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ORIGINAL ARTICLE

Analysis of future water demands in Al-Madinah (1990–2030) based on the modified IPAT model and sheared socio-economic pathways scenarios

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Abstract

Arid regions such as Saudi Arabia are facing water scarcity and availability issues and experiencing growing pressure by rapid water consumption. Determining the main driving forces contributing to rising water demands and future water demand prediction are considered the cornerstone for developing a good sustainable management plan. Al-Madinah city was chosen as a case study. In this study, the population, affluence, and technology (IPAT) model has been modified to apply in the water sector to analyse water needs in Al-Madinah from 1990 to 2020 and examines factors including population, GDP-per capita, agricultural lands/GDP and built-up area/agricultural lands. In addition, Sheared Socio-economic Scenarios (SSPs) have been developed to predict water demands in Al-Madinah from 2020 to 2030. The results confirm that population was the most important in explaining water consumption trends. Moreover, water demand under all IPCC_SSP scenarios is expected to increase by between 17 to 28%. The scenarios of SSP3 and SSP4 are projected to experience an increase in water demands by an average of 25% and 26%, respectively. In contrast, the water demand is forecasted to lower under the SSP1 and SSP5 by around 20% and 17%, respectively. This evaluation could highly reinforce and improve sustainable water resource management strategies, which have recently become increasingly essential to face growing water challenges and demands.

Keywords Water demand · IPAT model · Driving factors · Sheared socio-economic pathways scenarios (SSPs)

Introduction

The accelerated development of global economies as well as the steady increase in urbanization rate and the population residing in cities have led to rapid increase water consumption and caused a negative effect on the extent of water availability and quality (Liang et al. 2020; Zhao et al. 2014). Globally, the urban population grew from 29.6% in 1950 to 56.2% in 2020, which also is predicted to approach 68.4% by 2050, with above one billion residents living in cities suffering from water shortage (He et al. 2021; McDonald et al. 2011).

The city of Al-Madinah is the fourth largest urban agglomerations, by population, in the Kingdom of Saudi Arabia (UN-HABITAT 2019), with a population of 1.278 million and a population density of around 5000 km^2 (UN-HABITAT 2019, 2018). The population growth rate in 2016 was nearly 4.5% (UN-HABITAT 2019, 2018). In addition, its religious importance in the Islamic world, means that many religious occasions occur annually, including the pilgrimages to Umrah and Ramadan, which host over 8 million visitors per year (UN-HABITAT 2019). These put additional stress on natural water resources. Water resources are considered scarce not only in Al-Madinah city but also in the whole of the Kingdom of Saudi Arabia (KSA). KSA is deemed to be one of the largest dry areas in the Middle East,

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with scant rainfall (Al-Ibrahim 1991). It is devoid of permanent watercourses and freshwater sources such as rivers and lakes (Al-Ibrahim 1991; Amin et al. 2016). This highly implies the challenges of current water deficiency and meeting growing water demand in the future. Consequently, seawater desalination and groundwater exploitation are the main solutions for water supply in many large cities and in arid countries, such as Al-Madinah (He et al. 2021). However, the desalination process is costly, energy intensive and may have impacts on the marine environment (Almutaz et al. 2012; He et al. 2021). In addition, in recent decades, the growing water demand has caused a substantial rise in groundwater extraction, leading to a notable decrease in the quantity and quality of these resources (Esteban et al. 2021).

Therefore, sustainable management to mitigate such pressure is considered the best solution to avoid any potential future water demand issues or scarcity problems (Cosgrove and Loucks 2015). This requires an understanding of future water demand in cities under changing demographic and Sheared socio-economic factors (Johannsen et al. 2016). This is critical to establishing adequate planning and improving water conservation measures (Babel et al. 2006). Moreover, identifying such factors contributing to increasing water demands or those causing supply–demand imbalances is considered the cornerstone for sustainable management plan.

In the literature, the IPAT model or extended forms such as STIRPAT and Kaya have been widely used to measure the impact of human activities on environment related to growth in carbon dioxide emissions, as well as to determine driving factors.

Lin and Li (2020), Majeed et al. (2020), Wang et al. (2017a) and Li et al. (2015) have all investigated the relationship between carbon emission, population, affluence, and urbanization by implementing the STIRPAT model, their results revealed that urbanization level, production industry and population, were the primary factors for increasing carbon emission. Furthermore, Gao et al. (2010), Qin et al. (2019); have generated scenarios based on the STIRPAT to 2020 and 2050 to predict the environmental load and growth of carbon emissions.

Although these models appear flexible and manageable to operate, there have been limited attempts to adapt and apply them to water resource issues. Quéfélec and Allal (2014) have highlighted developing water demand management employing the IPAT model combined with a sustainable energy model, as well as creating trend and adaptation scenarios for water demand to 2050 in North Africa. These scenarios are based on population, GDP, electricity for water and energy bill factors. The results indicated that under both scenarios demand for drinking and industrial water increases rapidly over the studied period. Moreover, Jin et al. (2016), Long et al. (2020),, Yan et al. (2023) have investigated the factors affecting agricultural water consumption in various regions of China, using the STIRPAT model to consider socio-economic factors such as population growth, economic development (GDP), and urbanization. (Yan et al. 2023) also highlighted the importance of natural conditions. The findings revealed that in Beijing, food expenditure and urbanization had the most significant positive impact on increased agricultural water use. In Xinjiang, population growth, agricultural added value, and the expansion of irrigated areas were key contributors to the rise in crop water footprint (CWF). At the national level, managing the water footprint of major food crops depended heavily on distributional equity across provinces. In Liuyang City, natural meteorological conditions were the primary factors affecting the blue, green, and grey water scarcity indexes.

Generally, the principal benefit of conducting scenarios based on the IPAT or the STIRPAT models is that such scenarios not only enable the analysis and prediction of the relationships between the environment and human activities, but also identify the fundamental driving forces and the most influential factors (Yan et al. 2023; Gao et al. 2010); these help to suggest potential improvement measures and appropriate protection measures for maintaining environmental quality (Gao et al. 2010; Fan and Lei 2015).

