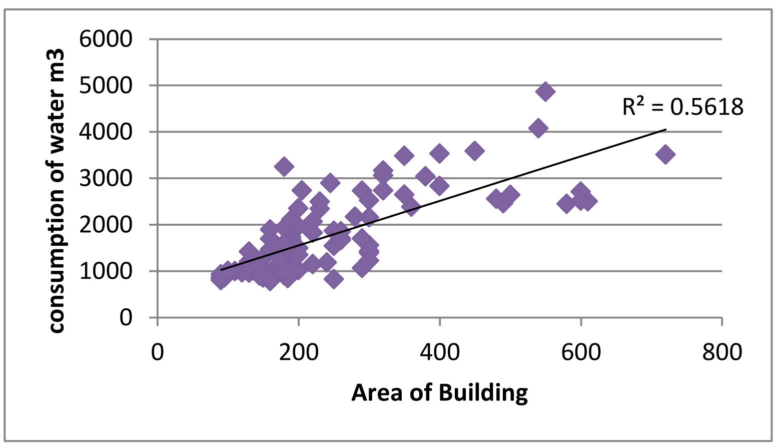


Figure 3.16: Relationship between the water consumption and the habitation surface area

3.2.5.1.3 Garden area

Figure 3.17 shows the relationship between the water consumption and the garden area. High discrepancy was found between the water consumption and the garden area. However, a global increase was noticed in the water consumption with the increase in the garden area (Pearson correlation = 0.49).

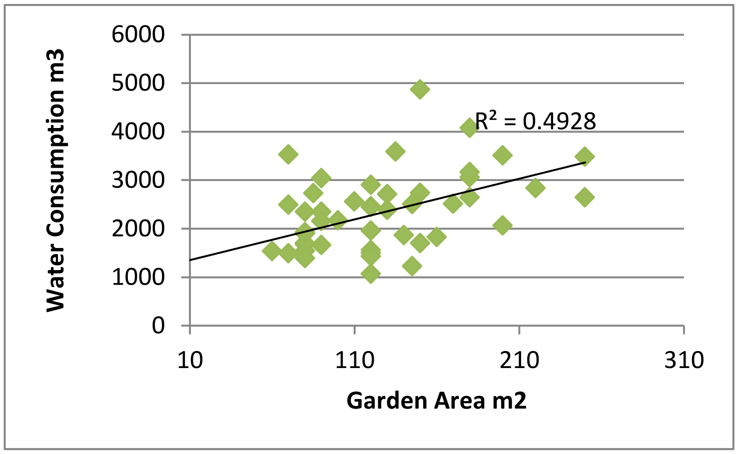


Figure 3.17: Relationship between the water consumption and the garden area

3.2.5.1.4 Swimming pool volume

Figure 3.18 illustrates the relationship between the water consumption and the swimming pool volume. A high discrepancy between the water consumption and the swimming pool volume was observed, but with a global increase in the water consumption with the increase in the garden area (Pearson correlation = 0.33).

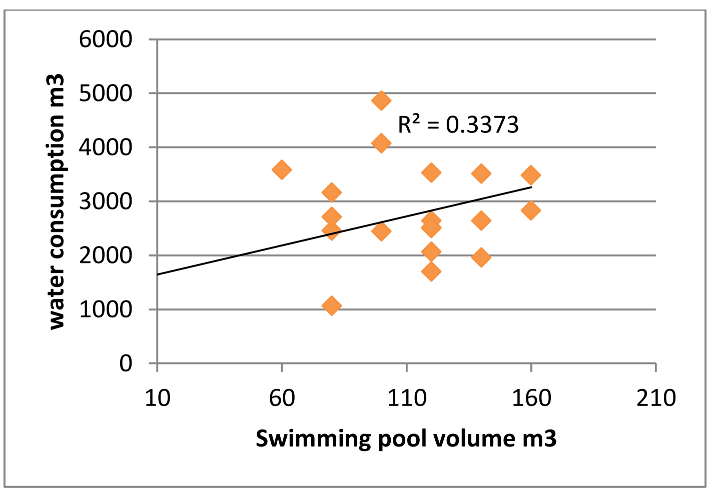


Figure 3.18: Relationship between the water consumption and swimming pool volume

3.2.5.2 Influence of the socio-economic parameters

3.2.5.2.1 Household size

Figure 3.19 shows the relationship between the water consumption and the household size. It could be observed that the water consumption increases as the household size increases (significant positive correlation, with Pearson correlation = 0.99). The average water consumption per person was equal to 55 liter per day; this value was close to the average consumption in Palestine according to PSSB.

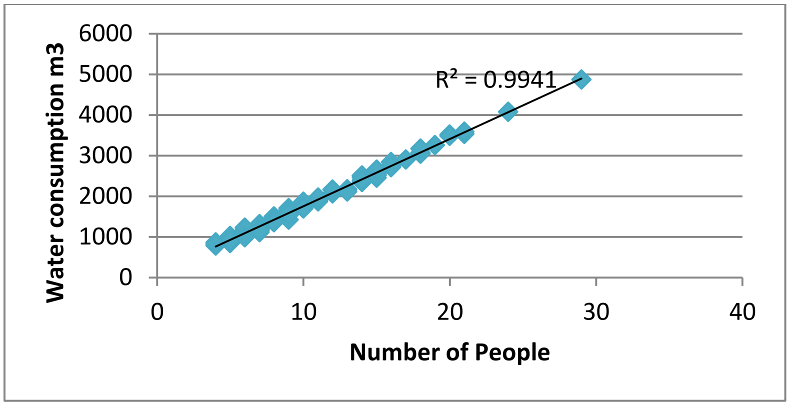


Figure 3.19: Relationship between the water consumption and the household size

3.2.5.2.2 Education level

The household education level was classified into three groups (1) without higher education certificate, (2) undergraduate level with B.A degree and (3) graduated level with Master and Doctorates degree. Figure 3.20 shows the relationship between the water consumption and the household education level. A high discrepancy was noticed, which shows that the education level does not impact the water consumption.

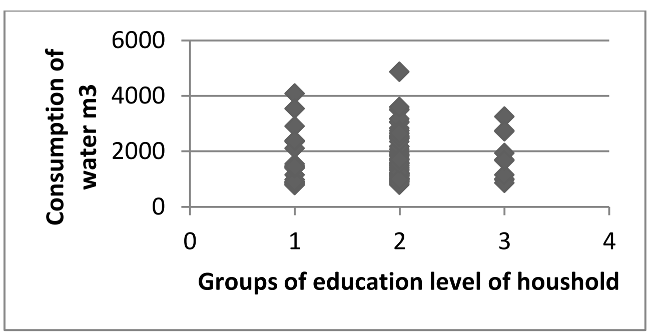


Figure 3.20: Relationship between the water consumption and education level of household

3.2.5.2.3 Household income

The household income in Ramallah as well as in Palestine is generally low with small variation. The annual family income was classified into five groups. Figure 3.21 shows the variation of the water consumption for each category. For each category, a high range of variation in the water consumption was observed. This high variation indicates that the household income is not a determinant parameter in the water consumption.

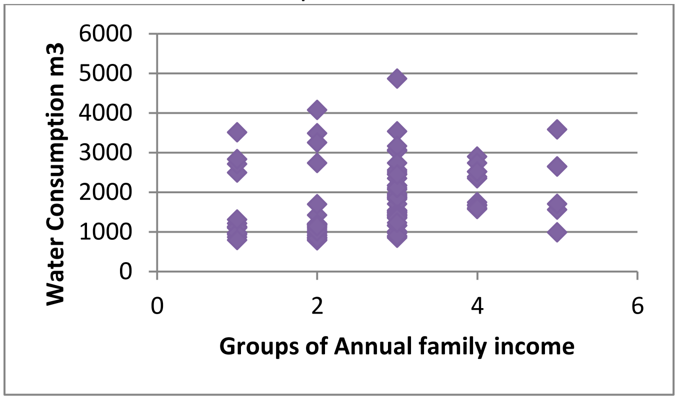


Figure 3.21: Relationship between the water consumption and annual household income

3.2.5.2.4 Numbers of cars

A figure 3.22 illustrates the relationship between the water consumption and the number of the household cars. It is observed there is a high discrepancy in this relationship, which means that the number of cars does not impact the water consumption.

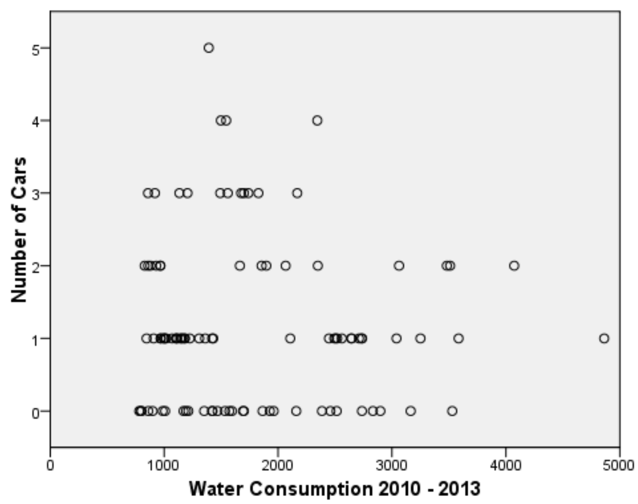


Figure 3.22: Relationship the relationship between the water consumption and number of cars

3.2.5.3 Influence of climatic characteristics

3.2.5.3.1 Mean temperature

Figure 3.23 illustrates the relationship between the water consumption and the mean temperature. A high discrepancy between the water consumption and the mean temperature was found, but with a global increase in the water consumption with the increase in the average temperature.

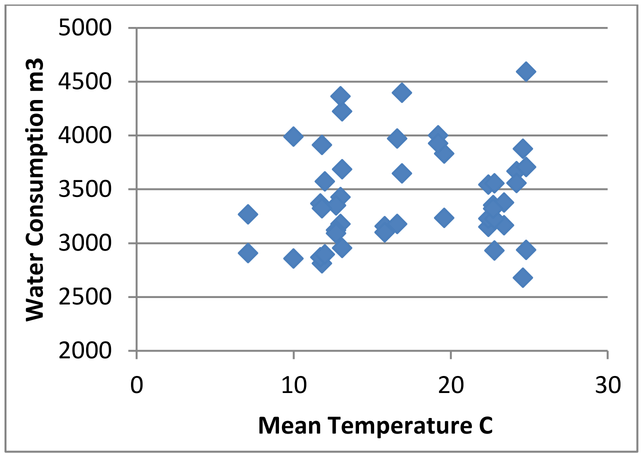


Figure 3.23: Relationship between the water consumption and mean temperature

3.2.5.3.2 Humidity

Figure 3.24 shows the relationship between the water consumption and the humidity. It shows a high discrepancy in this relationship. However, higher level of water consumption was found at low humidity than at high humidity.

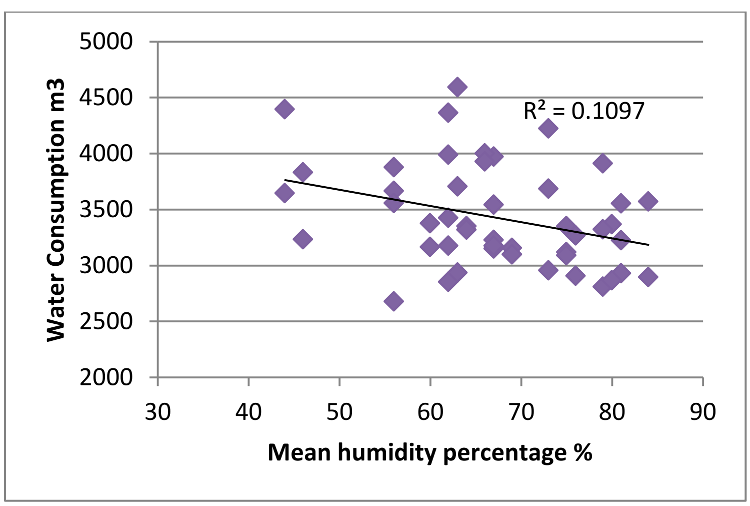


Figure 3.24: Relationship between the water consumption and humidity

3.2.5.3.3 Mean rainfall

Figure 3.25 summarizes the relationship between the water consumption and the monthly mean rainfall. It shows a tendency for an increase in water consumption in the absence of rainfall.

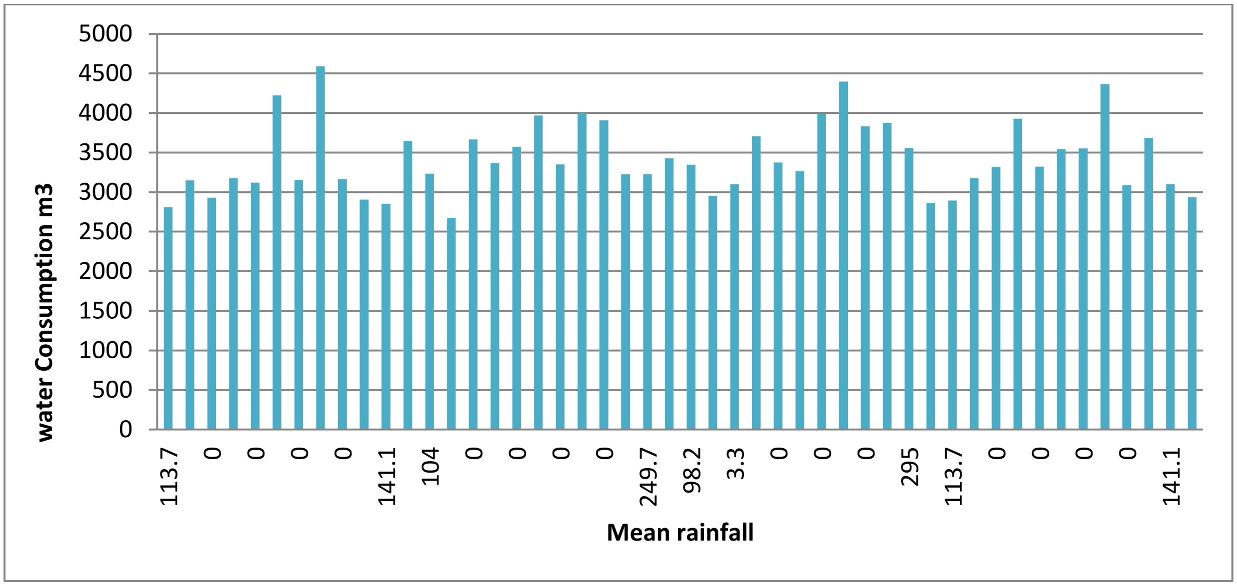


Figure 3.25: Relationship the relationship between the water consumption and mean rainfall

3.3 Khan Younis City

3.3.1 Global Overview of Water Consumption in Khan Younis

The collected data for Khan Younis city regarding the water consumption of 100 habitation units (houses or dwellings) in the period 2011 – 2014 includes the monthly water consumption provided by the water authority. The yearly demographic data was obtained from the State Statistical Authority (PCBS) and then transformed into monthly basis.

Figure 3.26 shows the monthly water consumption for each yearly in the observation period (2011-2014). Table 3.5 summarizes the statistical characteristics: minimum, maximum, mean; and standard deviation. The yearly average water consumption varies between 299 m3 (2011) and 313 m3 (2013).

Table 3.5: The statistical parameters for yearly consumption water (m^3)

	Max	*Min*	*Mean*	*Std. Deviation*
2011	682	170	299	118
2012	844	169	310	119
2013	861	174	313	121
2014	598	181	304	91

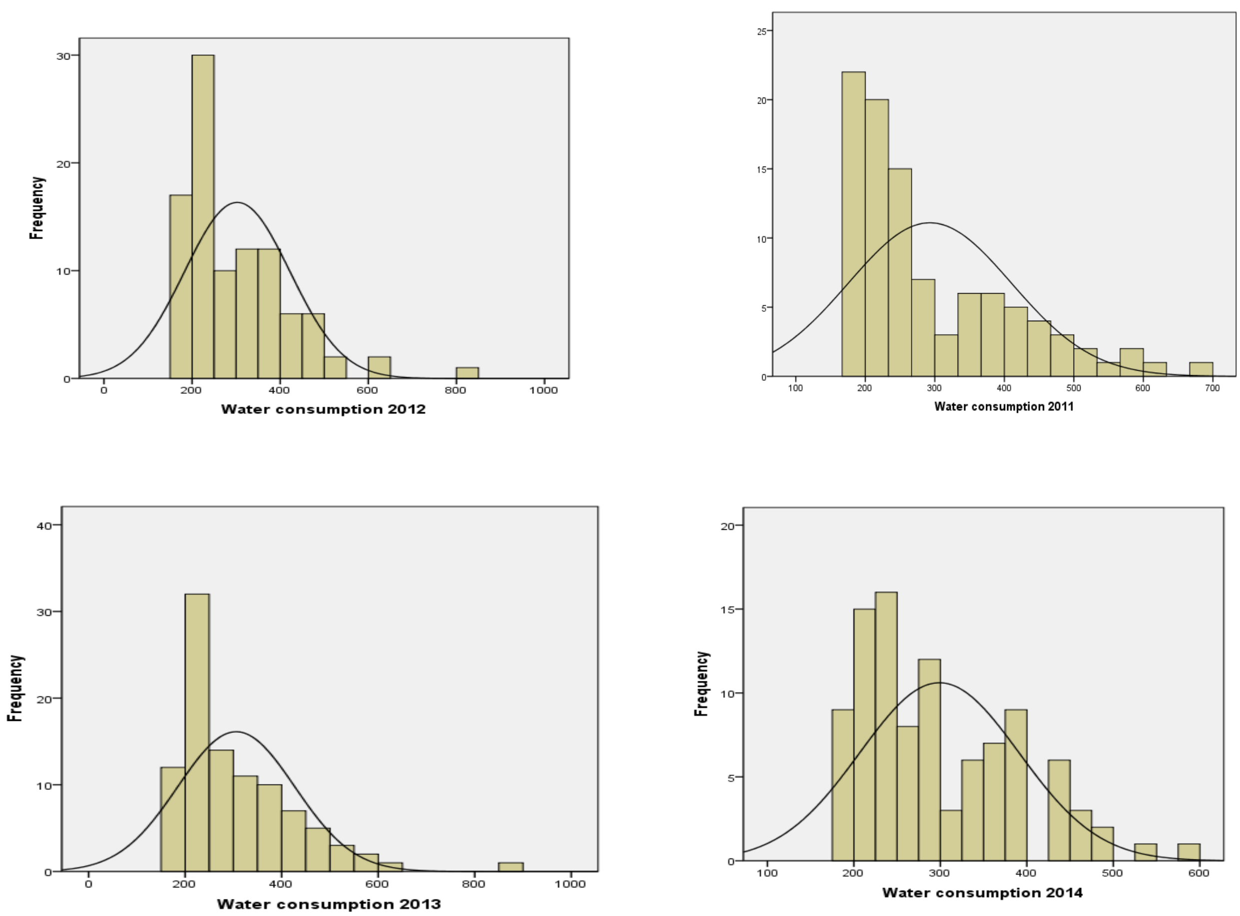
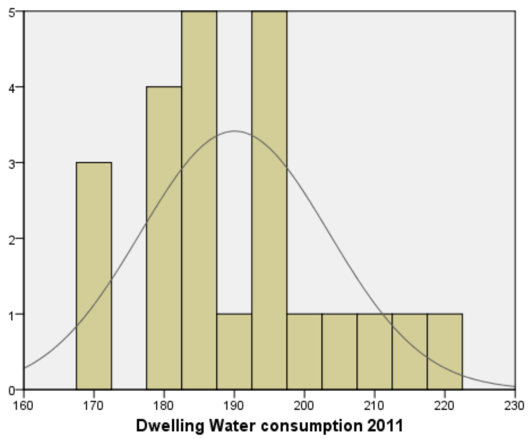
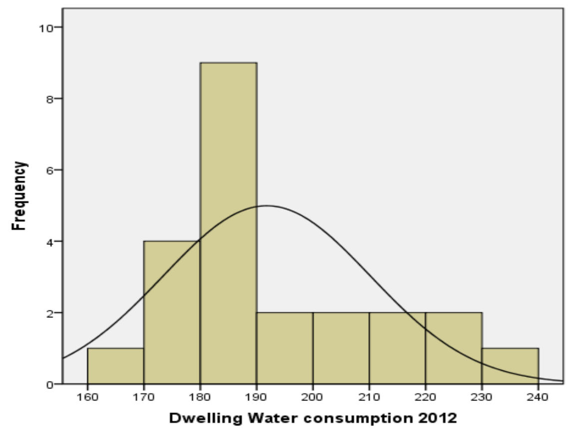
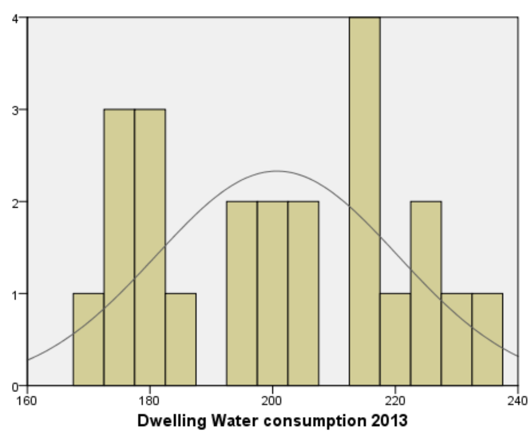
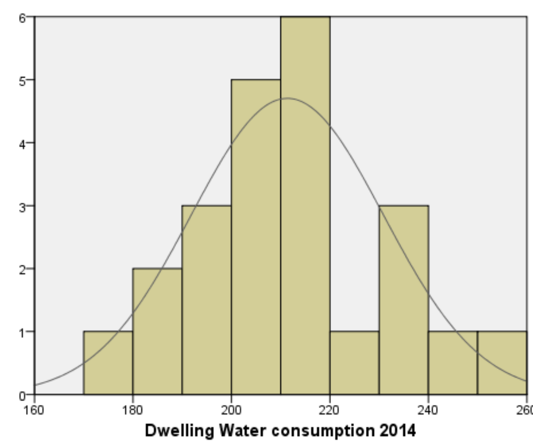