Hanasaki et al. (2012) developed water usage scenarios consistent with Shared Socioeconomic Pathways (SSPs) assumptions on the global scale. These factors included potential industrial water demand, municipal water consumption demand and the agriculture-related factors that comprised irrigation (area and efficiency), as well as crop intensity. According to water developed SSPs assumptions, about 39 to 55% of the population would live under exceptional water-stress conditions and scarcity by 2071–2100. This is expected to be caused by population growth and economic activities. Graham et al. (2018) also investigated global water demand via the end of the century, using future water sector assumptions for all SSPs that included water technology assumptions. The results showed that technological change affects the water sector and would assist in minimizing water demand by more than 32% by 2100. Furthermore, low-income areas would be more likely the most influential driver of future water demands resulting from improve irrigation systems. Alcamo et al. (2007) and Li et al. (2017) have investigated future water demand under different socio-economic and climatic changes in relation to the factors of GDP and population growth. The findings revealed that income growth and increased GDP were the most important factors associated with increased water consumption.

This study aims to comprehensively understand and predict water demand in Al-Madinah from 1990 to 2030, incorporating the city's development plans and future growth. By adapting the IPAT model into IPAUT (Impact of Population, Affluence, Urbanization, and Technology), it seeks to identify and analyze the primary factors influencing water consumption. The specific purposes include analyzing historical water demand trends, adapting the IPAT model to include urbanization and new factors in the technology, and identifying fundamental driving forces and the most influential factors. This will also predict future water demands using IPCC's SSP (population and GDP) scenarios. Therefore, this study would provide valuable insights for policymakers on effective water resource management and contribute to the water research discipline with a novel methodological approach to understanding and forecasting water demand, especially in arid and semi-arid regions such as Al-Madinah that this will be the first application of the IPAT model to water demand forecasting in a major Saudi Arabian city.

Methods

The flowchart in Fig. 1 shows the steps of the implemented methodology.

The IPAT model

The IPAT model was suggested by Ehrlich and Holdren (1971) for studying the relationship between environmental resources and economic growth (Ehrlich and Holdren 1971). It seeks to understand the environmental impacts (I) (Ehrlich and Holdren 1971) by changes in population (P), affluence (per capita GDP) (A), and technology (T) (Vélez-Henao et al. 2019; Jin et al. 2016).

$$I = P \times A \times T \tag{1}$$

Waggoner and Ausubel in 2002 developed the IPAT identity as the ImPACT model by dividing the T factor into consumption per unit of GDP (C) and impact per unit of consumption (T) (York et al. 2003). The ImPACT model has targeted identifying the factors that could be changed to reduce impacts and the fundamental factors that affect each factor (York et al. 2003). The IPAT model has strength in defining the principal forces that influence environmental changes and showing their relationships, which are often interconnected and cannot operate individually in determining or accounting for environmental impacts (York et al. 2003; Uddin et al. 2016).

The IPAT formula assumes linearity between variables, which are often not linear (Uddin et al. 2016; Vélez-Henao et al. 2019). Therefore, the IPAT model has been reformulated by Dietz and Rosa in 1997 (Vélez-Henao et al. 2019),

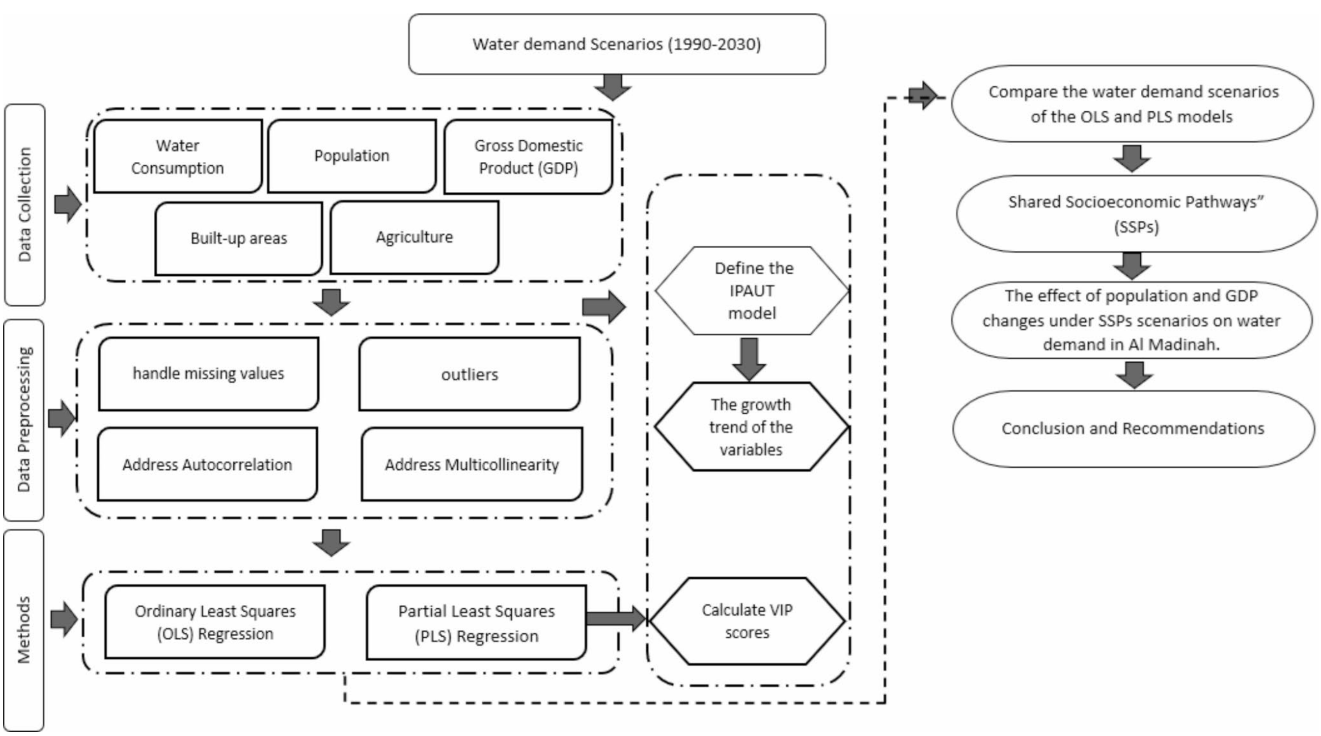

Fig. 1 Flowchart detailing the methodological steps for predicting water demand in Al-Madinah using the IPAUT model

to take this into account, and is named STIRPAT, STochastic Impacts by Regression on Population, Affluence, and Technology (Liang et al. 2020). STIRPAT is characterized by treating the links among drivers of impacts as hypotheses that can be tested rather than assuming the causal relationships between them, as well as to estimate the weights or importance of the factors (Vélez-Henao et al. 2019; Aguir Bargaoui et al. 2014). Liang et al. (2020), Jin et al. (2016), and Uddin et al. (2016) have displayed the reformalised model as follows:

$$I\mathrm{i} = aP_i^b A_i^C T_i^d e_i \tag{2}$$

where (P) population, affluence (A) and technology (T) as drivers of environment change (I); b, c, d = the exponents of P, A, T; e = the error term; i = individual observations in the study and a = the constant of the model. The logarithmic from STIRPAT is expressed:

$$\ln\left(I_i\right) = a + bln\left(P_i\right) + cln\left(A_i\right) + dln\left(T_i\right) + e_i \tag{3}$$

The STIRPAT model is based on the decomposition analysis approach that provides decomposing, combining or modifying the associated influencing factors (Feng 2017). Therefore, in the present study, the water demand issue could be decomposed into its different drivers. The IPAT identity has been modified slightly in the present study to be I = PAUT, where AL/GDP and W/BA represent the T (technology factors), while BA/AL describes an U (urbanisation) factor. The equation of the adapted IPAT or STIRPAT model for the present study is expressed as follows:

$$W = P * \frac{GDP}{P} * \frac{\mathrm{AL}}{GDP} * \frac{\mathrm{BA}}{\mathrm{AL}} * \frac{\mathrm{W}}{\mathrm{BA}} \tag{4}$$

where P represents the population; GDP/P is Gross domestic product per capita; AL/GDP is the productivity of agricultural lands (AL); W/BA is the water intensity of built-up areas (W = water consumption and BA = built-up areas), and BA/AL is the ratio between built-up areas and agricultural land. Water intensity of built-up areas (W/BA) represents the amount of water consumed per unit of built-up area. It directly links water consumption and urban development, also reflecting water use efficiency (or inefficiency) in urban areas. The ratio between built-up areas and agricultural land (BA/AL) allows for assessing the spatial relationship between urbanization (built-up areas) and agricultural land that can significantly alter water demand and availability. A higher ratio, for example, suggests increased urbanization, leading to higher water demand. By including, AL/GDP, the model accounts for how efficiently and technologically advanced the land is used for agricultural production and how this efficiency impacts water consumption.In the modified IPAT, one factor needs to be removed to run the regressions and to avoid the result being zero. The missing factor has been determined based on the residuals and examining the p-values of coefficients variables in the model. The ratio between water and built-up areas (W/BA) negatively affected the model with a Durbin-Watson d-statistic value of about 0.83 and chi is 3.44; thus, it has been excluded. The linear logarithmic of IPAT or STIRPAT of the present study is expressed as follows:

$$In\left(W\right) = In\left(P\right) + In\left(\frac{GDP}{P}\right) + In\left(\frac{AL}{GDP}\right) + In\left(\frac{BA}{AL}\right) \tag{5}$$

Ordinary least squares (OLS)

Several statistical models have been used in order to develop water demand future scenarios efficiently, whether they have been applied individually or combined with further models such as time series approach. The regression analysis is considered the most common by employing linear forecast functions (Wang et al. 2017b). The multiple regression equation takes the form:

$$\mathrm{Y} = \mathrm{B}_0 + \mathrm{B}_1\mathcal{X}_1 + \mathrm{B}_2\mathcal{X}_2 + \epsilon, \tag{6}$$

where Y = dependent variable; $\mathrm{B}_{0=}$ intercept; X = independent variables, and ε = random error with Eε = 0.Ordinary least squares (OLS) have been applied to conduct a regression analysis of the IPAT model, with the examination of the VIFs, Durbin Watson and Normality, as well as multicollinearity and autocorrelation to employ the model in scenarios accurately. OLS has been implemented on time series water demand data in Al-Madinah City (1990–2020). Autocorrelation refers to correlation among the variables in two successive time intervals (Jin et al. 2016). Data unaffected by autocorrelation is considered one of the critical assumptions of regression analysis to avoid misleading predictions. This issue could be present in the time series. Outliers' observations could also significantly affect the model's coefficients. Accordingly, the inclusion of a lagged value or dummy variable or standardizing the values has been suggested to reduce such issues. Generally, the dummy variable in the quantitative analysis could be defined as a numeric substitute for a qualitative statement or a logical proposition, taking on values of either 1 or 0 (Garavaglia and Sharma 1998).

Partial least squares regression (PLS-R)

Multicollinearity refers to correlation between two or more predictor variables; it is usually caused by using the same information in two or more predictor variables (Adnan et al. 2006; Jin et al. 2016). The PLS-R, which was developed by the Svante Wold group (Long et al. 2020), has proved efficient in diminishing the multicollinearity issue (Adnan et al. 2006). Generally, in the PLS-R model, the primary data X and Y or sampled factors and responses are projected into T and U respectively, which are the latent variables, where the extracted factors T (X-scores) are utilised to predict U (Y-scores) (Tobias 1995). The t1/t2 oval plot and the t1/u1 scatter plot are viewed as significant outputs that could be examined to establish the appropriateness of applying PLS-R modelling, where the t1/u1 scatter plot will determine the extent of the linear relationship between the variables whereas the t1/t2 oval plot (confidence ellipse) displays the range of homogeneity of the independent variables in the interpretation of the dependent variable, as the occupation of all variables within the boundaries of the ellipse indicates the possibility of reliance on the results of the model (Liang et al. 2020; Shawul et al. 2019; Li et al. 2015). The decomposition carried out by PLS-R can be expressed as:

Table 1 Description of the study variables

The variables	Type	Unit of measurement	Years	Source
Water Consumption	Historical data	Thousand Cubic Meters	2003–2019	MWE (2012, 2014) and MEWA (2019)
	projection data		2020–2030	SWPC (2019)
Gross domestic product (GDP)	Historical data	USD per capita in current prices	1990	World Bank (2016)
	projection data		1991–2020	Gastat (2020)
			2021–2030	Cuaresma (2017)
population	Historical data	Number of people	1974,1992, 2004, 2010	GaStat (2010)
	projection data		2020–2030	UN (2018)
Land Use/Land Cover (Built-up area, Agricultural lands)	Historical data	Square kilometers	1990, 2000, 2020	Landsat images
	projection data		2030	MOMRA (2020)

$$\begin{aligned} x &= t_1 P_1^T + t_2 P_2^T + \mathrm{th} p_h^T + e_h \\ y &= U_1 q_1 + u_2 q_2 + u_h q_h + f_h \end{aligned} \tag{7}$$

where t_i and u_i ($i = 1, 2, \ldots, h$) are the latent variables extracted from the sample data of the explanatory variable *X* and the explained variable *y* respectively, *pi* is the loading vector or weights for *X*, and q_i ($i = 1, 2, \ldots, h$) is the loading value or weights for *y*, and *eh* and f_h are the residual vectors" (Chai et al. 2018).In order to implement these models (OLS and PLS-R) the Stata and XLSTAT software packages have been used. Furthermore, the OLS and PLS model projections for water demand in the study area will be compared with the local authority forecast presented by the Saudi National Water Company, which was mainly based on the population growth variable.

The variables' importance in the projection (VIP)

The variables' importance in the projection (VIP) has also been estimated by the PLS-R model, which identifies each explanatory variable's contribution degree in the projection model; generally, the average of the squared VIP-scores is 1, due to the total of the squares of VIP scores being equivalent for all the variables in X; therefore, if all variables would contribute with the same degree of importance in the produced model, the sum of the VIP would be 1, accordingly; if the value of a variable is more than 0.8, the variable will be considered important and has contributed enormously (Liu et al. 2020; Li et al. 2015; Mendez et al. 2020), the VIP is calculated based on Eq. (7) (see Appendix I, Eq. (8)).

Materials data sources

The Sheared socio-economic development pathways (SSPs) are scenarios for global socioeconomic changes projected until 2100 (IPCC 2017),which have been used to generate greenhouse gas emissions scenarios with multiple climate strategies (Riahi et al. 2017). These SSPs involved the main elements represented in Gross Domestic Product (GDP), population (age, sex, education) and urbanization (Yang and Cui 2019). Moreover, the SSPs were divided into five pathways or five storylines that consist of (SSP1) sustainability, (SSP2) middle of the road, (SSP3) fragmentation, (SSP4) inequality, and (SSP5) fossil-fuelled development (Chen et al. 2020; Riahi et al. 2017; Yang and Cui 2019). The process of developing a scenarios model for water demand required the preparation of multiple datasets, as listed in Table 1. Future projections of the Al-Madinah population (2020–2030) were unavailable under SSPs scenarios. Therefore, firstly, the relationship between the UN historical population data (1990–2019) and the country-scale SSPs data was established. A correlation of 0.98 was obtained for the relationship, which indicates that the UN population data for Saudi Arabia would also represent Al-Madinah well. Secondly, to simulate SSPs scenarios of the population for Al-Madinah, the growth rate calculated between each scenario in the SSPs for Saudi Arabia was used to apply to the UN population projections data for the city to obtain the scenarios. The present study used the population and GDP PC from the socio-economic determinants that have followed the five scenarios as showing in the Table 2 describes the population and GDP_PC variables under SSPs scenarios. The other factors' data were obtained for the same period from the relevant ministries in the Kingdom of Saudi Arabia; all missing data then has been processed by the linear forecasting method to complete all the time series.

In terms of the future data of built-up areas and agricultural lands variables are derived from the city's development plans named 2030 Vision. This plan showed a high growth for built-up areas in Al-Madinah city by about 746 square kilometres with a low density of about 28.2 population/ha, as well as proposing to increase the cultivation lands by adding about 91 km^2 by 2030.

Table 2 The SSPs scenarios descriptions of the Population and GDP_PC variables

SSP element	Population	Growth (GDP_ per capita)
SSP1	Low	Moderate
SSP2	Moderate	Moderate
SSP3	High	Low
SSP4	Moderate	Low
SSP5	Low	High

*Adapted from (O'Neill et al. 2017; Yang and Cui 2019; Riahi et al. 2017; Abt et al. 2019; O'Neill et al. 2013; Van der Mensbrugghe 2015)

Results

Determination of influencing factors under IPAUT model

The growth trends are displayed in Fig. 2.The Pearson bivariate correlation analysis of the influencing factors is shown in Fig. 5 (see Appendix II) and Table 3. The variables water consumption, population and GDP-PC showed steady growth over the years, where water consumption increased around six times and the population growth tripled from the baseline year 1990. Therefore, the correlation coefficients of the water consumption variable with population and GDP per capita are both above 0.9. In addition, the water consumption / urban areas relationship that indicates

Fig. 2 Growth trend of the variables and models in Al-Madinah (1990–2030) (W-water consumption, P—population, GDP PC—Gross domestic product per capita, AL/GDP represent agricultural lands/ GDP, BA/AL represent built-up area/ agricultural lands and W/BA represent water consumption/ built-up area)