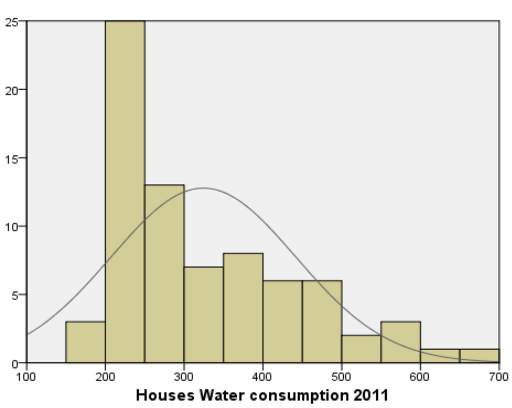
Figure 3.26: The distribution of water consumption during the period 2011-2014

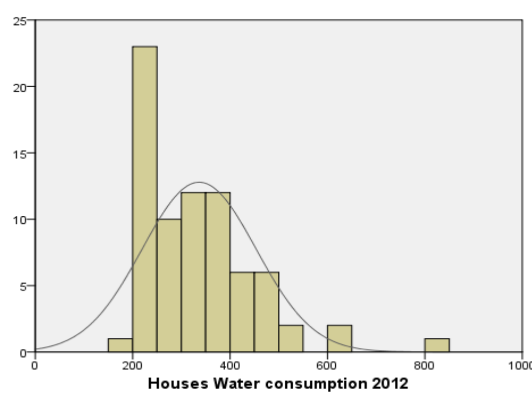

0
1
2
3
4
5
160 170 180 190 200 210 220 230
Dwelling Water consumption 2011


Frequency
0
2
4
6
8
10
160 170 180 190 200 210 220 230 240
Dwelling Water consumption 2012


0
1
2
3
4
160 180 200 220 240
Dwelling Water consumption 2013


0
1
2
3
4
5
6
160 180 200 220 240 260
Dwelling Water consumption 2014


0
5
10
15
20
25
100 200 300 400 500 600 700
Houses Water consumption 2011


0
5
10
15
20
25
0 200 400 600 800 1000
Houses Water consumption 2012

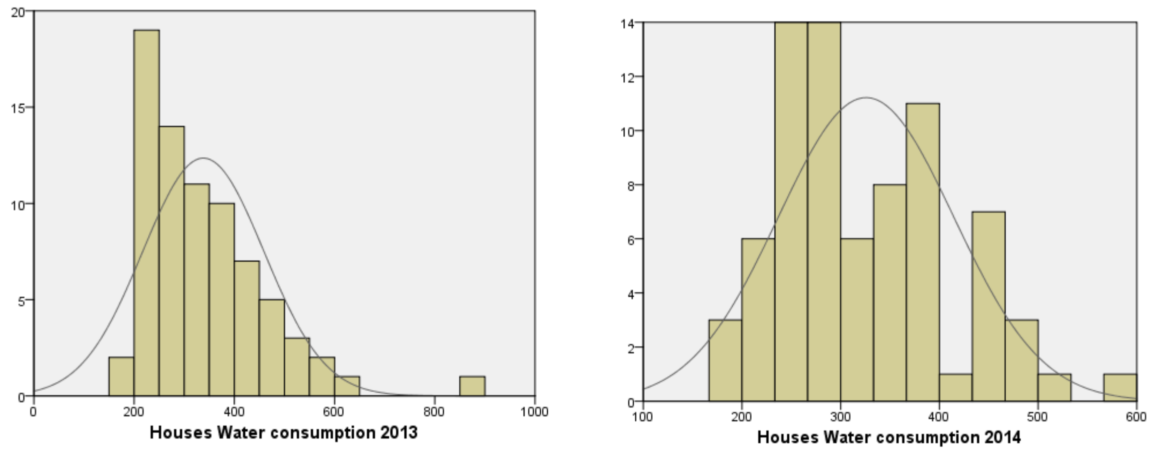


Figure 3.27: The distribution of water consumption with type of building during the period 2011-2014

3.3.2 Physical parameters of habitation units

In the following sections, the physical characteristics of the housing units will be presented:

- Type of habitation unit
- Surface area
- Garden area
- Swimming pool volume

3.3.2.1 Type of habitation unit

Figure 4 shows the repartition the habitation units into dwellings and houses, the percentage of dwellings was found around 23% and the percentage of houses was 77%. This result indicates that the numbers of houses was larger than numbers of dwellings, these facts common in Gaza, where large size families prefer to live in houses.

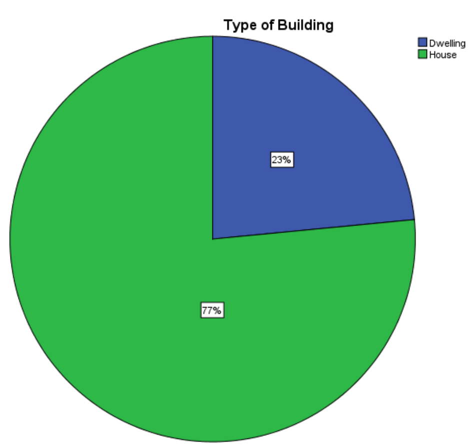


Figure 3.28: Type of building (percentage)

3.3.2.2 Surface area

Figure 3.29 illustrates the distribution of buildings according to their surface area, the maximum surface area was equal to 650 m^2, while the minimum was equal to 120 m^2 and the average was equal to 248 m^2 with a standard deviation of 128 m^2.

For dwellings, the maximum surface area was equal to 200 m^2; the minimum was equal to 120m^2. For houses, the maximum surface area was equal to 650 m^2, while the minimum was equal to 130m^2.

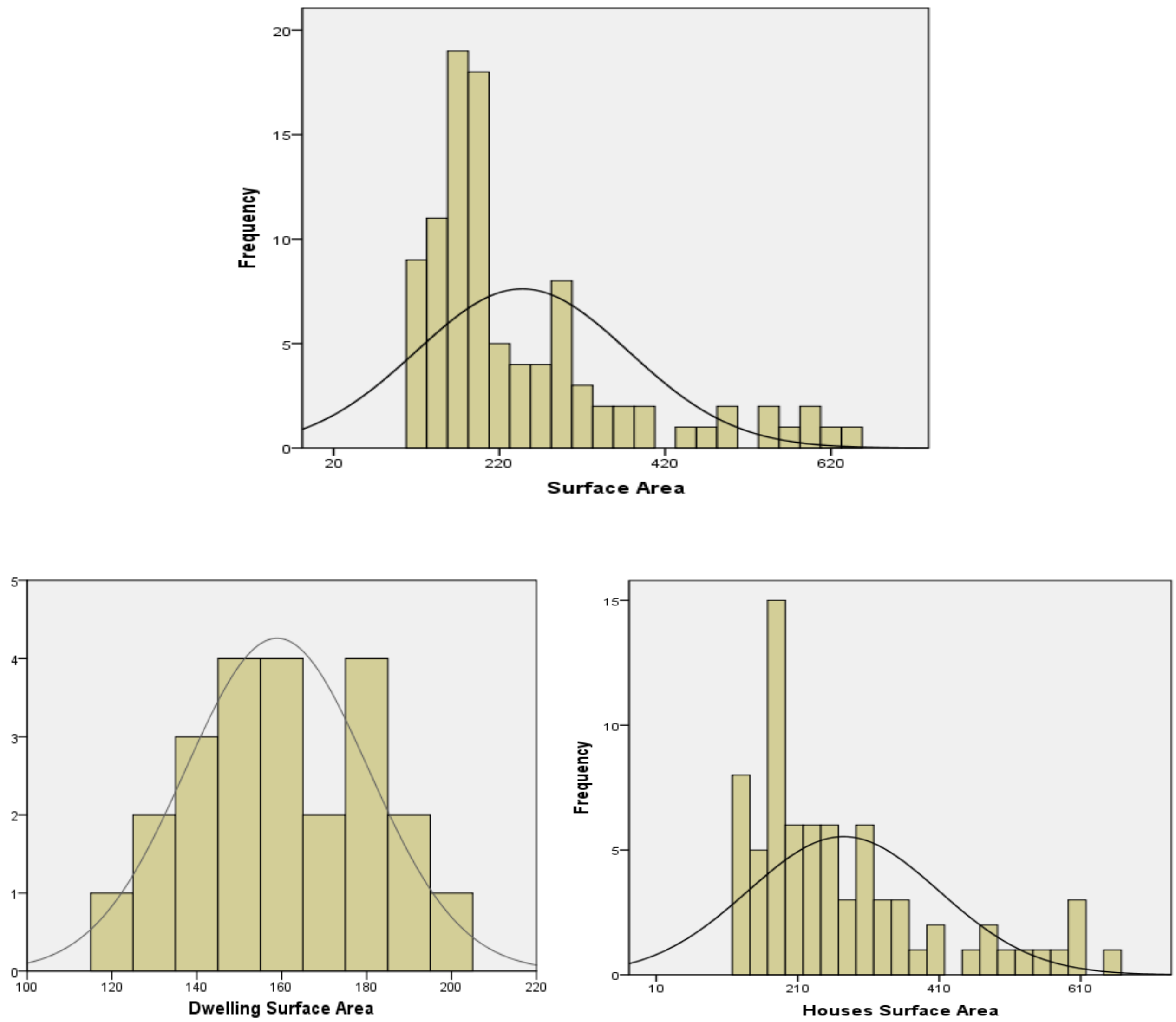


Figure 3.29: Distribution of building according to their surface area

3.3.2.3 Garden area

Figure 3.30 shows the distribution of buildings according to their garden area, the maximum garden area was equal to 380 m^2, the minimum was equal to 50 m^2 and the average was equal to 84 m^2 with a standard deviation of 81 m^2, the total number of buildings with a garden is 61.

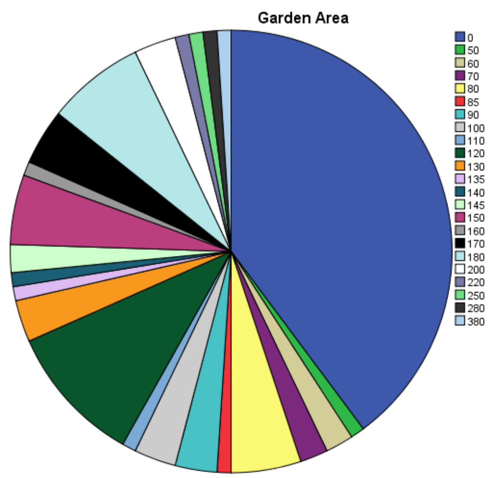


Figure 3.30: Distribution of building according to their garden area

3.3.2.4 Swimming Pool Volume

There is no swimming pool in the cases analyzed in Khan Younis. Indeed, Gaza strip is a coastal region with large possibilities to access the sea beach and swimming pools resorts.

3.3.2.5 Correlation Analysis

The Pearson correlation Matrix is used for the analysis of the relationship between the physical parameters of the study area buildings. Table 3.6 presents the matrix of correlations between the following parameters: type of building (dwelling or houses), surface area and garden area, a significant positive correlation was noticed between the type of building, the surface area and the garden area.

Table 3.6: Pearson correlation Matrix between physical parameters

		Type of Building	Surface Area	Garden Area
Type of Building	Pearson Correlation	1	0.684**	0.571**
	N	100	100	100
Surface Area	Pearson Correlation	0.684**	1	0.610**
	N	100	100	100
Garden Area	Pearson Correlation	0.571**	0.610**	1
	N	100	100	100

3.3.3 Socioeconomic indicators

The following socioeconomic indicators were collected:

- Household size
- Education level
- Annual family income,
- Numbers of cars per habitation unit.

3.3.3.1 Household Size

The household size is a significant indicator that affects the water consumption. Figure 3.31 shows the distribution of buildings according to the household size. The maximum household size was equal to 33, the minimum was equal to 5 and the average was equal to 12 with a standard deviation of 5. For the dwellings habitation, the maximum of the household size was equal to 8, the minimum was equal to 5. For the house habitation the maximum of the household size was equal to 33, the minimum was equal to 7. Figure 3.31 shows the following repartition of the habitation units according to the household size:

- 34 % : between 5 - 8 persons
- 29 % : between 9 - 12 persons
- 37 % : more than 12 persons

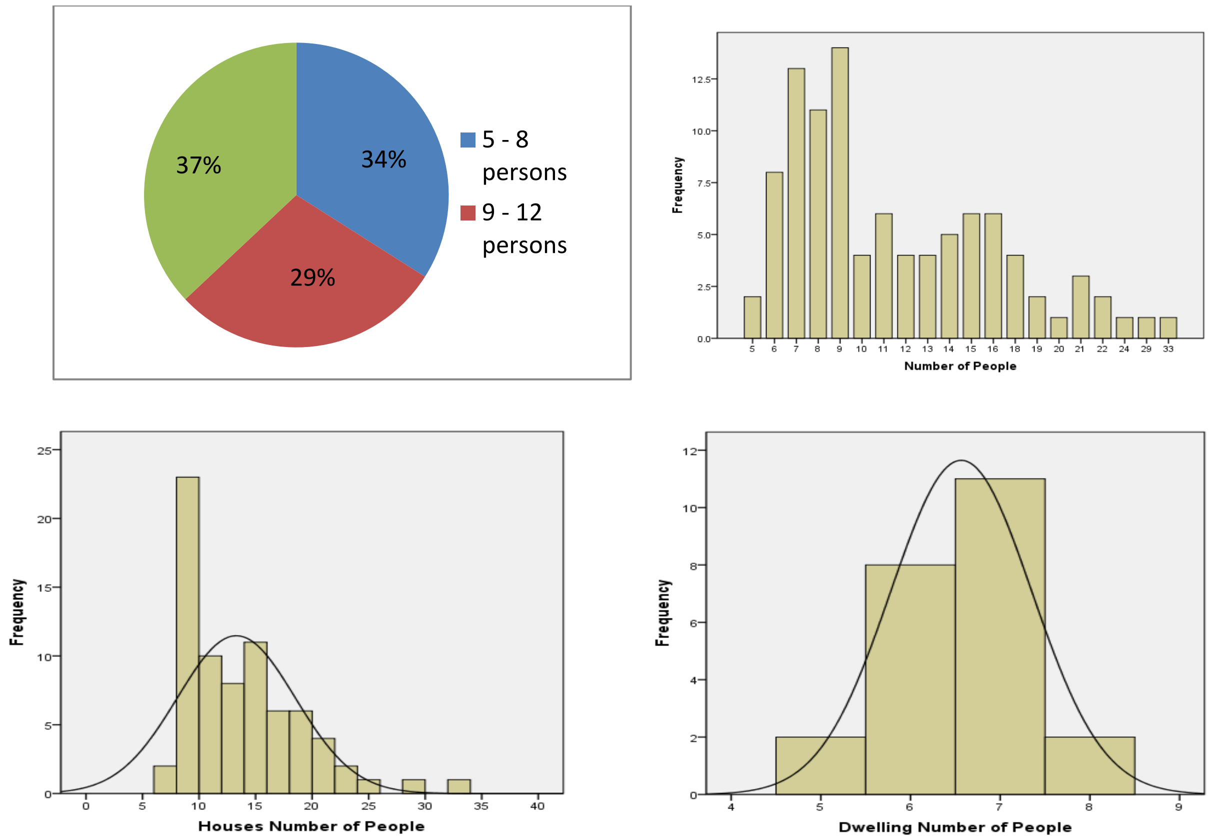


Figure 3.31 :Distribution of household according to their size

3.3.3.2 Educational Level

The repartition of the households according to their education level is summarized in figure 3.32. It shows the following repartition:

- 13% : without any education certificate
- 73 % : undergraduate level with secondary school degree
- 13% : graduated level with BSc Master and Doctorates degree

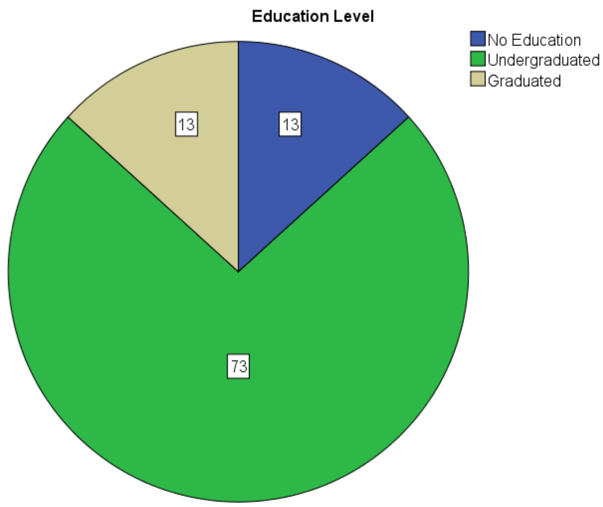


Figure 3.32: Distribution of households according to their education level

3.3.3.3 Annual Family Income

Table 3.7 and Figure 3.33 show the repartition of the households according to their annual income, 18% of the households have an annual income less than 10,000 $, 69% have an annual income between 11,000 and 30,000 $ and 13% have an income greater than 31,000 $. If the large size of families is taken into account (the average of the household is equal to 12), around 18% of the families have an annual income inferior to 830 $ /person (2,28 $ /day). This situation reflects the high level of poverty in Gaza, which is estimated to 39% by the World Bank[1].

Table 3.7: Percentage of sub-classes of annual income for families

[1]	Less than 10,000 $	18%
[2]	11,000 to 20,000 $	36%
[3]	21,000 to 30,000 $	33%
[4]	31,000 to 40,000 $	8%
[5]	More than 40,000 $	5%

[1] http://www.worldbank.org/content/dam/Worldbank/gaza-fact-sheet-final140801-ECR.pdf

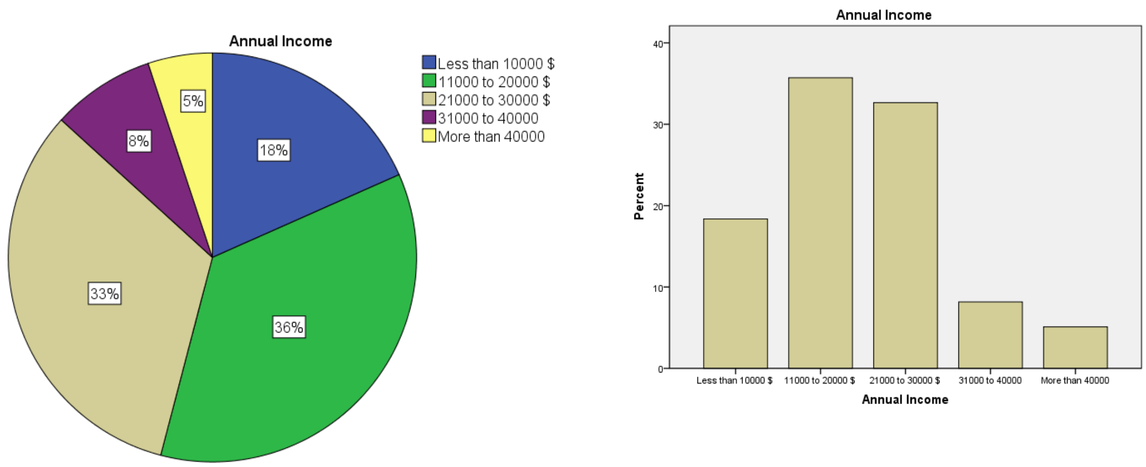


Figure 3.33 Distribution of building according to their Annual Income

3.3.3.4 Numbers of cars

Figure 3.34 illustrates the repartition of the households according to the number of cars/family. The maximum number of cars was equal to 4, the minimum was equal to 0 and the average was equal to 1.0 with a standard deviation of 1.0.

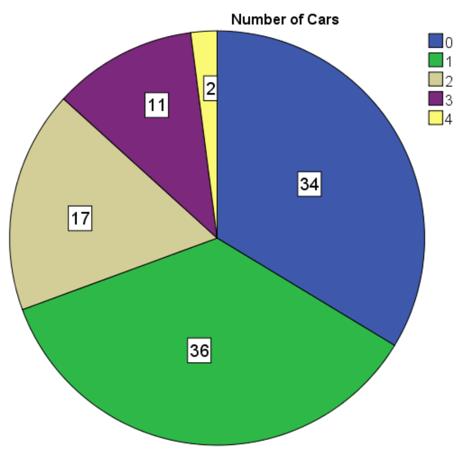


Figure 3.34: Distribution of building according to cars number

3.3.3.5 Correlation Analysis

Table 3.8 summarizes the results of correlations of both the physical and socio-economic indicators, a significant positive correlation between the household size and the surface area was noticed, and it indicates that the increase in the household size is accompanied by an increase in the surface area.

Table 3.8: Correlation Matrix between physical and socioeconomic parameters

		Type of Building	Surface Area	Garden Area	Number of People	Annual Income	Number of Cars
Type of Building	Pearson Correlation	1	.884**	.571**	.931**	.760**	.587
	Sig. (2-tailed)		.000	.000	.000	.000	.397
	N	100	100	100	100	100	100
Surface Area	Pearson Correlation	0.884**	1	0.610**	0.620**	.725*	0.541
	Sig. (2-tailed)	0.000		0.000	0.000	.026	0.691
	N	100	100	100	100	100	100
Garden Area	Pearson Correlation	0.571**	0.610**	1	0.573**	0.435**	0.586**
	Sig. (2-tailed)	0.000	0.000		0.000	0.001	0.004
	N	100	100	100	100	100	98
Number of People	Pearson Correlation	0.931**	0.620**	0.573**	1	0.503**	0.410
	Sig. (2-tailed)	.000	.000	.000		0.002	0.924
	N	100	100	100	100	100	100
Annual Income	Pearson Correlation	0.760**	0.725*	0.435**	0.503**	1	0.414
	Sig. (2-tailed)	0.000	0.026	0.001	0.002		0.893
	N	100	100	100	100	100	100
Number of Cars	Pearson Correlation	0.587	0.541	.586**	0.410	0.414	1
	Sig. (2-tailed)	0.397	0.691	0.004	0.924	0.893	
	N	100	100	100	100	100	100

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

3.3.3.6 Analysis of the climatic indicators

The climate in Khan Younis will be analyzed throughout the following parameters (Palestinian Meteorological reports):

- Temperature
- Humidity
- Rainfall

3.3.3.7 Temperature

Figure 3.35 illustrates the variation of the mean temperature in Khan Younis during the period 2011–2014, the maximum mean temperature was equal to 30.4 C (in 2013), the minimum was equal to 14.4 C (in 2011) and the average was equal to 22.8 C.

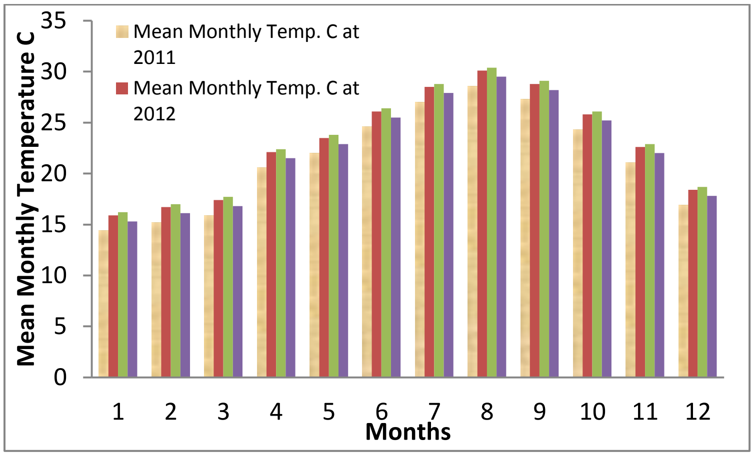


Figure 3.35: Mean temperatures in Khan Younis (2011 – 2014)

3.3.3.8 Humidity

Figure 3.36 shows the variation of the humidity in Khan Younis during the period 2011–2014. The maximum mean humidity was equal to 86% (in 2012), the minimum was equal to 62% (in 2011) and the average was equal to 73.8%.

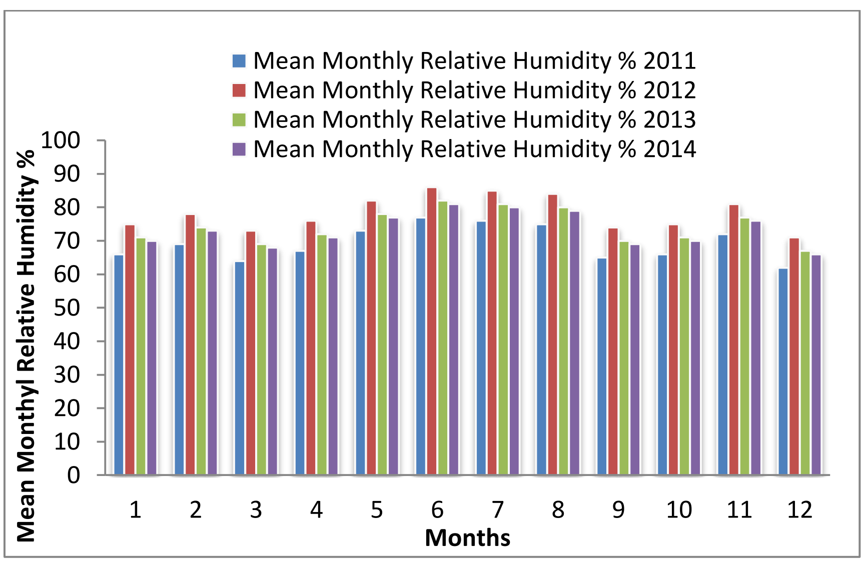


Figure 3.36: Variation of the mean humidity in Khan Younis (2011 – 2014)

3.3.3.9 Rainfall

Figure 3.37 shows the variation of the mean rainfall in Khan Younis during the period 2011–2014. The maximum mean rainfall was equal to 108 mm (in 2014); the minimum was equal to 0 mm in summer.

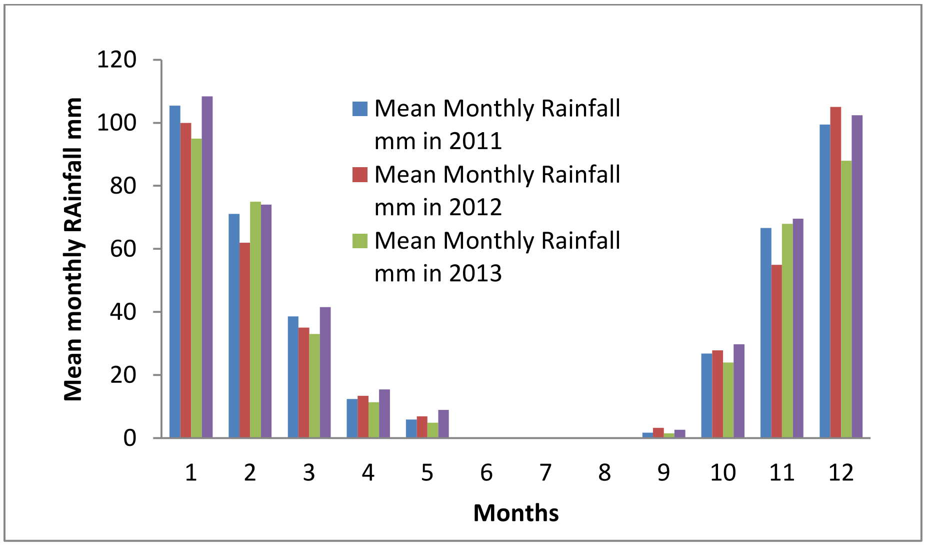


Figure 3.37: Variation of the rainfall in Khan Younis (2011 – 2014)

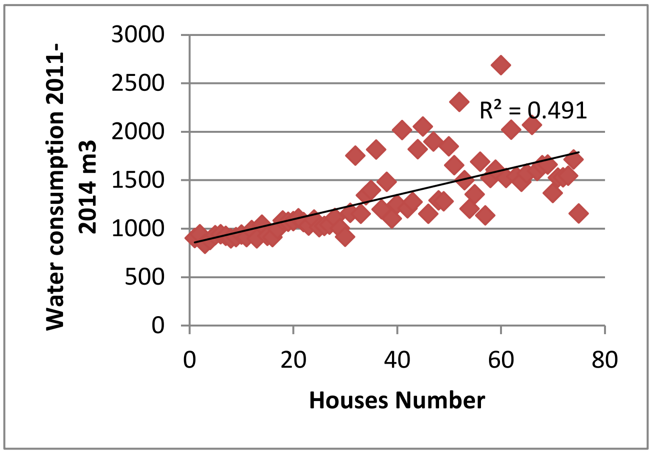
3.3.4 Influence of physical and socio-economic parameters on water consumption

This section presents an analysis of the physical influence (type of building, surface area, garden area, swimming pool volume) as well as socio-economic (household size, education level, family income and numbers of cars) and the climate indicators (temperature, humidity and rainfall) on the domestic water consumptions in of Khan Younis.

3.3.4.1 Physical indicators

3.3.4.1.1 Type of Building

As explained earlier, the type of building is an important parameter that affects the water consumption. Figure 3.38 shows the variation of water consumption during the period 2011 to 2014 with type of building. For the dwelling habitations, a high variation in the consumption of water was observed with a maximum of 840 m^3 and a minimum of 733 m^3. For the house habitations, a higher consumption was also observed than dwelling habitation. The maximum consumption was equal to 2685 m^3 (840 m^3 in dwelling); the minimum consumption was equal to 840 m^3 (733 m^3 in dwelling)



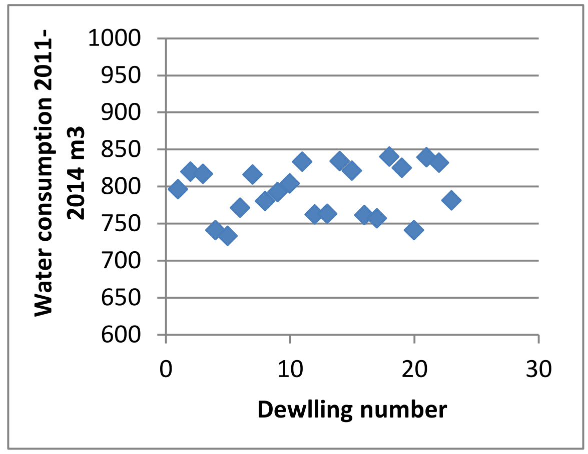


Figure 3.38: The variation of water consumption with dwelling and houses habitation

3.3.4.1.2 Surface area

Figure 3.39 illustrates the relationship between the water consumption and the building surface area. It shows that the increase in the buildings' area globally leads to an increase in the water consumption (Pearson correlation = 0.58).

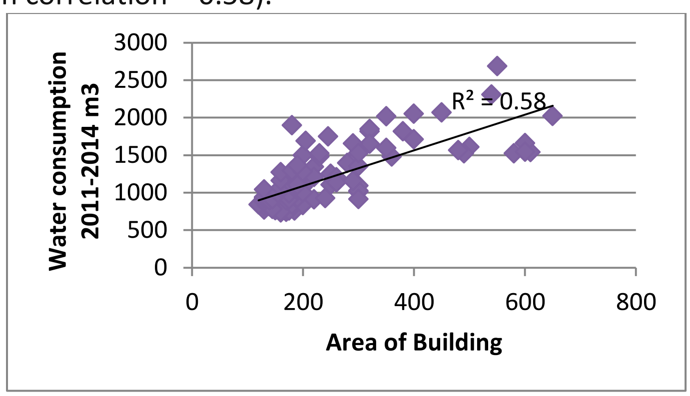


Figure 3.39: The relationship between the water consumption and building surface area

3.3.4.1.3 Garden area

Figure 3.40 shows the relationship between the water consumption and the garden area. The global increase in garden area led to an increase in the water consumption (Pearson correlation = 0.52).

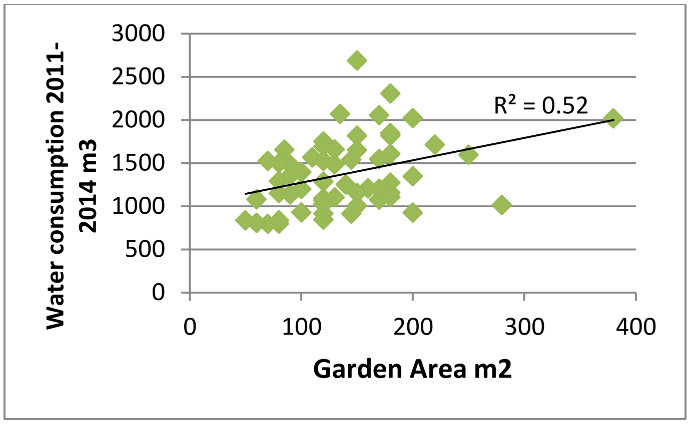


Figure 3.40: The relationship between the water consumption and garden area

3.3.4.2 Socio-economic parameters

3.3.4.2.1 Household size

Figure 3.41 summarizes the relationship between the water consumption and the household size. It shows that the water consumption increases with the increase in the family size, a significant positive correlation (Pearson correlation = 0.74).

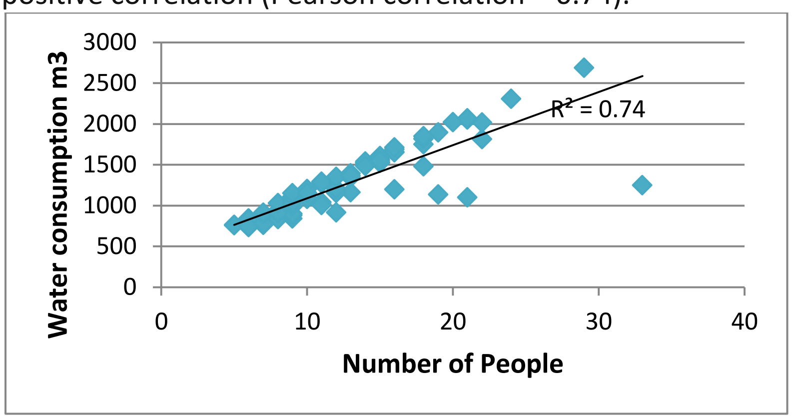


Figure 3.41: The relationship between the water consumption and number of people

3.3.4.2.2 Education level

The education level of the households was classified into three groups (1) without any education certificate, (2) undergraduate level with B.A degree and (3) graduated level with Master and Doctorates degree.

Figure 3.42 shows the relationship between the water consumption and the education level of the households. It shows the absence of correlation between these parameters.

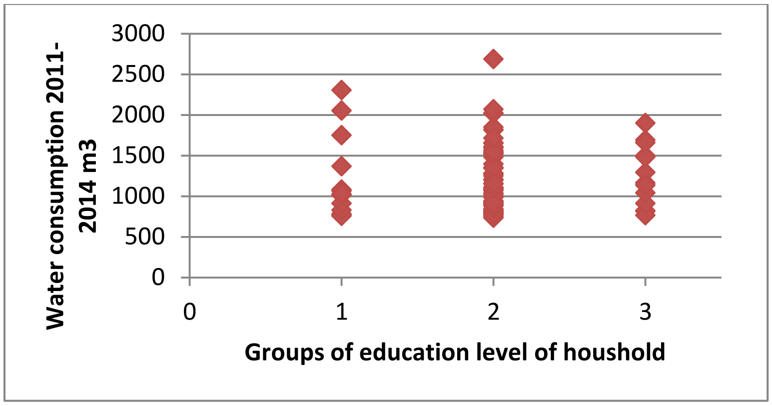


Figure 3.42: The relationship between the water consumption and the education level

3.3.4.2.3 Annual income

Figure 3.43 shows the variation of the water consumption with the annual family income. A high scattering was found in the relationship between the family annual income and the water consumption.