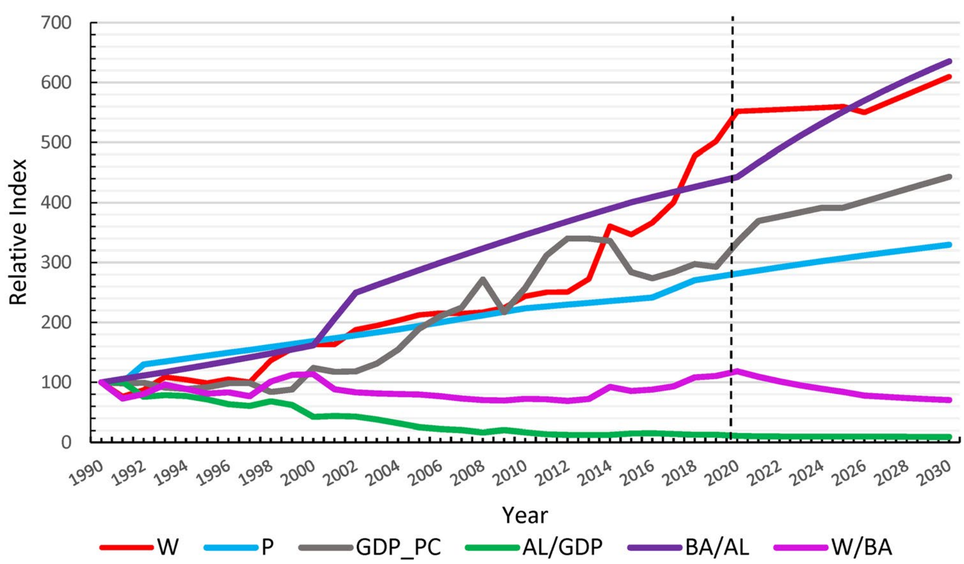

Table 3 The Pearson correlation between variables

Variables	W/BA	W	P	BA/AL	GDP_PC	AL/GDP
W	0.137	**1**	**0.969**	**0.956**	**0.923**	**-0.781**
P	-0.018	**0.969**	**1**	**0.987**	**0.956**	**-0.888**
GDP_PC	-0.133	**0.923**	**0.956**	**0.970**	**1**	**-0.860**
BA/AL	-0.120	**0.956**	**0.987**	**1**	**0.970**	**-0.874**
AL/GDP	0.110	**-0.781**	**-0.888**	**-0.874**	**-0.860**	**1**
W/BA	**1**	0.137	-0.018	-0.120	-0.133	0.110

Values in bold are different from 0 with a significance level alpha = 0.05

the extent of water consumption in urban areas appeared to have changed little across the period. This relationship was weakly correlated with water consumption (P = 0.14). This relationship indicates water consumption intensity under technological change or advancements to implement water conservation measures or improve water management practices. However, it is expected that Al-Madinah city will have an increase in population and a massive expansion of built-up areas. Therefore, the water intensity of built-up areas (W/BA) decreases could mean that the water consumption within urban areas will not increase proportionally to the extent of urban development or the expansion of built-up areas, caused by, for example, limited investment in water infrastructure.

The relationship between agricultural lands /GDP measuring the agriculture sector's contribution to the GDP, showed that the economic growth of Al-Madinah is developing faster than agricultural lands, which do not contribute meaningfully to GDP. Thus, water consumption correlated strongly and negatively (-0.78) with the model of agricultural lands/GDP. To clarify, when using the agricultural land to GDP ratio to represent the technology factor (T) in the IPAT model, a low contribution of agricultural land to GDP suggests that agricultural advancements may not keep pace with economic growth, leading to a declining share of agricultural land in GDP. This could also indicate a need for more investment and innovation in agricultural technologies to improve efficiency and reduce water demand, as well as imply that other factors, such as population growth, changes in consumption patterns, or policies, are playing a more significant role in driving water demand.

The relationship between built-up and agricultural lands detected the efficiency aspect of consuming water. Urban areas in Al-Madinah city expanded faster than agricultural areas, with an expectation of that the increase will continue. The BA/AL model showed a significantly positive correlation with water consumption. Overall, water consumption/ urban areas rate variable has the weakest correlation with other variables. Water consumption has the highest correlation with the built-up areas/agricultural lands and the population variable, respectively, as shown in Fig. 2.

Autocorrelation and multicollinearity diagnostic

The examined residuals of the OLS model showed that there are a number of outliers observations in the dependent values that correspond to 2014, 1993 and 1997, which would have a significant effect on the model's coefficients. Accordingly, a dummy variable for the year 2014 was included in the independent variables due to 2014 being the most irregular year among serial data. The Durbin-Watson statistic was used to test for autocorrelation. The DW value of the present model was 0.986, which indicated the existence of positive autocorrelation that needed to be improved. Consequently, a Lag variable (Lag_W) of the dependent variable (W) by one slow period for one year (1990), has been placed within the independent variables. The result showed a satisfactory DW value of 1.93 with no remaining autocorrelation. The variance inflation factor (VIF) values, as shown in Table 4, indicate a high level of collinearity between most of the independent variables, especially those related to GDP_PC and agricultural lands/ GDP_PC factors. Therefore, Partial least squares (PLS) regression was also applied

Table 4 OLS Regression results including the VIFs, Durbin Watson

Model	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig	Tolerance	VIF
	B	Std. Error					
Model_OLS							
(Constant)	-11.627	4.963		-2.34	0.027		
P	3.975	.7602	1.999	5.23	.000	0.013	79.151
GDP_PC	2.591	.616	2.480	4.20	.000	0.005	188.823
AL/GDP	2.990	.7126	4.099	4.20	.000	0.002	516.831
BA/AL	.753	.252	0.703	2.99	0.006	0.033	29.989
DW-OLS	.986						
Model_OLS_L.W. Dummy							
(Constant)	-11.627	2.892	-11.406	-3.944	0.001		
L.W	0.619	0.106	0.597	5.821	0.0001	0.056	17.906
P	1.996	0.538	0.935	3.713	0.001	0.01	107.912
GDP_PC	0.672	0.429	0.649	1.569	0.13	0.004	291.608
AL/GDP	0.955	0.487	1.284	0.687	0.499	0.002	731.519
BA/AL	0.116	0.169	0.105	1.96	0.062	0.026	39.86
Dummy	0.239	0.075	0.081	3.164	0.004	0.907	1.104
DW-OLS_L.W_dummy	1.93						
Heteroscedasticity	Variables: fitted values of W chi2(1) = 4.71 Prob > chi2 = 0.0300						

Table 5 PLS Coefficients and Variable Importance in the Projection (VIP)

Variable	Coefficient	Std. deviation	VIP	Standard deviation
Intercept	-2.444	2.863		
P	0.525	0.310	1.102	0.024
GDP_PC	0.031	0.193	1.026	0.02
BA/AL	0.198	0.032	1.098	0.019
AL/GDP	-0.072	0.070	1.077	0.017
R^2	0.944			
Std. deviation	0.137			
MSE	0.017			
RMSE	0.130			
Cumulative Q^2 quality	0.913			

to avoid the multicollinearity problems (Liang et al. 2020; Li et al. 2015). Firstly, as shown in Fig. 6 (see Appendix III), examining the viability of the PLS method indicated that the PLS results were consistent and reliable for utilising in prediction scenarios. The PLS regression revealed that the variable Al/GDP became negatively associated with a low impact. It was also evident from the coefficients in Table 5 that the population and the built-up areas/agriculture rate were the essential variables explaining water consumption trends in Al-Madinah city with VIP more than 0.8. In contrast, the GDP_PC was the lowest variable, less important by 1.02.