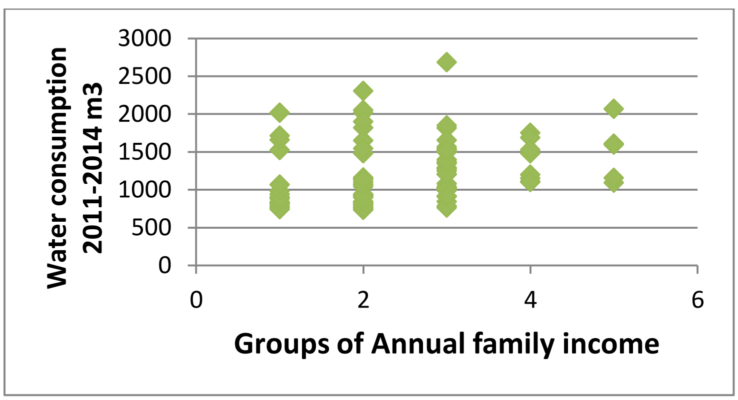


Figure 3.43: The relationship between water consumption and annual family income

3.3.4.2.4 Numbers of cars

Figure 3.44 summarizes the relationship between the water consumption and households number of cars. It shows also a large scattering in the relationship between the water consumption and the household's number of cars.

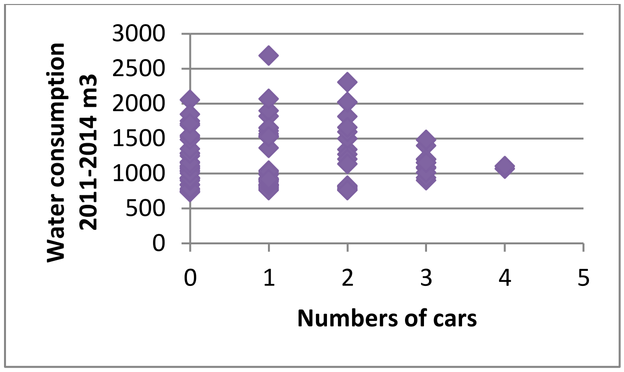


Figure 3.44: Relationship between the water consumption and number of cars

3.3.4.3 Climatic characteristics

3.3.4.3.1 Mean temperature

Figure 3.45 illustrates the relationship between the water consumption and the mean temperature. It shows an increase in the water consumption with the increase in the temperature (R2 = 0.58), an expected result as the increase in the temperature, in particular in summer, more water for cleaning, shower,...etc is needed.

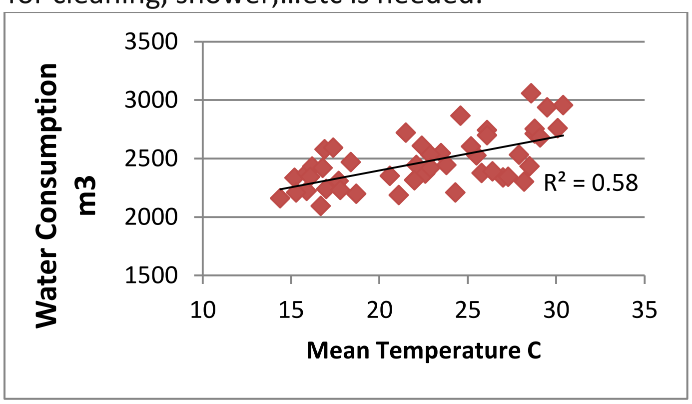


Figure 3.45: Relationship between the water consumption and mean temperature

3.3.4.3.2 Humidity

Figure 3.46 summarizes the relationship between the water consumption and humidity. It shows an increase in the water consumption with the increase in humidity; high humidity was observed in summer. This result incorporates also the influence of the temperature.

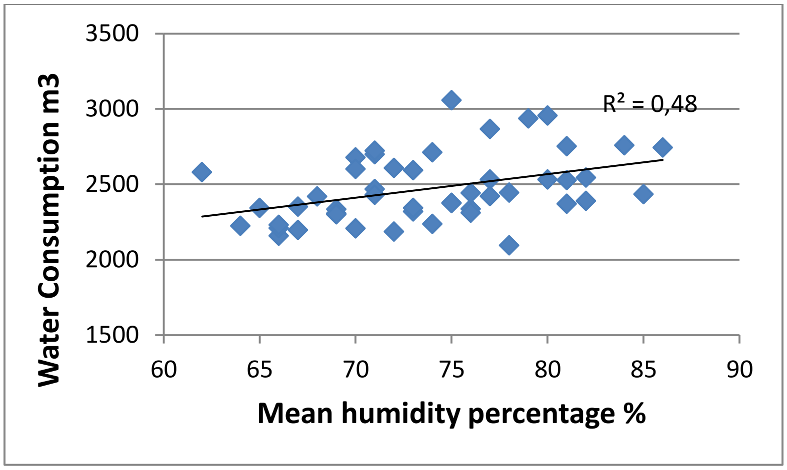


Figure 3.46: Relationship between the water consumption and humidity

3.3.4.3.3 Rainfall

Figure 3.47 summarizes the relationship between the water consumption and the rainfall. It shows large water consumption in summer. Winter rainfall can cause an immediate drop in the water use followed by a gradual increase which reduces the influence of rainfall on water consumption.

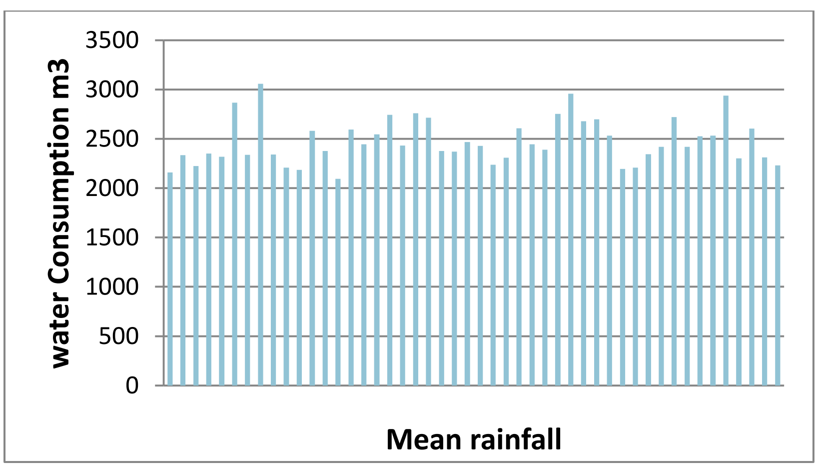


Figure 3.47: The relationship between the water consumption and mean rainfall

3.4 Conclusion

This chapter presented an overview of the water consumption for both cities Khan Younis and Ramallah, the yearly average water consumption for Khan Younis was found to vary between 299 m3 (2011) and 313 m3 (2013), while for Ramallah the mean value of the water consumption was varied between 409 and 434 m^3/month.

The water consumption was found to be affected by the following parameters: Temperature, garden area, surface area, household size and rainfall while other parameters as the education level, the number of cars and income had no important effect on the water consumption, this could be reasoned to the traditional hygiene habits.

It was found also that in terms of humidity, in city of Khan Younis, as the humidity increases the water consumption increases which were not the case in Ramallah city as higher level of water consumption was found at lower humidity than at higher humidity.

More large-scale studies are required that should analyze the different lifestyles that rely on different cultural levels of different cities.

4 Water Demand modeling using the Artificial Neural Network Method

4.1 Introduction

A water demand forecast is required for proper planning, development and management of water resources. Mathematical models can be used to analyze the factors influencing the water demand, understand their effects, predict the future demand and develop management plans.

This chapter presents the use of an ANN (Artificial Neural Network) for modeling the urban water demand in Ramallah and Khan Younis. The model uses the input parameters presented in previous chapters, as well as the water consumption data for the period 2010 - 2012 for Khan Younis and 2011 - 2013 for Ramallah.

The input parameters were divided into 3 categories:

- The habitation parameters (type, area, garden area, swimming pool volume),
- The household parameters (size, educational level, income, number of cars), and
- The climate parameters (temperature, humidity and rainfall).

In the following, the ANN method will be presented in order to model the water demand in Ramallah and Khan Younis. For each city, 36 ANN models will be used by different combinations of the input parameters. The performances of these models will be discussed and compared to the Multiple Linear Regression (MLR) method.

4.2 Presentation of the Artificial Neural Networks (ANN)

The artificial neural networks (ANN) methods are inspired by biological neural networks. Similar to the neurons and the electrical signals, they build relations between input and output indicators, but are very effective at their intended tasks (e.g. classification or segmentation).

The artificial neural networks (ANN) method has been recently accepted as an efficient alternative tool for modeling water resources systems. Fewer works were reported in the use of ANN in water consumption modeling. Griñó (1992) applied the neural network approach for urban water demand forecasting. Froukh (2001) attempted to integrate both mathematical and heuristic approaches for long-term water-demand forecasts by developing a decision-support system that integrates demand forecasting with demand management using decision tools. Liu et al. (2003) used the ANN technique to model and forecast the water demand in urban areas.

Bougadis et al. (2005) investigated the relative performance of regression, time series analysis and ANN models for short-term peak water demand forecasting.

Wong and Mui (2007) carried out a mathematical model in determining the flushing water demands for high-rise residential buildings in Hong Kong. Babel et al. (2007) developed a multiple coefficient water demand forecast and management model for the domestic sector considering various socio-economic, climatic and policies related factors.

In the following we present the main ANN approaches.

4.2.1 Feed Forward Neural Networks (FFNN)

The feed forward neural network was the first and simplest type of artificial neural network methods. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes (Figure 4.1). A FFNN consists of at least three layers, input, output and hidden.

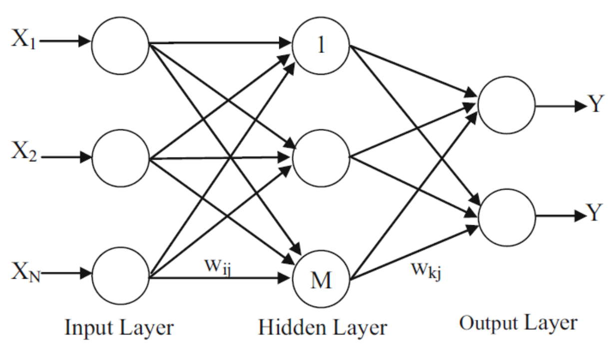


Figure 4.1: General structure of FFNN

The summation of the weighted input signals calculated by Eq. 1 is transferred by a nonlinear activation function given in Eq. 2. The response of network is compared with the actual observation results and the network error is calculated with Eq. 3.

$$Y_{\text{net}} = \sum_{i=1}^{N} X_i . w_i + w_0 \qquad (1)$$

$$Y_{\text{out}} = f\left(Y_{\text{net}}\right) = \frac{1}{1 + e^{-Y_{\text{net}}}} \qquad (2)$$

$$J_{\text{r}} = \frac{1}{2} . \sum_{i=1}^{k} \left(Y_{\text{obs}} - Y_{\text{out}}\right)^2 \qquad (3)$$

Y_{out} is the response of system, f (Y_{net}) is the nonlinear activation function, Y_{net} is the summation of weighted inputs, Xi is the neuron input, $\boldsymbol{w_i}$ is weight coefficient of each neuron input, $\boldsymbol{w_0}$ is bias, $\boldsymbol{J_r}$ is the error between observed and network result, Y_{obs} is the observation output value.

4.2.2 Radial Basis Neural Networks (RBNN)

Radial basis functions are powerful techniques for interpolation in multidimensional space. Figure 4.2 shows a RBNN model having input layer, output layer and one hidden layer (Lin and Chen 2004).

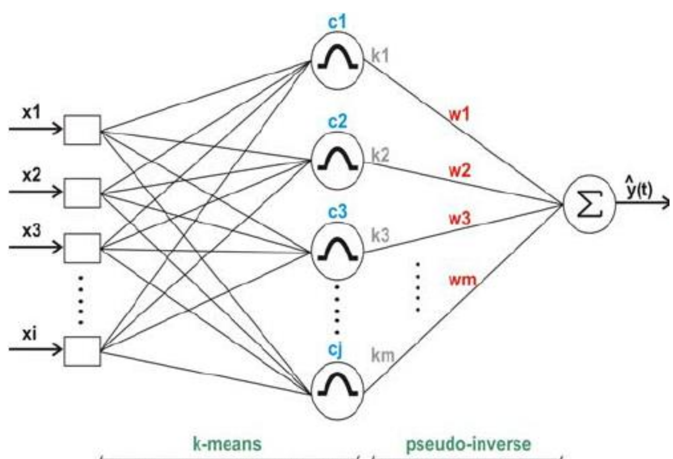


Figure 4.2: General structure of RBNN

The response of the network and the standard deviation (i.e. width) of the j_{th} neuron are calculated by Eqs. 4 and 5, respectively.

$$\psi_j = \exp\left[-\frac{\|x - c_j\|^2}{2\sigma^2}\right] \tag{4}$$

$$\widehat{y}_k = w_0 + \sum_{j=1}^{N} w_{jk}.\psi_j(x) \tag{5}$$

$$\sigma = \sqrt{\frac{d_{\max}^2}{j+1}} \tag{6}$$

$$J_r = \frac{1}{2}.\sum_{i=1}^{k}\left(y_{\mathrm{obs}} - \hat{y}_{\mathrm{net}}\right)^2 \tag{7}$$

Where, d_{max} is the maximum distance between training data set, $\hat{y}_{net}$ is response of the network, y_{obs} is observation value. where, x is the input sets of training, ***J_r*** is the error between observed and response of network, c j is center values, and σ is variance, ψj(x)is response of the j_{th} hidden neuron, w_{jk} is the weight coefficient between (j) the hidden unit and k_{th} output unit, and w_0 is the bias.

4.2.3 Generalized Regression Neural Network (GRNN)

A GRNN is a variation of the radial basis neural networks, which is based on kernel regression networks (Celikoglu and Cigizoglu 2007). A GRNN includes four layers: input layer, pattern layer, summation layer and output layer as shown in Figure 4.3.

The first layer is connected to the pattern layer and in this layer each neuron presents a training pattern and its output. The pattern layer is connected to the summation layer. The summation layer has two different types of summation, which are a single division unit and summation units. Each pattern layer unit is connected to the two neurons in the summation layer, S and D summation neurons. S summation neuron computes the sum of weighted responses of the pattern layer. On the other hand, D summation neuron is used to calculate unweight outputs of pattern neurons. The output layer merely divides the output of each S-summation neuron by that of each D-summation neuron, yielding the predicted value to an unknown input vector x as (Kim et al. 2004).

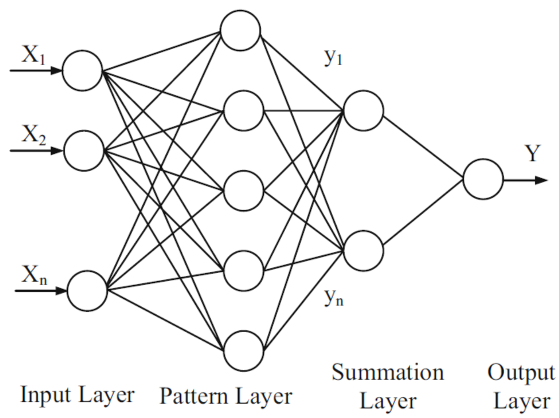


Figure 4.3 :General structure of GRNN

$$Y_i' = \frac{\sum_{i=1}^{n} y_i \cdot \exp[-D(x, x_i)]}{\sum_{i=1}^{n} \exp[-D(x, x_i)]} \tag{8}$$

$$D(x, x_i) = \sum_{k=1}^{m} \left(\frac{x_i - x_{ik}}{\sigma} \right)^2 \tag{9}$$

Yi is the weight connection between the i_{th} neuron in the pattern layer and the S-summation neuron, n is the number of the training patterns, D is the Gaussian function, m is the number of elements of an input vector, x_k and x_{ik} are the j_{th} element of x and xi, respectively, σ is the spread parameter, whose optimal value is determined experimentally.

4.3 The performances of ANN models

The performances of ANN models are evaluated according to statistical criteria such as, Correlation Coefficient (CORR), Root Mean Square Error (RMSE) (Nash and Sutcliffe 1970; Kitanidis and Bras 1980) and Average squared of error (ASE) (S. RIAD et al.,2004).

Correlation – often measured as a correlation coefficient – indicates the strength and direction of a linear relationship between two variables (for example model output and observed values). A number of different coefficients are used for different situations. The best known is the Pearson product-moment correlation coefficient (also called Pearson correlation coefficient or the sample correlation coefficient), which is obtained by dividing the covariance of the two variables by the product of their standard deviations. If we have a series of n observations and n model values, then the Pearson product-moment correlation coefficient can be used to estimate the correlation between model and observations.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}} \qquad (11)$$

The correlation is +1 in the case of a perfect increasing linear relationship, and -1 in case of a decreasing linear relationship, and the values in between indicates the degree of linear relationship between for example model and observations.
The correlation coefficient is a commonly used statistic and provides information on the strength of linear relationship between the observed and the computed values.

The Root Mean Square Error (RMSE) (also called the root mean square deviation, RMSD) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modeled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power.
The RMSE of a model prediction with respect to the estimated variable Xmodel is defined as the square root of the mean squared error:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}} \qquad (12)$$

Where X_{obs} is observed values and X_{model} is modeled values at time/place *i*.

The calculated RMSE values will have units, and RMSE for phosphorus concentrations can for this reason not be directly compared to RMSE values for chlorophyll a concentrations etc. However, the RMSE values can be used to distinguish model performance in a calibration period with that of a validation period as well as to compare the individual model performance to that of other predictive models.

Average squared of error (ASE) is one of the widely employed statistics to evaluate model performance.

$$\mathrm{ASE} = \frac{\sum_{i=1}^{N} \left(Qt_i - \hat{Q}t_i\right)^2}{N}, \qquad (13)$$

The ASE and MARE statistic measures are used to quantify the error between observed and predicted values. The optimal value for ASE and RMSE is equal to 0.0.
The values of CORR close to 1.0 indicate good model performance.

4.4 Analysis of the water consumption in Ramallah

4.4.1 Input Variables and Data

The water consumption (WD) can be characterized as a function of various variables such as, type of building (TB), building surface area (SA), garden area (GA), swimming pool volume (SPV), household size (NP), education level (EL), annual income (AI), number of cars (NC), mean monthly temperature (MT), mean monthly rainfall (MR), and mean monthly humidity (MH). The relationship of between water consumption and input variables can be expressed by;

$$\mathrm{WD} = f\,(\mathrm{TB, SA, GA, SPV, NP, EL, AI, NC, MT, MR, MH}) \qquad (14)$$

The statistical parameters, minimum value; xmin, maximum value; xmax, mean; x, standard deviation; SD, for the data sets are calculated and given in Tables 4.1. Figure 4.4 shows the monthly water consumptions in Ramallah city.

Table 4.1: The Statistical parameters for data sets

Variables	Max	Min	Mean	SD
Water consumption WD (m3)	1542	158	403	233
Surface area (SA)	720	90	245	134
Garden area (GA)	250	60	37	73
Swimming pool volume (SPV)	160	60	11.5	38
Number of persons (NP)	29	4	10.5	4.2
Number of cars (NC)	5	0	1.19	1.15
Temperature MT (°C)	27.2	7.1	18.50	5.26
Monthly humidity MH (%)	84	44	65.5	9.13
Rainfall MR (mm)	249.7	0	47.71	67.02

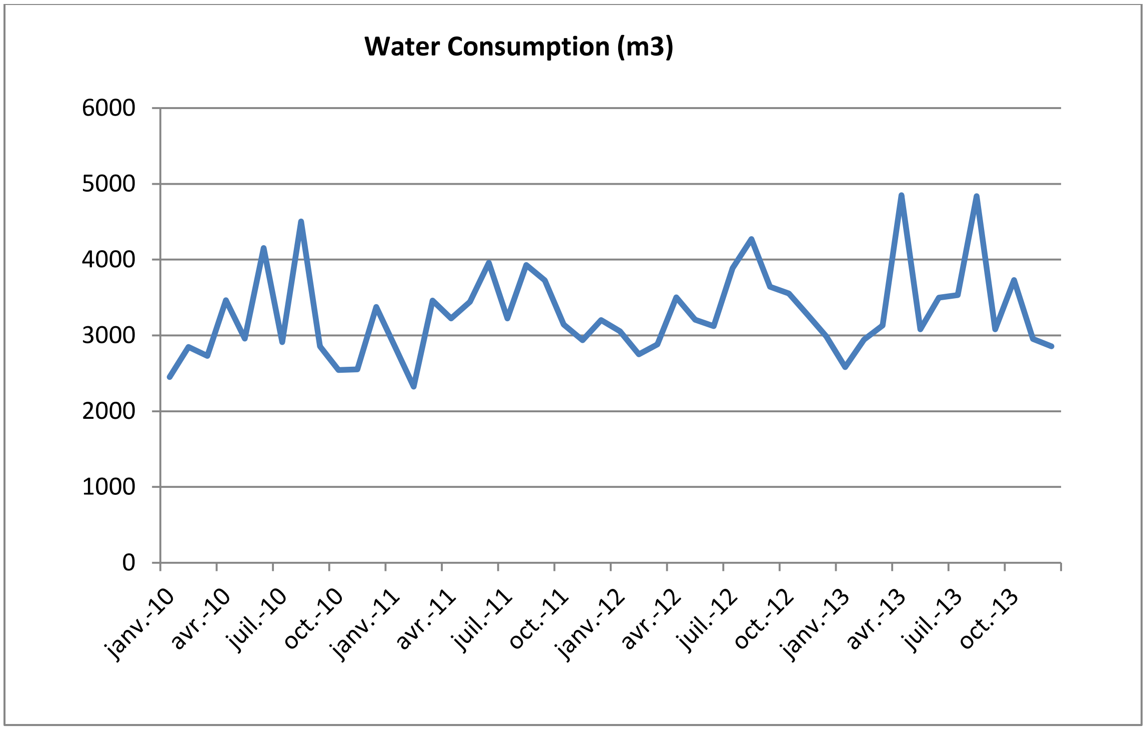


Figure 4.4: Monthly water consumptions in Ramallah city (period 2010 – 2013)

4.4.2 Model Structure and Data reparation

The determination of the network architecture constitutes one of the major tasks in the use of the ANN. The overall performance of an ANN model depends on the numbers of hidden layers and hidden nodes. The optimal ANN structure is generally determined by fixing the number of layers and the number of nodes in each layer. It has been shown that one hidden layer is sufficient for approximating any continuous function provided arguments that a single h idden layer of neurons, operatinga sigmoidal activation function, is adequate for modeling any s olution surface of practicalinterest. In some applications, one hidden layer is commonly used. (Najjar et. al., 1997)

The use of the ANNs approach is based in splitting the data into three sets:

- The training set, which is used to train the neural network and adjust the connection weights.

- The testing set, which measures the ability of the model to be generalized; the performance of the model is checked during this phase, which is also used to determine the optimum network architecture.
- The validation set, which is used to determine the performance of a neural network on patterns, which were not used in the previous phases.

Table 4.2 shows the scenarios tested in the model. Since scenario 3 gives the best results (R = 0.66 in model A, 0.82 in model B,0.66 in model C, 0.99 in model D) it will be used in the analyses presented below.

Table 4.2: the scenarios tested in the model

Repartition Scenarios	% of training	% of testing	% of validation	Total R for Habitation parameters	Total R for household parameters	Total R for Climate parameters	Total R for Habitation and household parameters
1	50	25	25	0.46	0.71	0.46	0.78
2	70	20	10	0.53	0.78	0.43	0.82
3	80	20	0	0.66	0.82	0.66	0.99

The data set was divided into two subsets: training and testing data set. The training data set includes 80% of total data records. It is evident that the training set must cover all the characters of the problem in order to get effective forecasting.

Matlab software program was used for the development of ANN model during the training and testing processes.

4.4.3 Models based on one input variable

Table 4.3 summarizes the 11 models used in this analysis. The results of modeling are given in table 4.4. A significant variation was found in the performance of these models. Model M5 produced the lowest value of the RMSE (0.0171), while model M10 produced the highest value of the RMSE (0.2864). Model M10 produced the highest value of ASE (0.0820; while M5 produced the highest CORR (0.9947). Globally, the performances of the ANN model with the physical and socioeconomic parameters are better than those with the climate parameters.

The models M5, M2 and M1 presented the best performances in testing. The best results were obtained from models M5, M2, M1 and M3. Figure 4.5 shows the results obtained with these models.

Table 4.3: ANN models based on a single input variable

Model	Input structure	Output
M1	TB	WD
M2	SA	WD
M3	GA	WD
M4	SPV	WD
M5	NP	WD
M6	EL	WD
M7	AI	WD
M8	NC	WD
M9	MT	WD
M 10	MH	WD
M11	MR	WD

Table 4.4: Performances of ANN models based on a single input variable

Models	Train			Test			All		
	ASE	**R**	**RMSE**	**ASE**	**R**	**RMSE**	**ASE**	**R**	**RMSE**
M1	0.0217	0.7056	0.1472	0.0206	0.7405	0.1434	0.0214	0.7128	0.1464
M2	0.0163	0.8024	0.1276	0.0089	0.8977	0.0942	0.0148	0.8144	0.1216
M3	0.0209	0.7133	0.1446	0.0257	0.7115	0.1604	0.0219	0.7075	0.1479
M4	0.0222	0.6980	0.1489	0.0360	0.4331	0.1899	0.0250	0.6530	0.1581
M5	0.0002	0.9983	0.0125	0.0003	0.9947	0.0171	0.0002	0.9979	0.0136
M6	0.0464	0.0480	0.2155	0.0322	0.1083	0.1795	0.0435	0.0473	0.2086
M7	0.0399	0.3265	0.1998	0.0428	0.1379	0.2069	0.0405	0.2768	0.2013
M8	0.0439	0.1467	0.2096	0.0386	0.0752	0.1965	0.0428	0.1339	0.2070
M9	0.0213	0.7900	0.1459	0.0525	0.4469	0.2292	0.0278	0.7165	0.1667
M10	0.0293	0.6419	0.1713	0.0820	0.0327	0.2864	0.0403	0.5229	0.2008
M11	0.0382	0.5229	0.1954	0.0589	0.4923	0.2426	0.0425	0.4882	0.2062

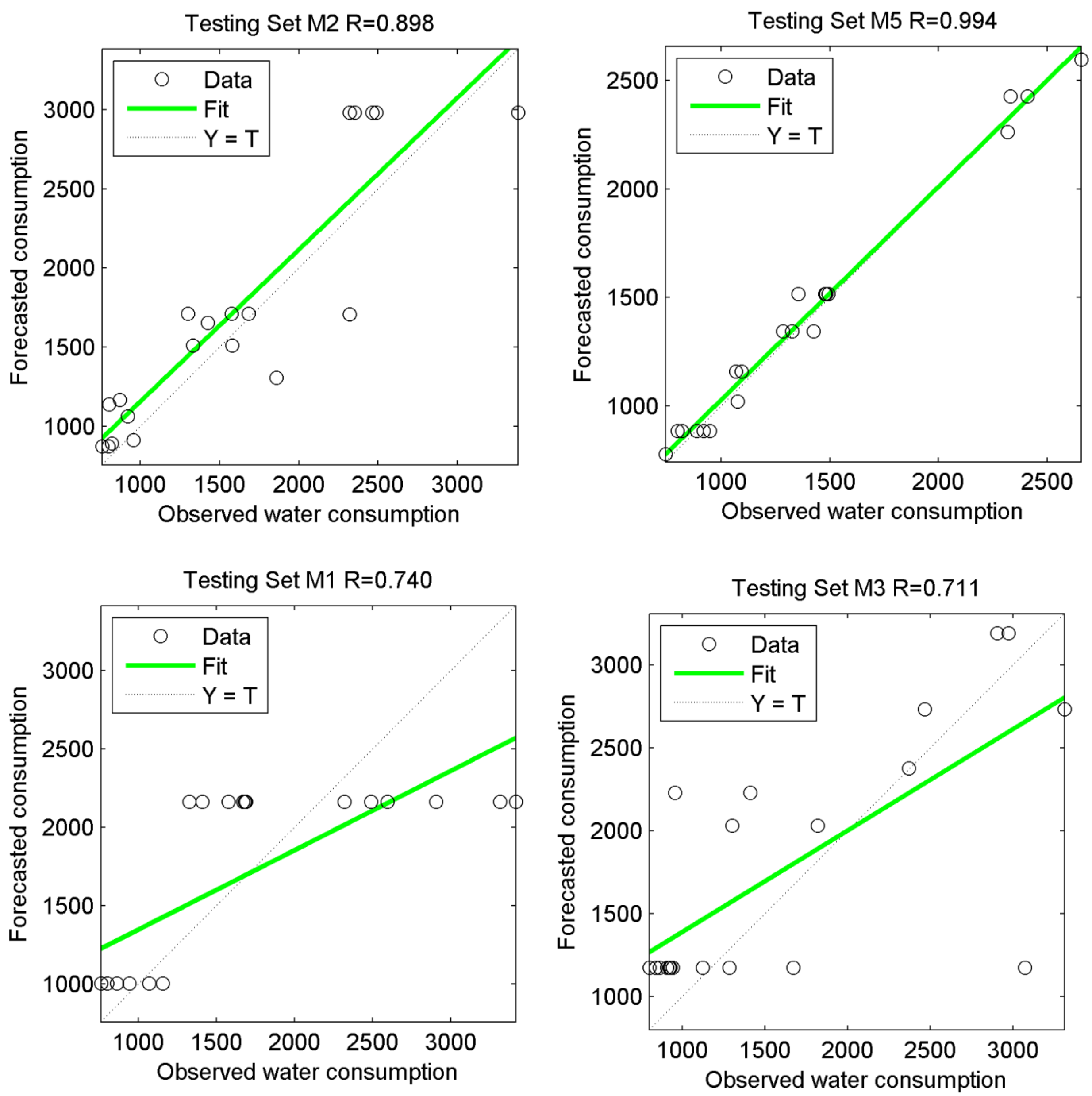


Figure 4.5: Results of ANN modeling for models M2, M5, M1 and M3 (input parameters are given in table 4.3).

4.4.4 Models with Multiple input variables

Four models were developed for modeling the water consumption with the ANN method using multiple input parameters:

- Habitation parameters (Model A),
- Socio-economic parameters (Model B),
- Climate parameters (Model C),
- Habitation and socio-economic parameters (Model D).

4.4.4.1 Model (A): habitation parameters

Table 4.5 summarizes the input parameters which were used in the construction of 5 ANN models in considering only the physical parameters: Type of building (TB), Surface area (SA), Garden area (GA) and Swimming pool volume (SPV). Table 4.6 shows the performances of the 5 ANN models. It shows that the model M14 presented the best performances: for the testing phase, it produced ASE = 0.0120; R = 0.753. This model uses Type of building (TB), Surface area (SA) and Garden area (GA) as input parameters. This result was obtained with the configuration: 1 hidden layer and 10 Neurons. Figure 4.6 shows the results obtained by this model for the phases of training and testing as well as the results obtained with the whole data. The good performances were observed of this model for the whole data. Model M12 presented less performance: for the testing phase, it presented ASE = 0.0390; R = 0.5535, this shows that taking the garden area (GA) into consideration improves the performances of the model.

Table 4.5: ANN models based on habitation parameters (Model A)

Model	Input structure	Output
(model A)	**Habitation Parameters**	
M12	TB SA	WD
M13	SA GA	WD
M14	TB SA GA	WD
M15	SA GA SPV	WD
M16	TB SA GA SPV	WD

Table 4.6: Performances of ANN models based on habitation parameters (Model A)

Models	Train			Test			All		
	ASE	**R**	**RMSE**	**ASE**	**R**	**RMSE**	**ASE**	**R**	**RMSE**
M12	0.0043	0.9490	0.0658	0.0390	0.5535	0.1976	0.0114	0.8690	0.1068
M13	0.0076	0.9166	0.0870	0.0378	0.5957	0.1944	0.0137	0.8421	0.1172
M14	0.0041	0.9568	0.0638	0.0120	0.7531	0.1095	0.0057	0.9340	0.0754
M15	0.0065	0.9286	0.0809	0.0158	0.6593	0.1256	0.0084	0.8995	0.0918
M16	0.0053	0.9385	0.0725	0.0235	0.6633	0.1532	0.0090	0.8915	0.0947

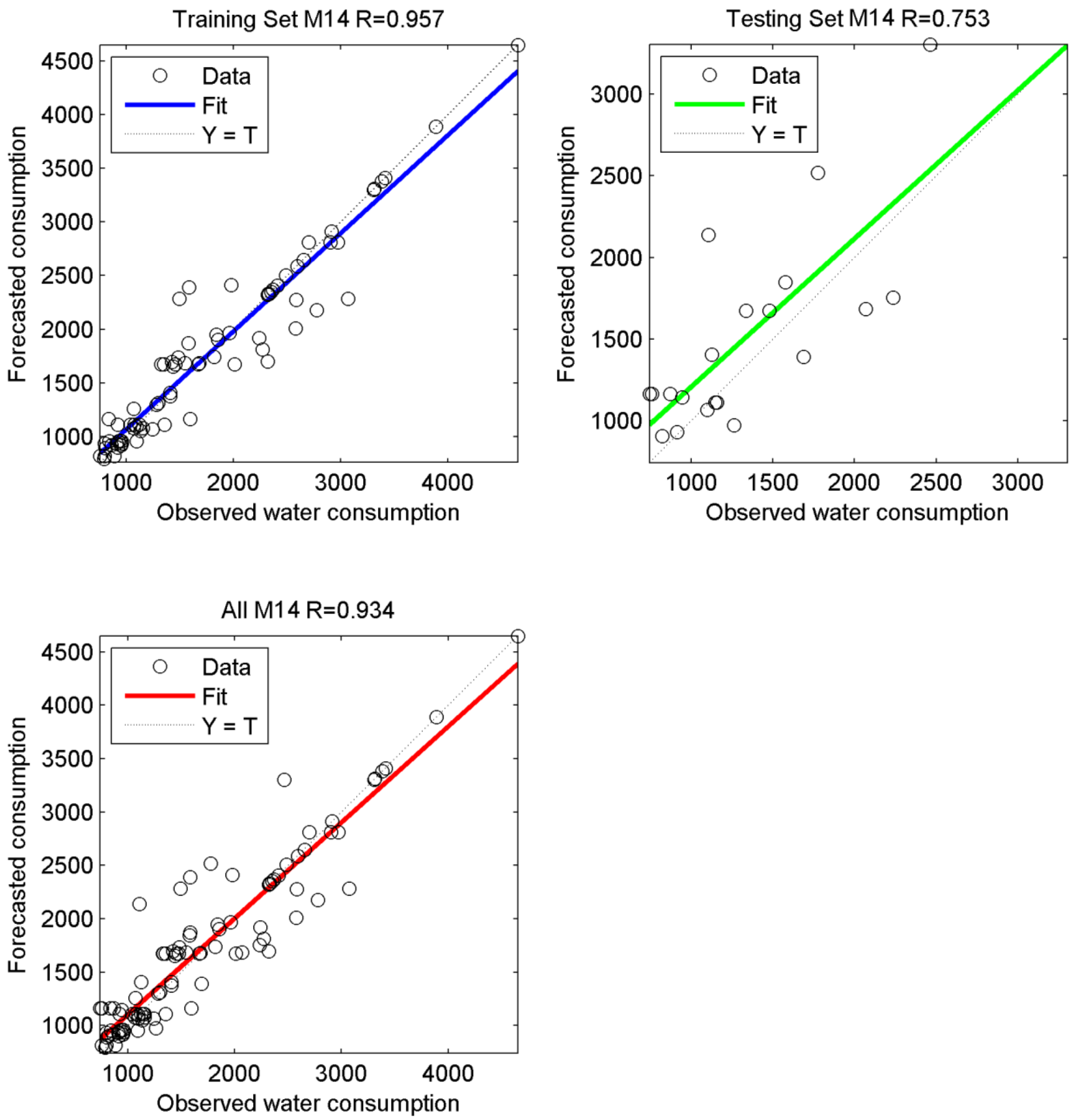


Figure 4.6: Results of the best model M14 based on a habitation parameters Model A

Input parameters: TB, SA and GA

The weights of the ANN model M 14 are as shown in table 4.7; the result indicates that the weight of each input parameters on the ANN model prediction. It can be observed that the surface area has the highest weight (27.86), followed by the garden area (21.68) and the type of building (5.27).

Table 4.7: The weights of the ANN model M 14

M14 (3 Inputs - 10 Nodes)					
Input Weights				Layer Weights	
TB	SA	GA	Bias	Y1	Bias
-3.60646	-23.2153	21.68146	5.399984	7.412081	-2.4156
5.273745	-27.6589	17.08446	3.104428	-11.2881	
-2.74602	17.6159	-11.644	-1.98649	-21.145	
-0.28588	22.09956	-23.0096	-3.59408	-19.6718	
0.421824	24.98716	-32.2726	-1.76648	4.706972	
-1.30085	27.86462	-27.687	-4.33776	14.59881	
5.029643	4.427021	-3.2333	0.901214	2.994707	
1.673044	20.86566	-10.2097	0.053475	0.461112	
0.681356	16.05766	-12.8549	-3.29845	17.74409	
-2.01097	-3.08146	2.347491	1.057831	1.041285	

Ranking analysis of model M14 provided the following result in table 4.8. The result indicates that the weight of each input parameters on the ANN model prediction.
It can be observed that the surface area has the highest weight (161.92), followed by the garden area (129.44) and the type of building (13.74).

Table 4.8: Ranking analysis of model M14

M14		
Inputs	Weights multiplication	Absolute Value
TB	-13.7489	13.7489
SA	161.9204	161.9204
GA	-129.4414	129.4414

4.4.4.2 Model (B): socio-economic parameters

Table 4.9 summarizes the input parameters which were used in the construction of 5 ANN models in considering only socio-economic parameters: household size (NP), education level (EL), annual income (AI) and number of cars (NC). Table 4.10 shows the performances of the 5 ANN models. It shows that the model M21 provides the best performances: for the testing phase, it presented ASE = 0.0075; R = 0.8273. This model uses the totality of the socio-economic parameters. This result was obtained with the configuration: 1 hidden layer and 5 Neurons. Figure 4.7 shows the results obtained by this model for the phases of training and testing as well as the results obtained with all the data. Good performances of this model were noticed for the whole data.

Table 4.9: ANN models based on socio-economic parameters (Model B)

Model	Input structure	Output
(model B)	**socio-economic parameters**	
M17	NP EL	WD
M18	EL AI	WD
M19	NP EL AI	WD
M20	EL AI NC	WD
M21	NP EL AI NC	WD

Table 4.10: Performances of ANN models based on socio-economic parameters (Model B)

Models	Train			Test			All		
	ASE	R	RMSE	ASE	R	RMSE	ASE	R	RMSE
M17	0.0053	0.8490	0.0758	0.0390	0.8035	0.1876	0.0194	0.8690	0.1098
M18	0.0046	0.6166	0.0670	0.0378	0.5957	0.1644	0.0187	0.8421	0.1142
M19	0.0061	0.4568	0.0738	0.0120	0.6531	0.1595	0.0077	0.9340	0.0784
M20	0.0035	0.3286	0.0809	0.0158	0.7593	0.1656	0.0094	0.8995	0.0818
M21	0.0001	0.9940	0.0075	0.0168	0.8273	0.1295	0.0035	0.9672	0.0589

The model M18 showed less performance: for the testing phase, it produced ASE = 0.0378 and R = 0.5957. This result indicates that taking the Number of cars (NC) into consideration improved the performances of the model.