Scenario analysis and prediction of water demand in Al-Madinah

The water demand will continue to grow by a rate of 11% according to the projection of the local authority, as shown in Fig. 3, whereas the results revealed that all the SSPs scenarios expect that water consumption rate will increase on average by 17% and 28%, under OLS and PLS models respectively, almost two times higher than the local authority projection (Fig. 3). Generally, the predictions of the OLS model were closer to the local authority's estimations than the PLS model.

The results of the water demand scenarios (Fig. 4) in the present study are based on the high growth in the built-up areas and agricultural lands variables as established by the development plans of the city Vision 2030. Determinants of population and GDP change are based on the SSP predictions. The SSP1 represents assumptions of low population and moderate GDP that predicted growth in water demand for Al-Madinah of 16% and 24%, under the OLS and the PLS models, respectively. The SSP2 will experience a moderate increase in population and GDP that will lead to a rise in the water demand of 18% and 29% under OLS and PLS models, respectively. Furthermore, SSP3 (high population growth, lower GDP) and SSP4 (declining population, high GDP growth) were predicted to present major challenges by raising the water demand by 19% to 20% and 31% to 32%, under the OLS and the PLS models respectively. The results of the assumptions of low population rates with high GDP that were set in SSP5 for Al-Madinah predicted that the water demand would increase by 13% and 21%.

Discussion

Water availability and supply–demand imbalances are complex issues affected by various interacting factors, represented in changing socioeconomics, such as population, urbanisation, GDP per capita, and technological levels, as well as climatic factors. Therefore, a deep understanding of water demand requires analysing the water situation under potential driving factors (Zhao et al. 2014). These need to be examined and analysed by a method that has the capability to quantify such variables' impacts as driving forces on water demand.

The IPAT is considered an effective model to examine and extract the driving forces and identify the relationship between them and their impacts (Zhao et al. 2014; York et al. 2003). Accordingly, the adapted IPAT model in the present study helped effectively analyse and identify the fundamental driving forces in water demand in Al-Madinah, despite the fact that the IPAT model was not designed originally for application to water resource issues. This finding is consistent with the few previous studies that applied the IPAT model in the water field, such as Quéfélec and Allal (2014), Jin et al. (2016), Long et al. (2020), Yan et al. (2023) and Jin et al. (2016), who have indicated the IPAT model capability in examining the driving forces to identify their impacts whether under different assumptions or for quantifying water footprint for water demand. This study aligns with the work of Jin et al. (2016) and Long et al. (2020) by focusing on socio-economic factors, such as population growth and economic development, in the analysis of water demand. However, it diverges by applying the IPAUT model to project future water demand rather than examining current conditions or crop water footprints. Additionally, while natural conditions are incorporated by Yan et al. (2023) in their analysis, these factors are not considered in the current study, which emphasizes socio-economic variables and technological factors.

The IPAT model was adapted in the current study to be IPUAT and expanded to include additional factors: agricultural land/GDP and water consumption/built-up area that represent the technology factors, and built-up area/agricultural land describes the urbanisation factor, alongside the population and GDP variables. These as well as the standard