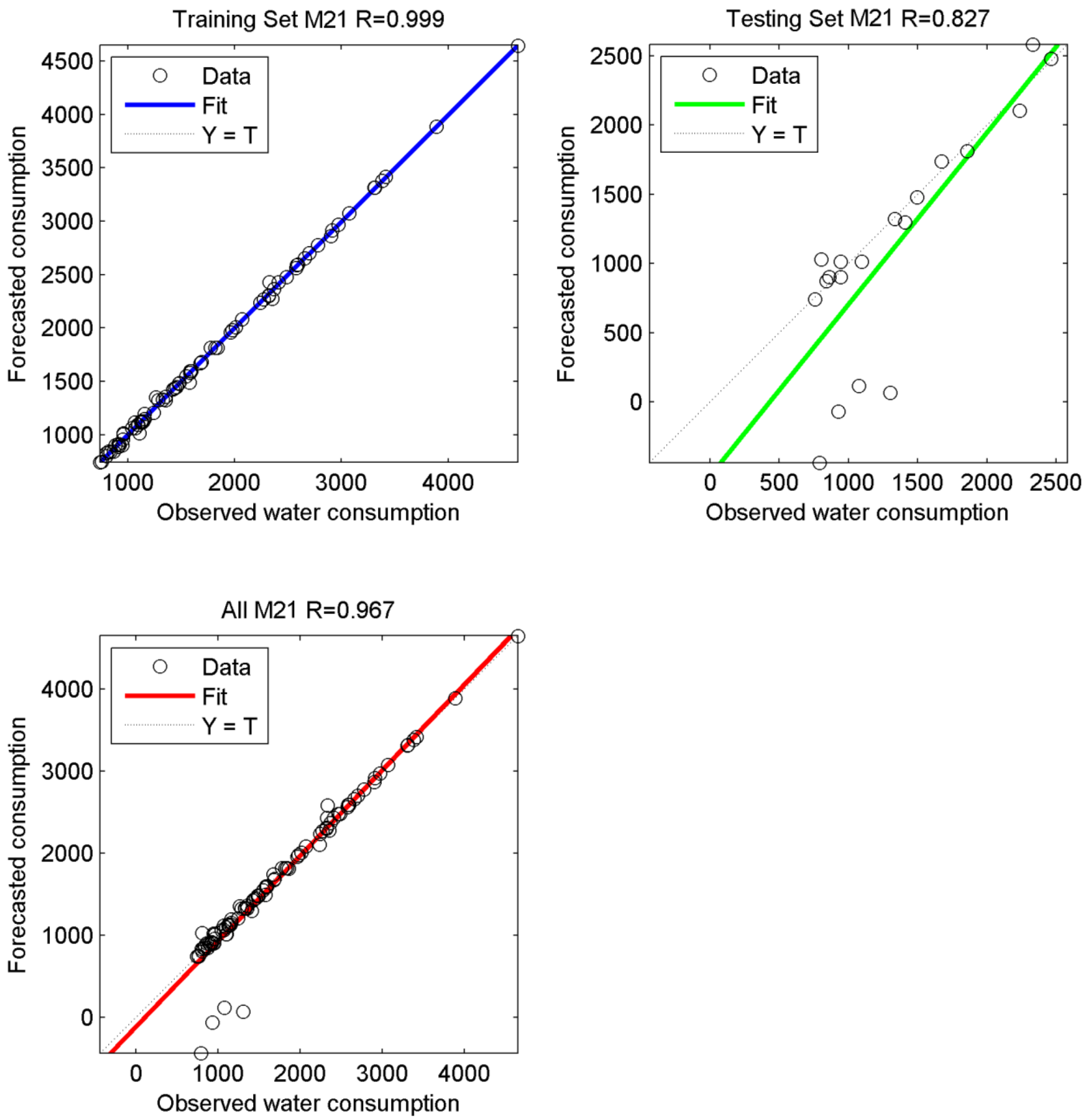


Figure 4.7: Results of the best model M21 based on socio-economic parameters (Model B)

Input parameters: NP, EL, AI and NC

The weights of the ANN model M 21 are as shown in table 4.11. The result indicates that the weight of each input parameters on the ANN model prediction.
It can be observed that the number of people (22.08) has the highest weight, followed by the annual income, the educational level and the number of cars.

Table 4.11: The weights of the ANN model M 21

M21 (10 Inputs - 5 Nodes)												
Input Weights											Layer Weights	
NP	**EL1**	**EL2**	**EL3**	**AI1**	**AI2**	**AI3**	**AI4**	**AI5**	**NC**	**Bias**	**Y1**	**Bias**
-2.34259	1.214204	-1.92749	-1.90584	0.892695	-0.51123	-1.82263	-1.66036	-0.30691	8.608867	-3.21364	-0.21401	-3.1218
1.852252	-0.2704	-0.25088	0.01405	0.22251	0.356649	0.099933	0.103087	0.064691	-0.18575	-1.15089	0.525041	
1.56828	-0.00811	0.31971	-0.52846	-0.58879	-1.13574	-0.14403	-0.56847	2.863059	0.213402	0.053831	0.203619	
5.47099	-3.18003	2.501852	1.564297	0.726784	1.395453	4.0837	-7.04066	3.063016	-14.8761	2.462411	-0.04595	
22.08597	-0.40358	-0.82923	2.121454	0.098494	3.809254	-0.36374	-0.41214	-0.69573	0.220824	2.953858	3.513466	

Ranking analysis of model M21 provided the following result in table 4.12. The result indicates that the weight of each input parameters on the ANN model prediction.
It can be observed that the number of people (9.3) has the highest weight, followed by the annual income, the educational level and the number of cars.

Table 4.12: Ranking analysis of model M21

M27		
Inputs	**Weights multiplication**	**Absolute Value**
NP	9.3016	9.3016
EL1	-1.6753	1.6753
EL2	-2.6825	2.6825
EL3	7.6894	7.6894
AI1	0.1186	0.1186
AI2	13.385	13.385
AI3	-1.0524	1.0524
AI4	-0.8308	0.8308
AI5	-1.9025	1.9025
NC	-0.4371	0.4371

4.4.4.3 Model (C) climate parameters

Table 4.13 summarizes the input parameters which were used in the construction of 4 ANN models in considering only the climate parameters: Mean monthly temperature (MT), Mean monthly rainfall (MR) and Mean monthly humidity (MH). Table 4.14 shows the performances of these models. It shows that the model M25 provided the best performances: for the testing phase, ASE = 0.0465 and R = 0.6648. This model used all of the climate parameters. This result was obtained with the configuration: 1 hidden layer and 5 neurons. Figure 4.8 presents the results obtained by this model for the phases of training and testing as well as the results obtained with the whole data. The good performances for this model were found with the training data.

The model M22 presented less performance: for the testing phase, it gives ASE = 0.0390 and R= 0.4535. It shows that the consideration of the Mean monthly humidity (MH) in addition to the Mean monthly temperature (MT) and Mean monthly rainfall (MR) improves the ANN modeling.

Table 4.13: ANN models based on C climate parameters (Model C)

Model	Input structure	Output
(model C)	**climate parameters**	
M22	MT MH	WD
M23	MT MR	WD
M24	MR MH	WD
M25	MT MH MR	WD

Table 4.14: Performances of ANN models based on C climate parameters (Model C)

Models	Train			Test			All		
	ASE	**R**	**RMSE**	**ASE**	**R**	**RMSE**	**ASE**	**R**	**RMSE**
M22	0.0066	0.9490	0.0658	0.0390	0.4535	0.1976	0.0114	0.8690	0.1068
M23	0.0142	0.8559	0.1192	0.1279	0.5068	0.3577	0.0379	0.6784	0.1947
M24	0.0041	0.9568	0.0638	0.0120	0.5531	0.1095	0.0057	0.9340	0.0754
M25	0.0134	0.8458	0.1160	0.0465	0.6648	0.2157	0.0203	0.7959	0.1426

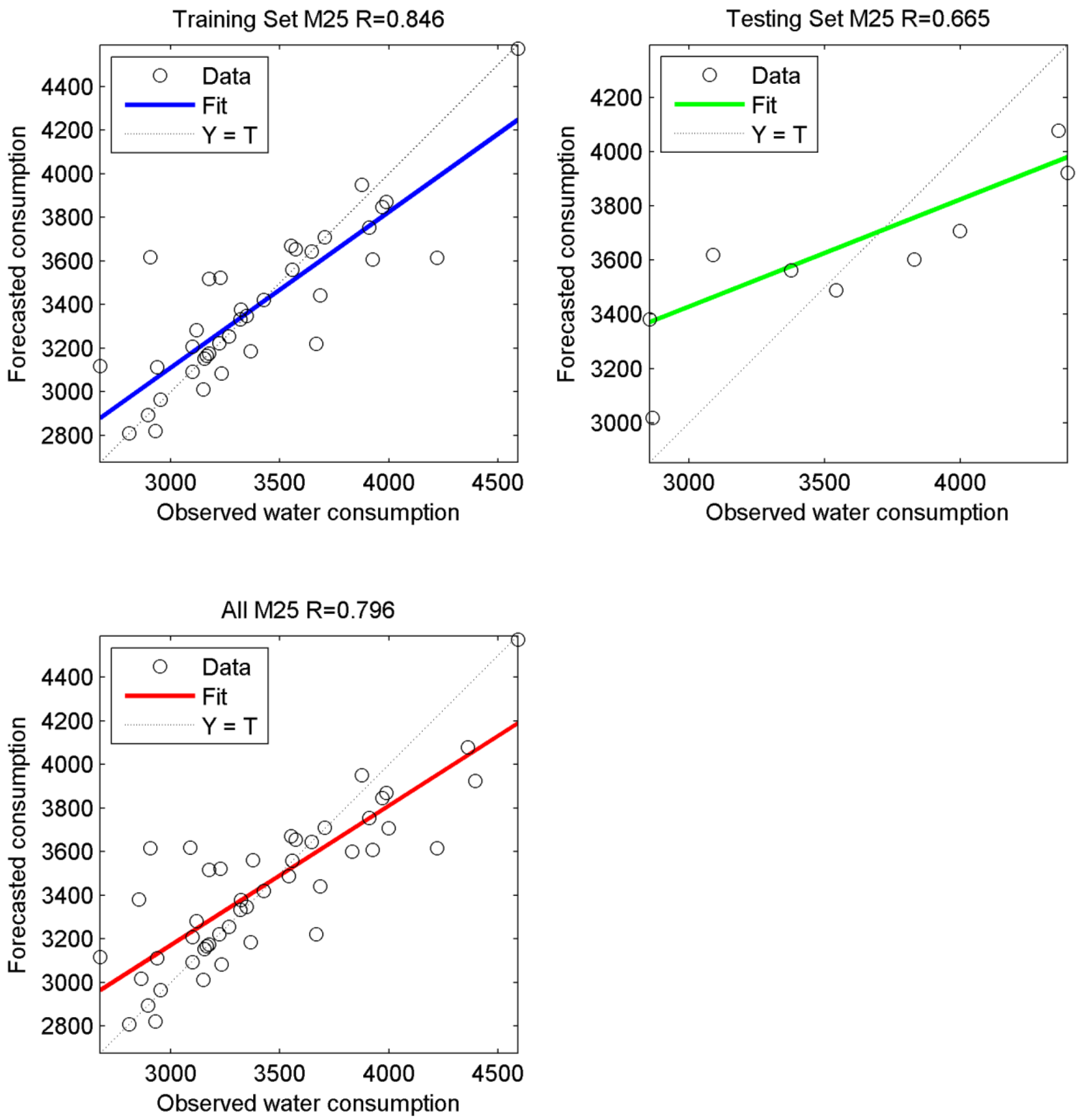


Figure 4.8 : Results of the best model M25 based on climate parameters (Model C)

Input parameters: MT, MH and MR

The weights of the ANN model M25 are given in table 4.15, the results indicate that the weight of each input parameters on the ANN model prediction.
It can be observed that the mean temperature (25.65) has the highest weight, followed by the mean humidity (22.07) and the rainfall (9.43).

Table 4.15: the weights of the ANN model M25

M25 (3 Inputs - 5 Nodes)					
Input Weights				Layer Weights	
MT	MH	MR	Bias	Y1	Bias
-7.71282	-22.0771	2.907561	10.93521	-0.53781	0.646662
-3.43388	5.192979	-9.43203	-0.12148	-32.0471	
3.112596	4.117178	1.842382	-3.51033	-0.76861	
3.330007	-5.24441	9.384751	0.223656	-32.0603	
-25.6555	19.13026	-3.78695	-9.76996	0.244728	

Ranking analysis of model M25 provided the following result in table 4.16 the results indicate that the weight of each input parameters on the ANN model prediction.
It can be observed that the mean temperature (19.23) has the highest weight, followed by the mean humidity (15.1) and the rainfall (2.5).

Table 4.16: Ranking analysis of model M25

M25		
Inputs	Weights multiplication	Absolute Value
MT	-19.2381	19.2381
MH	15.108	15.108
MR	-2.5152	2.5152

4.4.4.4 Model (D) habitation and socio-economic parameters

Table 4.17 summarizes the input parameters which were used in the construction of 11 ANN models in considering both habitation and socio-economic parameters. Table 4.18 and Figure 4.9 show the performances of these models. It shows that the model M32 provided the best performances: for the testing phase, ASE = 0.0002 and R = 0.9967. This result was obtained with the 4 input parameters: type of building (TB), building surface area (SA), garden area (GA) and household size (NP). This result was obtained with the configuration: 1 hidden layer and 5 Neurons. Figure 4.10 shows the results obtained by this model for the phases of training and testing as well as the results obtained with the whole data. Good performances for this model were noticed for the three sets of data.

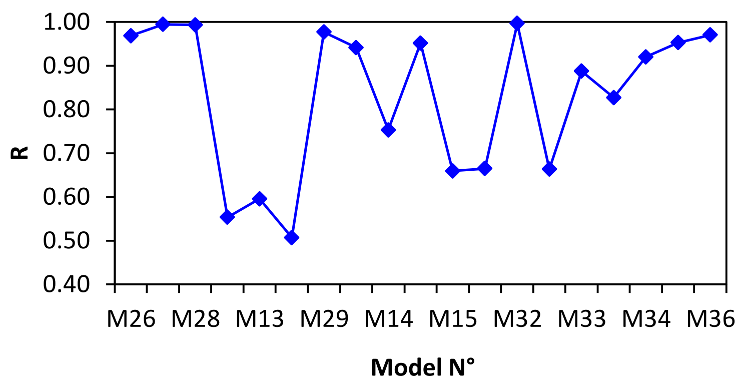
The model M33 provided less performance: for the testing phase, ASE = 0.0121 and R = 0.8876. However, this model has good performances (R = 0.8876). The comparison of the performances of models M32 and M33, shows that the replacement of the input parameter swimming pool volume (SPV) by the garden area (GA) improves the performances of the ANN model.

Table 4.17: ANN models based on habitation and socio-economic parameters (Model D)

Model	Input structure	Output
(model D)	**habitation and socio-economic parameters**	
M26	SA NP	WD
M27	TB NP	WD
M28	GA NP	WD
M29	TB SA NP	WD
M30	SA GA NP	WD
M31	SA SPV NP	WD
M32	TB SA GA NP	WD
M33	TB SA SPV NP	WD
M34	TB SA GA SPV NP	WD
M35	TB SA NP EL AI	WD
M36	TB SA NP EL NC	WD

Table 4.18: Performances of ANN models using habitation and socio economic parameters (Model D)

Models	Train			Test			All		
	ASE	R	RMSE	ASE	R	RMSE	ASE	R	RMSE
M26	0.0001	0.9991	0.0093	0.0016	0.9686	0.0401	0.0004	0.9955	0.0199
M27	0.0002	0.9984	0.0123	0.0002	0.9946	0.0148	0.0002	0.9981	0.0129
M28	0.0001	0.9987	0.0106	0.0006	0.9937	0.0247	0.0002	0.9976	0.0146
M29	0.0001	0.9991	0.0087	0.0023	0.9769	0.0481	0.0005	0.9939	0.0231
M30	0.0000	0.9995	0.0067	0.0039	0.9417	0.0628	0.0008	0.9905	0.0290
M31	0.0001	0.9992	0.0086	0.0055	0.9518	0.0739	0.0012	0.9873	0.0343
M32	0.0001	0.9990	0.0096	0.0002	0.9967	0.0152	0.0001	0.9986	0.0110
M33	0.0010	0.9991	0.0085	0.0121	0.8876	0.1100	0.0025	0.9710	0.0502
M34	0.0000	0.9995	0.0069	0.0062	0.9204	0.0790	0.0013	0.9850	0.0362
M35	0.0000	0.9995	0.0068	0.0039	0.9527	0.0627	0.0080	0.9904	0.0289
M36	0.0001	0.9994	0.0076	0.0015	0.9705	0.0392	0.0004	0.9960	0.0190



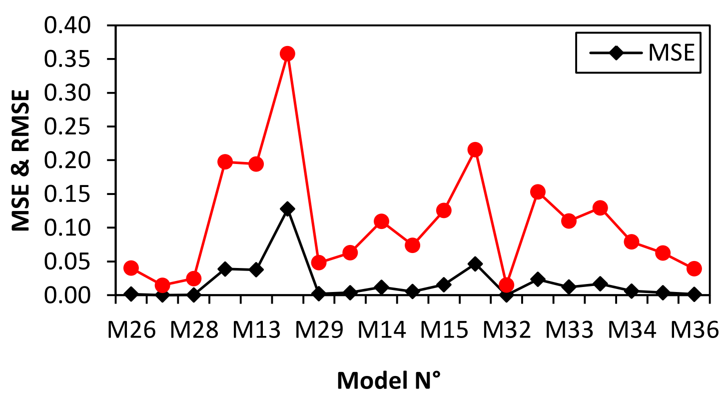


Figure 4.9: Performances of the ANN models using habitation and socio economic parameters (Model D)

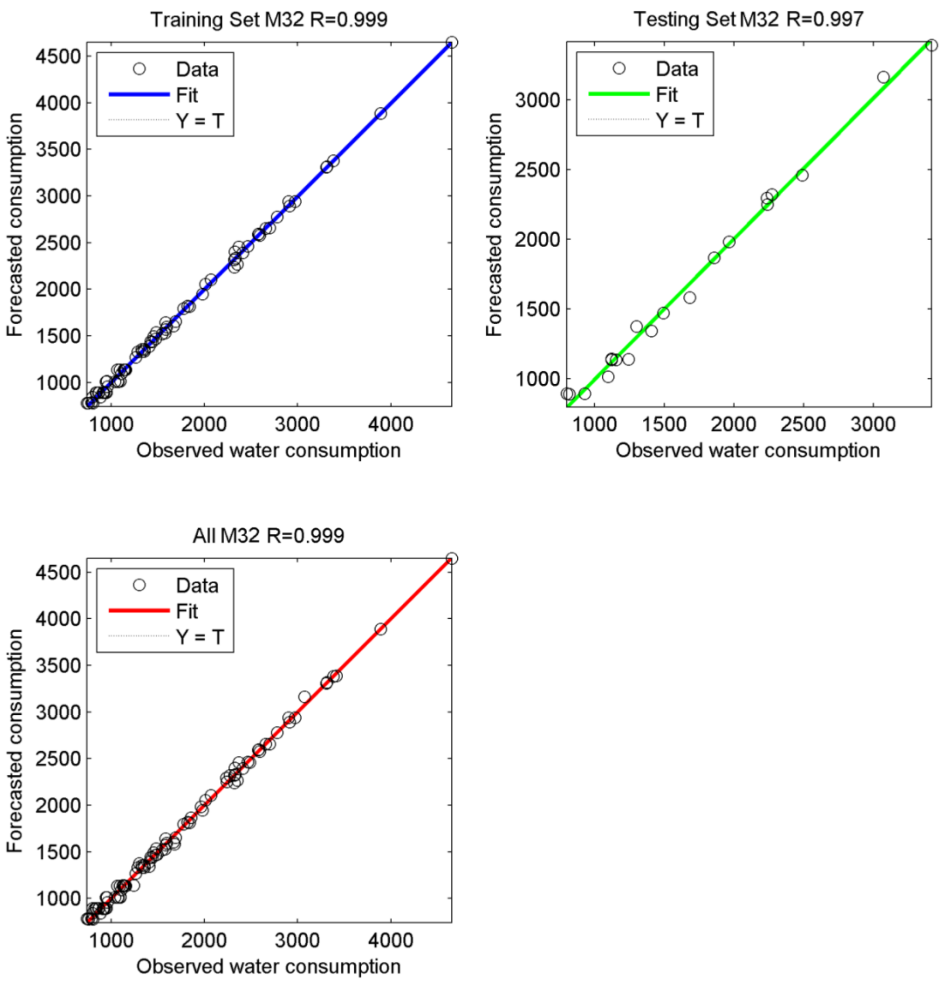


Figure 4.10: Performances of the model M32 - habitation and socio-economic parameters (ANN models based on habitation and socio-economic parameters (Model D)

The results obtained with the 36 ANN models showed that the best performances are obtained with Model 32, which uses the following input parameters number of persons (NP), building surface area (SA), Garden area (GA) and type of Building (TB). Models M27 and 28 provided also an excellent performance (R is close to 0.99). This result shows that taking the number of persons (NP), the Garden area (GA) and the type of Building (TB) into consideration improved the performances of the ANN modeling of the water consumption in the City of Ramallah.

The weights of the ANN model M32 are presented in table 4.19, the results show that the weight of each input parameters on the ANN model prediction.

The results indicate the weight of each input parameters on the ANN model prediction.

It can be observed that the results of number of people (172.10) has the highest weight,

followed by surface area (133.6), garden area (54.0) and type of building is at last (30.08).

Table 4.19: the weights of the ANN model M32

M32 (4 Inputs - 10 Nodes)						
Input Weights					Layer Weights	
TB	SA	GA	NP	Bias	Y1	Bias
30.0838	133.6284	1.490622	-172.109	26.76616	-0.01725	0.206259
11.63125	-33.2702	-34.7791	133.8518	-5.92007	-0.02451	
-0.03353	0.020319	0.088644	1.233586	-0.65884	0.853324	
24.37102	38.51636	-54.0684	1.72709	14.92883	0.339941	
3.165715	-2.09079	-2.94001	0.072851	-2.03812	0.053436	

Ranking analysis of model M32 provided the following result in table 4.20, the results indicate the weight of each input parameters on the ANN model prediction.
It can be observed that the results of number of people (41.3) has the highest weight, Followed by surface area (18.8), garden area (9.9) and type of building is at last (5.05).

Table 4.20: Ranking analysis of model M32 provided the following result

M20		
Inputs	Weights multiplication	Absolute Value
TB	5.0552	5.0552
SA	18.8483	18.8483
GA	-9.9624	9.9624
NP	41.3322	41.3322

4.4.5 Multiple Linear Regression (MLR)

The Multiple Linear Regression (MLR) was used for modeling the water consumption in considering the input parameters of the model M32, which provided the best results with the ANN method. This model uses the 4 input parameters: type of building (TB), building surface area (SA), garden area (GA) and household size (NP). Considering these parameters for the totality of the data, the MLR method gives the following regression:

$$WD = 82.3278 + 8.41455 \times TB - 0.00125 \times SA + 0.23203 \times GA + 154.701 \times NP \qquad (14)$$

It can be observed that the number of people has the highest weight, followed by the type of building. Figure 4.11 displays the performances of this multiple regression. An excellent result is observed with R = 0.9953, which is very close to that obtained with the ANN model M32.

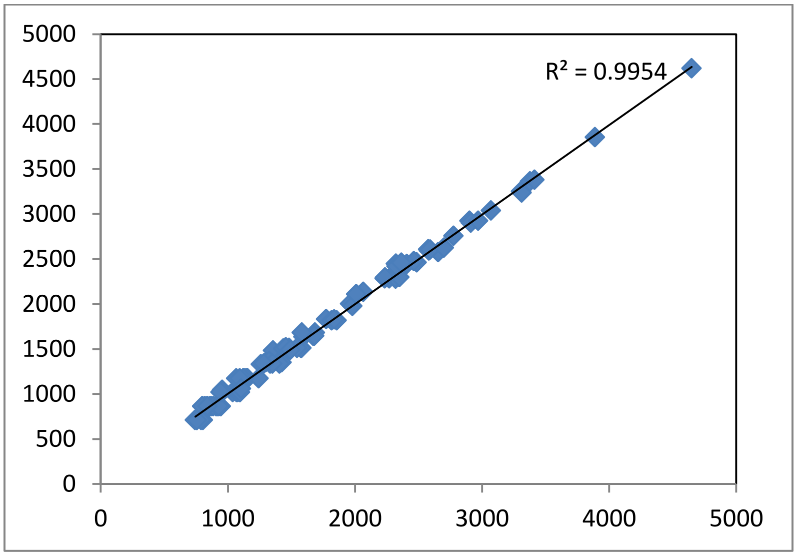


Figure 4.11: Performance results - correlation coefficient R for MLR model

4.5 Analysis of the water consumption in Khan Younis

4.5.1 Input Variables and Data

10 input parameters were collected for modeling the water consumption in Khan Younis: The type of building (TB), building surface area (SA), garden area (GA), household size (NP), education level (EL), annual income (AI), number of cars (NC), mean monthly temperature (MT), mean monthly rainfall (MR), and mean monthly humidity (MH). Different from the City of Ramallah, as the swimming pool volume (SPV) factor is not included.

The statistical parameters, minimum value; x_{min}, maximum value; x_{max}, mean; x, standard deviation; SD, for the data sets are summarized in Tables 4.21.

Table 4.21: Statistical parameters for the input parameters – Khan Younis

Variables	Max	Min	Mean	SD
Water consumption WD (m3)	861	169	306	112
Surface area (SA) m2	650	120	248	128
Garden area (GA) m2	380	50	84	81
Number of persons (NP)	33	5	12	5
Number of cars (NC)	4	0	1	1
Temperature MT (°C)	30.4	14.4	22.8	8
Monthly humidity MH (%)	86	62	73.8	12
Rainfall MR (mm)	108.4	0	36.4	73

4.5.2 Model Structure and Data reparation

Table 4.22 shows the scenarios tested in the ANN model. Since scenario 3 presented the best results (R = 0.95 in model A, 0.88 in model B,0.82 in model C, 0.99 in model D), it will be used in the analyses presented below. The data set was divided into two subsets: training (80%) and testing (20%).

Table 4.22: Scenarios tested in the ANN model (Khan Younis)

Repartition Scenarios	% of training	% of testing	% of validation	Total R for Habitation parameters	Total R for household parameters	Total R for Climate parameters	Total R for Habitation and household parameters
1	50	25	25	0.74	0.69	0.58	0.82
2	70	20	10	0.81	0.77	0.62	0.86
3	80	20	0	0.95	0.88	0.82	0.99

4.5.3 Modeling based on one input variable

Table 4.23 summarizes the 10 models used in this analysis. The results of modeling are given in table 4.24. Significant variation was observed in the performance of these models. The best performances are obtained with:

- Model M2: R = 0.9817, the Surface area (SA) is used as input parameter
- Model M4: R = 0.9984, the Number of persons (NP) is used as input parameter

Figure 4.12 shows the results obtained with the model M4, which provides the best results.

The less performance models are:

- M5: R = 0.4331, the education level (EL) is used as input parameter
- M7: R = 0.5083, number of cars (NC) is used as input parameter

Table 4.23: ANN models based on a single input variable (Khan Younis)

Model	Input structure	Output
M1	TB	WD
M2	SA	WD
M3	GA	WD
M4	NP	WD
M5	EL	WD
M6	AI	WD
M7	NC	WD
M8	MT	WD
M9	MH	WD
M 10	MR	WD

Table 4.24: Performances of ANN models based on a single input variable (Khan Younis)

Models	Train			Test			All		
	ASE	**R**	**RMSE**	**ASE**	**R**	**RMSE**	**ASE**	**R**	**RMSE**
M1	0.0382	0.8229	0.0954	0.0589	0.8923	0.0426	0.0425	0.8882	0.0062
M2	0.0003	0.9724	0.0276	0.0003	0.9817	0.0142	0.0148	0.9144	0.0216
M3	0.0209	0.5133	0.1446	0.0257	0.5525	0.1604	0.0219	0.7075	0.1479
M4	0.0002	0.9983	0.0125	0.0002	0.9984	0.0122	0.0002	0.9989	0.0136
M5	0.0222	0.6980	0.1489	0.0960	0.4331	0.2899	0.0250	0.6530	0.1581
M6	0.0502	0.5983	0.0125	0.0503	0.5947	0.0171	0.0502	0.5979	0.0136
M7	0.0464	0.0480	0.2155	0.0322	0.5083	0.1795	0.0435	0.0473	0.2086
M8	0.0399	0.7265	0.1998	0.0028	0.7379	0.2069	0.0405	0.7768	0.2013
M9	0.0039	0.7467	0.0096	0.0006	0.8752	0.0965	0.0428	0.7339	0.0070
M10	0.0213	0.5900	0.1459	0.0525	0.4469	0.2292	0.0278	0.6165	0.1667

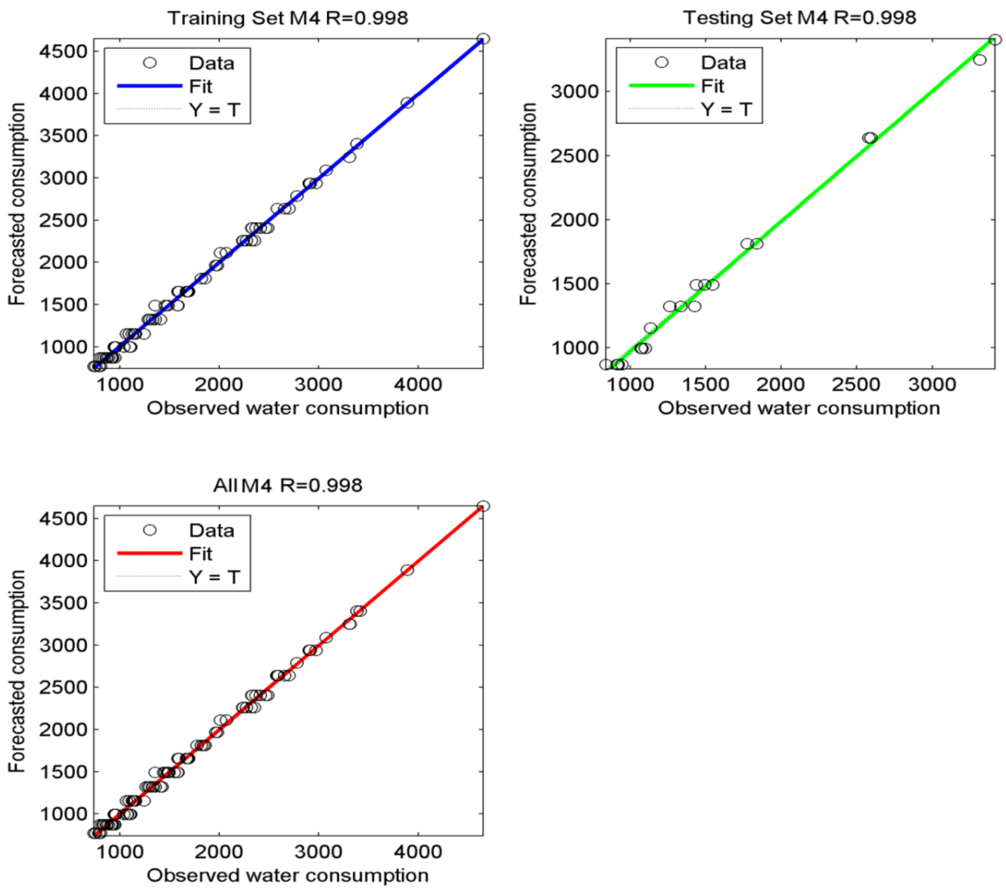


Figure 4.12: results obtained with the model M4, which provides the best results

Number of persons (NP) is used as input parameter (Khan Younis)

4.5.4 Models with Multiple input variables

Analyses are conducted with the 4 models used for modeling the water consumption in Khan Younis:

- Habitation parameters (Model A),
- Socio-economic parameters (Model B),
- Climate parameters (Model C),
- Habitation and socio-economic parameters (Model D).

4.5.4.1 Model (A) habitation parameters

Table 4.25 summarizes the input parameters which were used in the construction of 3 ANN models in considering only the physical parameters. The best result was obtained with model M11 (R = 0.95), which uses the Type of building (TB) and Surface area as input parameters. This result was obtained with the configuration: 1 hidden layer and 5 Neurons. Figure 4.13 shows the results obtained by this model for the phases of training and testing as well as the results obtained with all the data. The excellent performances were noticed if the type of building and the surface area were considered (R = 0.95).

Table 4.25: ANN models based on habitation parameters (Model A) (Khan Younis)

Model	Input structure	Output
(model A)	**Habitation Parameters**	
M11	TB SA	WD
M12	SA GA	WD
M13	TB SA GA	WD

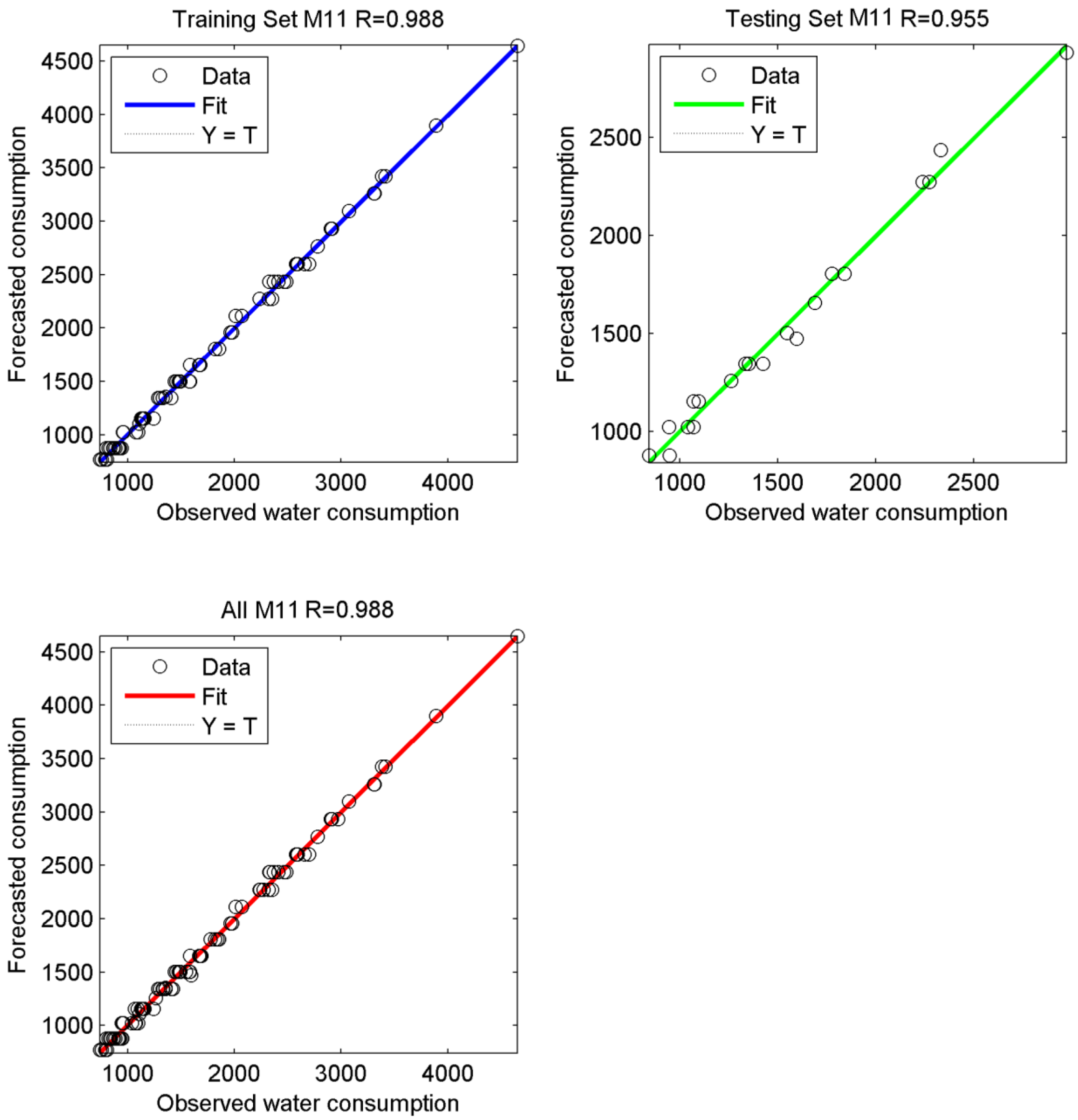


Figure 4.13: the results of the best model M11 based on a habitation parameters Model A

Input parameters: TB and SA (Khan Younis)

4.5.4.2 Model (B) the socio-economic parameters

Table 4.26 summarizes the input parameters which were used in the construction of 5 ANN models in considering the socio-economic parameters: household size (NP), education level (EL), annual income (AI) and number of cars (NC). The best result was obtained with model M14 (R = 0.88), which used the household size (NP) and the annual income (AI) as input parameters. This result was obtained with the configuration: 1 hidden layer and 10 Neurons. Figure 4.14 displays the results obtained with this model. Good performances of the model were found if the household size (NP) and the annual income (AI) were considered as input parameters.