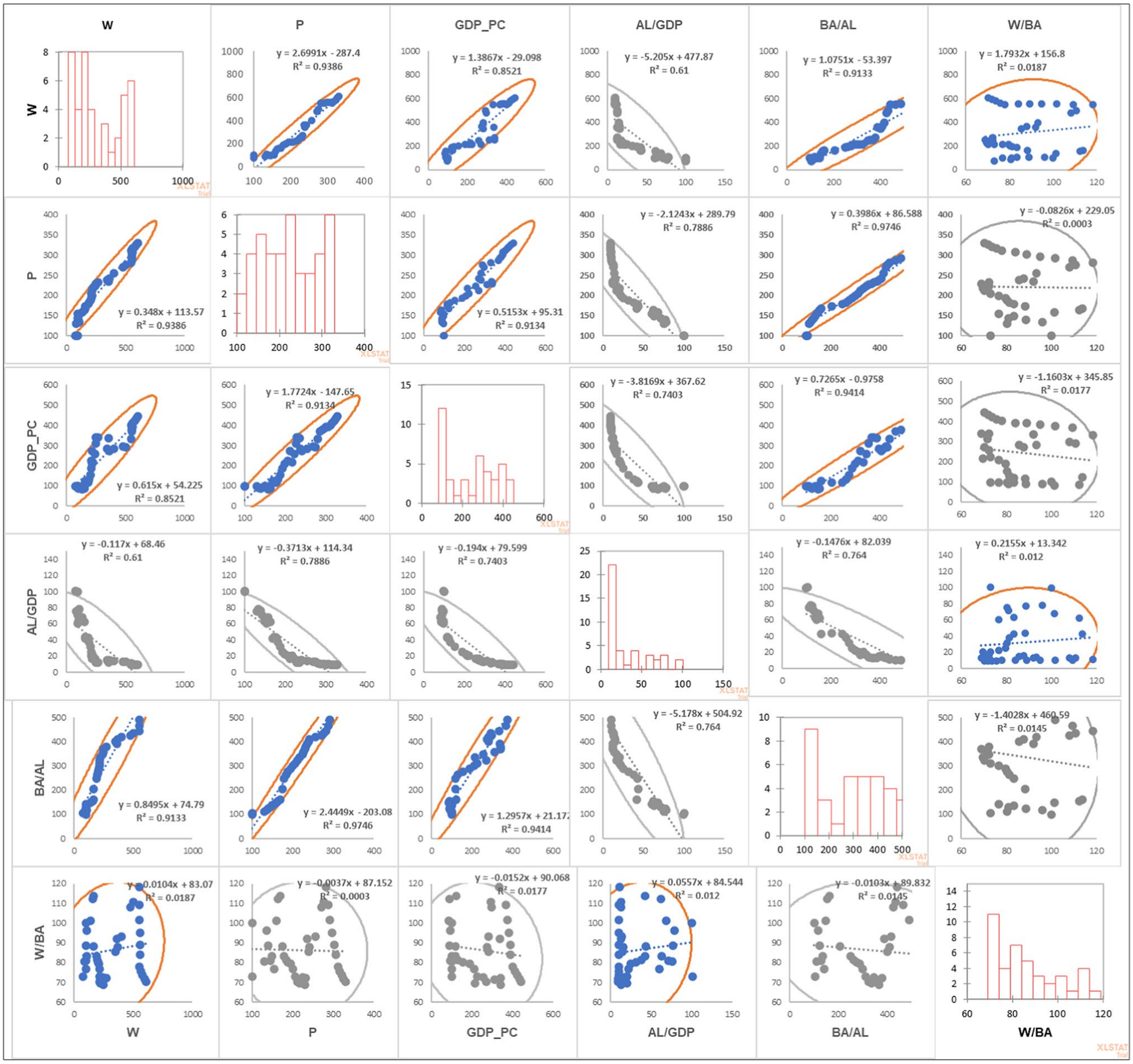

Fig. 3 The scatter plot and correlationsbetween study's variables

IPAT variables were found to be influential. All variables used have a VIP value of more than 0.8; hence, no element could be neglected as one of the influential drivers on water demand. The variables' importance in the projection (VIP) based on the IPUAT model has indicated that the population variable had a positive influence, and it was the most essential factor in explaining water demand trends in Al-Madinah city. This finding aligns with the estimate provided by Hanasaki et al. (2012) that increasing water stress and demand would be driven as a direct result of population growth. It is also predicted that from 2071 to 2100, about 39% and 55% of global residents will experience high stress on water due to population increase (Hanasaki et al. 2012).

In the present study, when the population increases by one per cent, water demand grows by about 0.52% based on the PLS-R coefficient.

The effective usage variable of water measured by the rate between built-up areas and agricultural lands, is considered the second most influential factor in water consumption. It also had a positive effect under the PLS-R coefficient, which indicated that if water consumption for urban area activities increases by 1%, water needs in Al-Madinah will grow by around 0.19% on the efficiency scale. This could be returned to urban expansion in Al-Madinah shows a faster growth trend than the agricultural areas; hence, a development strategy would be required to reduce such negative situations

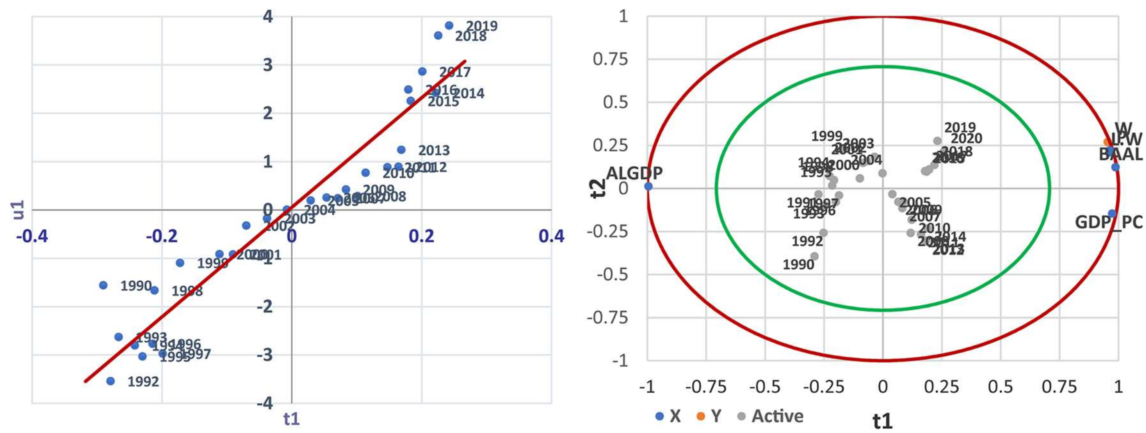

Fig. 4 The effect of population and GDP changes under Ordinary least squares (OLS), Partial least squares (PLS-R) regression and SSPs scenarios on water demand in Al-Madinah (2020–2030)

and manage water consumption sustainably. In contrast, the technology factors, represented by the agricultural land/GDP rate, had a negative relationship. The Al/GDP coefficient reveals that with every 1% increase in the technology factor represented in the productivity of agricultural lands (Al/GDP) variable, water demand is expected to decrease by not exceeding about -0.07%. This minor influence could be attributed to the economic development trend of Al-Madinah, which indicates that the other sectors are improving more rapidly than the agricultural sector that does not contribute meaningfully to GDP. According to the MCCI (2017), about 33% of the total Gross domestic product of Al-Madinah is obtained from the industry sector, while just about 2% is from the agricultural sector.

In addition, both Alcamo et al. (2007) and Li et al. (2017) have found that increasing income and GDP_PC were the more critical influences on increasing water demands. However, the situation was different in Al-Madinah, where GDP_PC was the least important variable in explaining water needs. The VIP value was around 1.02, and the PLS regression coefficient also showed that every increase of 1% in per capita GDP will only lead to an addition of about 0.03% in water demand. This low influence might be caused by the low water prices for municipal and residential use in Saudi Arabia that ranged from 0.10 Halala for consuming 50 cubic meters to 6.00 SAR for 300 cubic meters or more per month. These prices are the equivalent of about 0.019 and 6.00 British Pounds. Recently, these prices have been raised by the National Water Company (NWC) in an attempt to rationalize the growing consumption of water; the prices have become 0.10 Halala for consuming 15 cubic meters or less and 6.00 SAR for 60 cubic meters or more water consumption per month (NWC 2015; MEWA 2018). Accordingly, it is possible with these new policies that the GDP will have more impact on water demand in the future.