Table 4.26: the structures of forecasting model B socio-economic parameters

Model	Input structure	Output
(model B)	**socio-economic parameters**	
M14	NP AI	WD
M15	EL AI	WD
M16	NP EL AI	WD
M17	EL AI NC	WD
M18	NP EL AI NC	WD

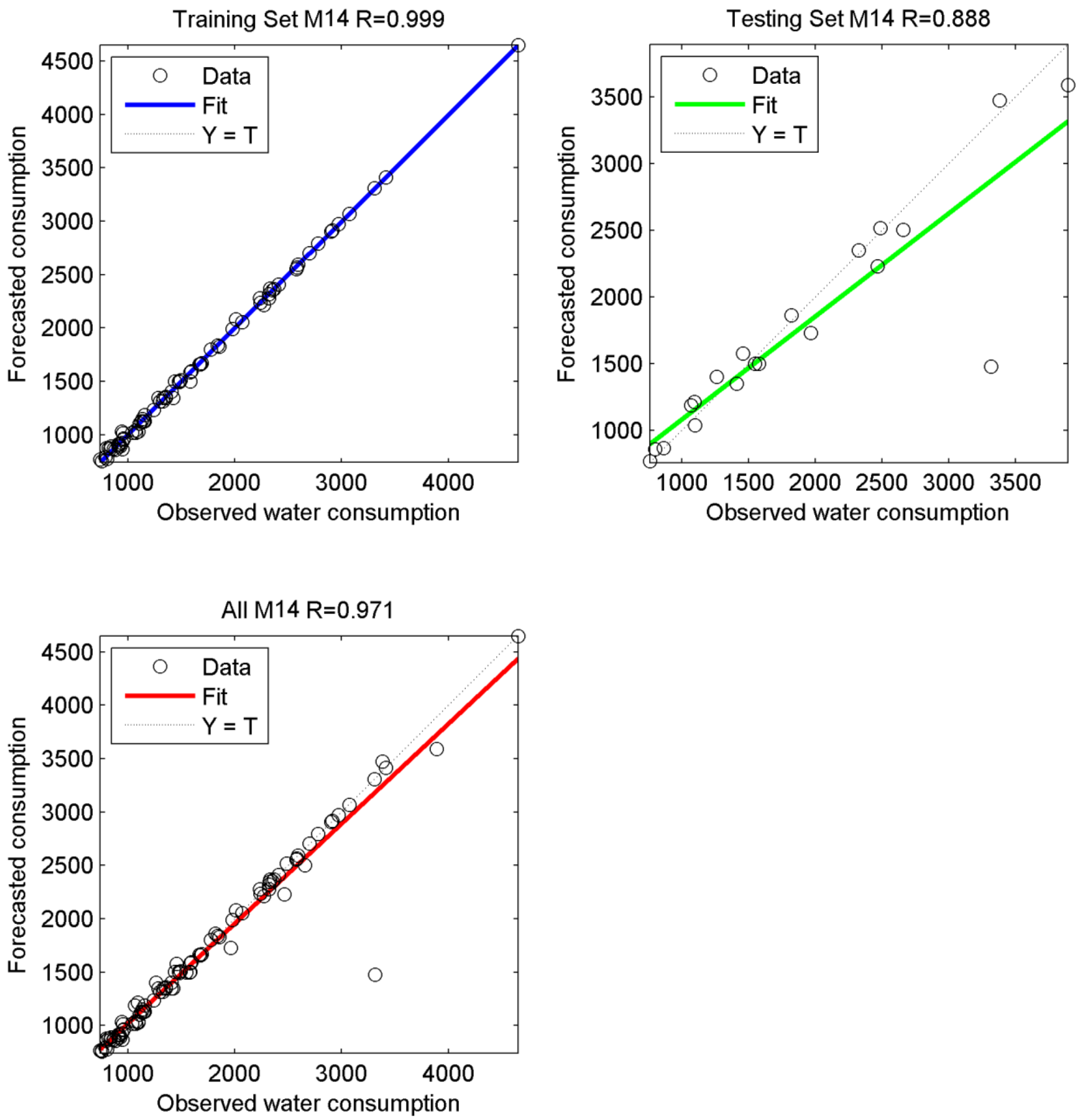


Figure 4.14: Results of the best model M14 based on socio-economic parameters (Model B)

Input parameters: NP and AI (Khan Younis)

4.5.4.3 Model (C) climate parameters

Table 4.27 summarizes the input parameters which were used in the construction of the 4 ANN models in considering the climate parameters. The best result was obtained with model M19 (R = 0.82), which used the mean monthly temperature (MT) and the mean monthly humidity (MH) as input parameters. This result was obtained with the configuration: 1 hidden layer and 5 Neurons. Figure 4.15 shows the results obtained by this model, good performance is also observed.

Table 4.27: ANN models based on C climate parameters (Model C) (Khan Younis)

Model	Input structure	Output
(model C)	**climate parameters**	
M19	MT MH	WD
M20	MT MR	WD
M21	MR MH	WD
M22	MT MH MR	WD

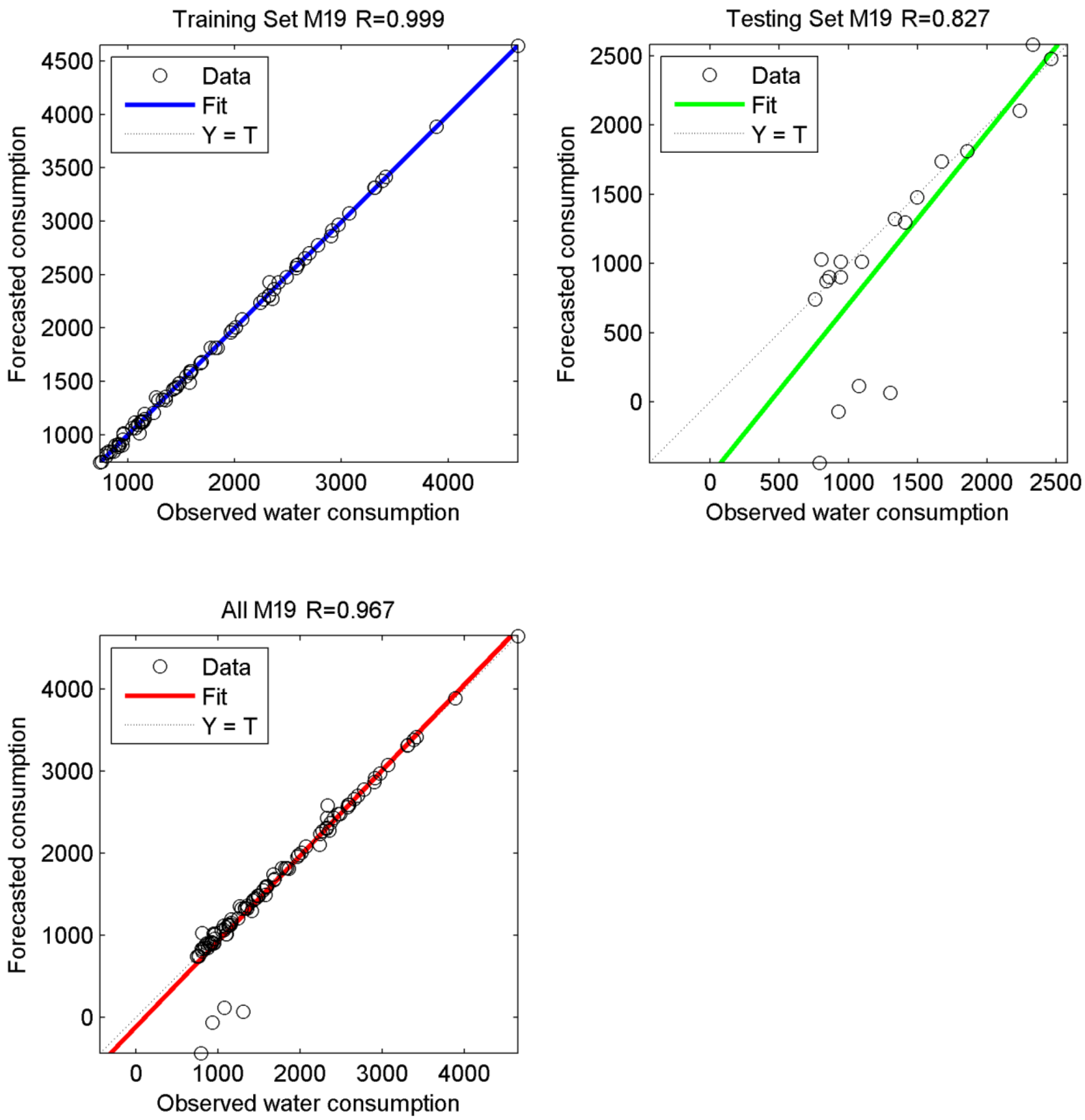


Figure 4.15: Results of the best model M19 based on climate parameters (Model C)

Input parameters: MT and MH (Khan Younis)

4.5.4.4 Model (D) habitation and socio-economic parameters

Table 4.28 summarizes the input parameters which were used in the construction of the 8 ANN models in considering both habitation and socio-economic parameters. The best result was obtained with the model M26 (R = 0.999). This excellent result is obtained with the 3 input parameters: type of building (TB), building surface area (SA) and household size (NP). This result was obtained with the configuration: 1 hidden layer and 5 Neurons. Figure 4.16 displays the results obtained by this model. We observe its excellent performance.

Table 4.28: ANN models based on habitation and socio-economic parameters (Model D)

(Khan Younis)

Model	Input structure	Output
(model D)	**habitation and socio-economic parameters**	
M23	SA NP	WD
M24	TB NP	WD
M25	GA NP	WD
M26	TB SA NP	WD
M27	SA GA NP	WD
M28	TB SA GA NP	WD
M29	TB SA NP EL AI	WD
M30	TB SA NP EL NC	WD

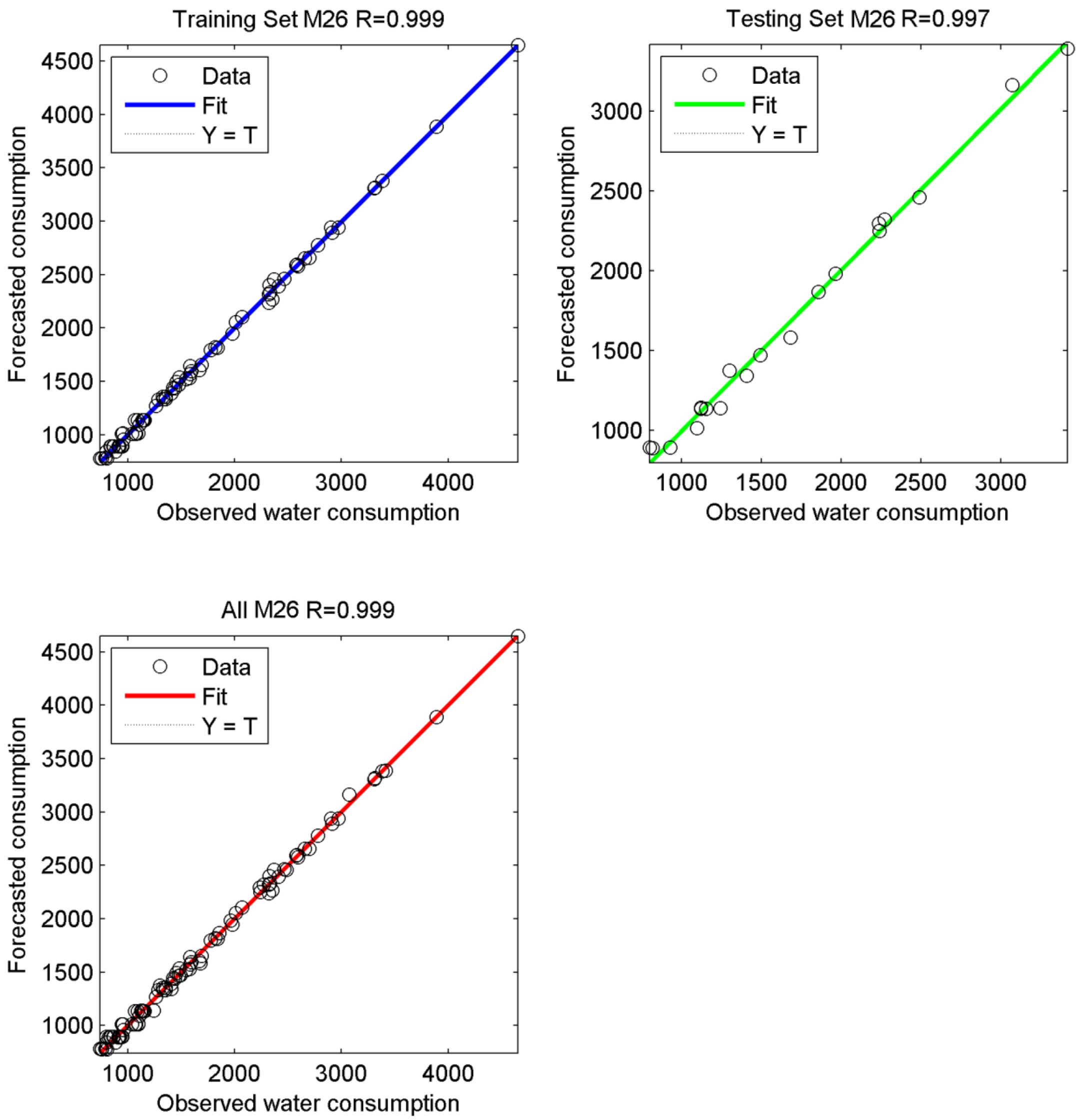


Figure 4.16: Performances M26 model D habitation and socio-economic parameters

Input parameters: type of building (TB), building surface area (SA) and household size (NP)

4.5.5 Modeling based on Multiple Linear Regression (MLR)

The Multiple Linear Regression (MLR) was used for modeling the water consumption in considering the input parameters of the model M26, which provided the best results with the ANN method. This model used the input parameters: type of building (TB), building surface area (SA) and household size (NP).

Considering these parameters for the totality of the data, the MLR method gives the following regression:

$$WD = 102.685 + 1540.302 \times TB + 12.5 \times SA + 2888.143 \times NP \quad (16)$$

Figure 4.17 displays the performances of this multiple regression. This model showed less performance (R = 0.76) than the ANN model M26 (R = 0.995).

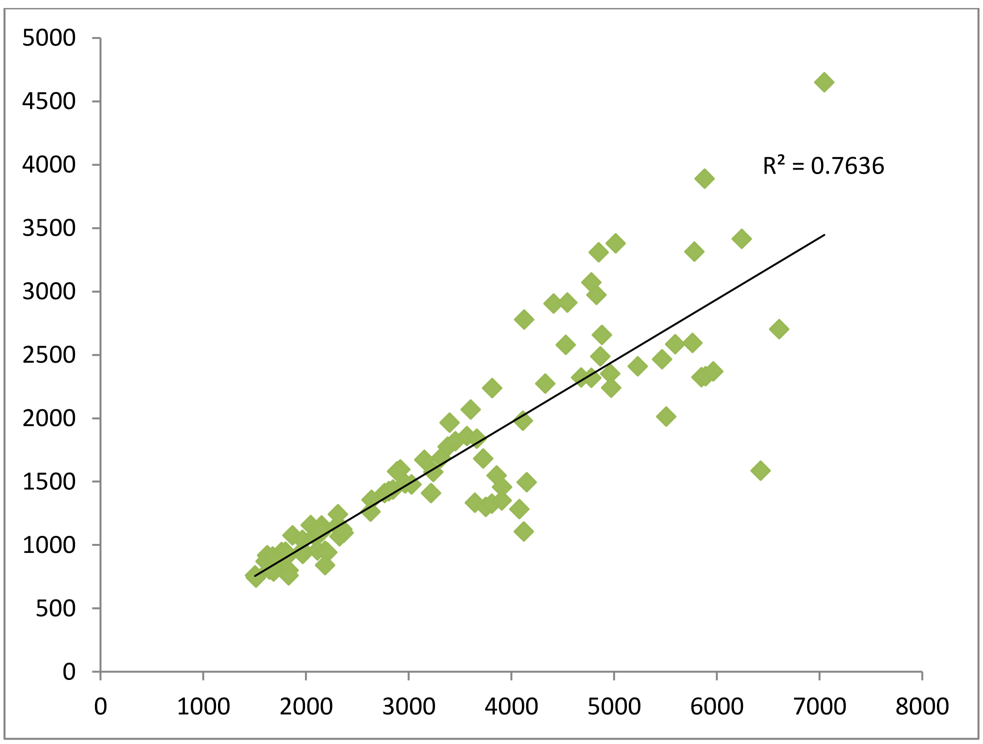


Figure 4.17: Performance results - correlation coefficient R for MLR model

4.6 Conclusion

This chapter presented the application of the Artificial Neural Network (ANN) method to model the water consumption in two Palestinian cities: Ramallah and Khan Younis. The modeling was based on collected data from both cities including the water consumption as well as the available factors which influence the domestic water consumption; these factors were classified into three categories:

- Physical parameters concerning the habitation: type, area, garden volume and swimming pool volume.
- Socio-economic parameters concerning the households: size, educational level, income and number of cars
- Climate parameters: Monthly Mean temperature, Mean humidity and Mean rainfall

For each city, 32 models were developed which included different combinations of the influencing parameters. The performances of the ANN models were presented, In order to reach the best performance model; some details about the ANN modeling were discussed.

For each city, the best performance model with the physical and socio-economic input parameter was compared to the Multiple Linear Regression (MLR). Generally, the ANN method provided equivalent or better results than the Multiple Linear Regression method.

Globally, the best performance ANN models was obtained using the input parameters which combined both physical and socio-economic input parameters.

For the City of Ramallah, the model M32 provided the best performances (R = 0.9967) using the 4 input parameters type of building (TB), building surface area (SA), garden area (GA) and household size (NP). The ranking analysis showed number of people has the highest weight, followed by surface area, garden area and finally the type of building.

For the City of Khan Younis, the model M26 provided the best performances (R = 0.999) using the 3 input parameters: type of building (TB), building surface area (SA) and household size (NP). The ranking analysis showed number of people has the highest weight, followed by surface area and finally the type of building.

The great interest of this study lies in the research methodology and its application to one of the major challenges for the Palestinian cities, in order to ensure an adapted water service for Palestinians in the following years.

General Conclusion

Understanding the factors that affect the household water demand is important for developing a pertinent strategy for water management. Descriptive statistical analysis was used to understand the affecting factors in water consumption.

The Artificial Neural Network (ANN) method was used in modeling the water consumption in tow Palestinian cities: Ramallah and Khan Younis. 32 models were developed for each city, the models included different combinations of the influencing parameters. The performances of the ANN models were presented, In order to reach the best performance model.

Modeling was based on collected data from these cities including the water consumption as well as the available factors which influence the domestic water consumption. These factors were classified into three categories:

- Physical parameters concerning the habitation: type, area, garden volume and swimming pool volume.
- Socio-economic parameters concerning the households : size, educational level, income and number of cars
- Climate parameters: Monthly Mean temperature, Mean humidity and Mean rainfall

One of the most important activities in the water demand management of household consumption is trying to understand the factors that shape the household pattern of water demand. The different patterns in this study showed that number of household persons and household water consumption had a significant and a positive trend, surface area responds more to water consumption, type of building also showed a positive trend with water consumption even though the trend was fluctuating and garden area also showed a positive relation along with the household water consumption.

The use of ANN in water demand forecasting is better than multiple linear regressions.

Water demand prediction is essential in any short or long-term management plans. The ANN method was used to model the water consumption in Ramallah and Khan Younis. The ANN was implemented based on the available monthly houses water consumption data, results showed that ANN models provided a good prediction of water consumption. These analyses can help water institutions managers in Palestine in order to understand the spatial and the temporal patterns of future water use, this better understanding is going to optimize the system operations and presenting better plans for water purchases, system expansion or revenue and expenditures in the future.

Future studies could develop more reliable models that forecast the water consumption evolution in Palestine by using bigger and more quality data; this will help to build scientific-based strategy for water policy including an investment in the water infrastructure, users' guidelines and water social-pricing.

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