Furthermore, in reviewing the development plans for Al Madinah under Vision 2030, the current and future status of water demand might be affected by an increase in built-up areas. These will amount to around 746 square kilometres with low-density, about 28.2 people/ha, which indicates that the urban area in Al-Madinah will increase by almost 54%. Moreover, it has been proposed the cultivated lands should increase by adding about 91 km^2, which would be approximately 29% higher than was in 2020. These development plans are accompanied by exaggerated expectations for population numbers, rising to 2,064,000 by 2030, an estimated growth rate of 2.9% per year. Therefore, the water demand would be affected, given the Saudi National Water Company expect demand will increase by 11% by 2030. However, this prediction might not reflect the actual needs because population growth for a few years was the only variable considered in the water demand assessment. It also disregards any future land use or agricultural development plans and GDP. On the contrary, the expectation of water demand under models OLS and PLS that included these variables was almost two times higher than the local authority projection by an average of 17% and 28%, respectively.

According to the expectation of The Saudi Water Partnership Company SWPC (2020), the supply deficit might range from 21.3% in 2022 to 24.2% in 2026 under current, and future development capacities of desalination plants, the principal water source. Thus, to satisfy the water shortage by operating the Yanbu 4 desalination plant that is planned enter into force in 2023, with a capacity of up to 450,000 m^3/d. About 70% of its production capacity could cover the city's water needs (SWPC 2020).

Therefore, as a result of identifying the socioeconomic variables as crucial driving forces of water demand changes (Graham et al. 2018), developing the future water needs scenarios under such factors would assist in the investigation and detection of any potential future challenges. Although the Shared Socioeconomic Pathways (SSPs) have been generated without definite assumptions related to the future of water (Graham et al. 2018), the socioeconomic factors could be adapted for use in the water sector. Thus, population and GDP determinants from SSP storylines have been applied to produce the water demand scenarios in Al-Madinah. These two factors were selected because the population was the most important factor in directing water demand according to the result of the IPUAT model, whereas the GDP represented the main factor that would be affected by the local authority plan that relied on rationalizing water consumption by raising prices.

The effect of population and GDP changes under SSP scenarios on water demand in Al-Madinah (2020–2030) showed that the water demand would increase within all scenarios. The water consumption under the SSP3 and SSP4, that experience higher growth in population than GDP are projected to increase using both OLS and PLS models. This result confirms what was also reported by Wada et al. (2016), who predicted that the domestic water withdrawals in Saudi Arabia would experience a continued increase of about 100–200% until 2050 because of population growth. In comparison, this study estimated that an increase in water demand in Al-Madinah will range between (SSP3 = 19% to 20%) and (SSP4 = 31% to 32%) by the end of 2030. This outcome is also consistent with that of Mazzoni et al. (2018), who expected that the SSP3 scenario would be characterised by a scarcer water supply in the MENA region caused by not only the dry climate predictions but also the increasing water requirements for the population and irrigation sector by 2050. In the same context, it has been estimated that Saudi Arabia will experience the most substantial deficit level in 2050, which represents about 20% of the total available freshwater, as well as the shortage of water budget in the MENA region mainly caused by anthropogenic drivers rather than climatic drivers (Mazzoni et al. 2018). Graham et al. (2018) also indicated that the expected growing global water demand in 2100 might be generated by slow technological and efficiency progress that may lead to more water withdrawals, which is accompanied in SSP3 by high population growth.

Furthermore, the increase in water needs would be relatively less under the SSP1 and SSP5, which have a higher GDP growth than population growth that might be attributed to the assumptions of enhanced education and employment opportunities for women presumed in these SSPs (Storylines 2018). This reduction might be caused by developing highly efficient and economic water-saving technologies under SSP1 and SSP5 (Graham et al. 2018; Mazzoni et al. 2018). There are similarities between these findings and those described by Mazzoni et al. (2018) that the MENA region's population is expected to decline significantly after 2050 with high economic development, especially in the SSP1, that would also be accompanied by wet climatic conditions contribute to reducing the demand for water for irrigation purposes. Moreover, the percentage of decline in water demand estimated in the study area under SSP1 and SSP5 ranges from an average of 8% to 11% compared to the SSP3 and SSP4 scenarios by 2030. The present result could almost accord with a previous study by Graham et al. (2018), which expected a global decrease in the water withdrawal trend after 2050, estimated at 32% by 2100 under SSP5. This decline might be associated with an improvement in irrigation operations resulting from technological development in the water sector, mainly because an increase in income has characterised these scenarios (Graham et al. 2018).

In SSP2, the Middle of the Road or Current Trends Continues, the population and GDP growth would be moderate. In Al-Madinah, an increase is expected of around 18% and 29% under the OLS and PLS models, respectively. These projected rates are considered in line with the highest growth water demand scenarios SSP3 and SSP4 for the study area. However, assumptions of the SSP2 scenario represented in the current trends may indicate an increase in water consumption, thus increasing demand and water pressure in many regions globally (Hanasaki et al. 2012). Therefore, according to this assumption, the study area could also suffer if water consumption continues under current conditions and rates. Generally, SSPs 1 and 5 envision relatively optimistic trajectories for human development, whereas SSPs 3 and 4 outline more pessimistic development trend scenarios (O'Neill et al. 2016). The reduction in water demand observed in Al-Madinah under the SSP5 scenario could be primarily attributed to factors irrelevant to climate policies, such as changes in population and economic growth (GDP), which may not necessarily reflect substantial climate mitigation measures emphasis. Mainly, the SSP5 scenario involved a continuous dependence on fossil fuels while implementing only limited climate procedures. Conversely, the SSP1 is featured by robust global collaboration, sustainability-driven practices and commitment to efficient resource usage.

Overall, water demand is driven not only by the growth in population numbers but also by GDP-PC, agricultural lands, and built-up areas explanation. Consequently, water request predictions under all these changing variables are critical for developing the efficient of future water preservation and resource sustainability, as well as to achieving the proposed vision for Al-Madinah.

Conclusions

This study reveals that future socio-economic scenarios predict a doubling of water demand in Al-Madinah compared to local authority expectations. Scenarios with higher population growth than GDP growth (SSP3 and SSP4) project greater increases in water demand, while those with faster GDP growth than population growth (SSP1 and SSP5) predict smaller increases. The population factor is identified as the most influential in driving up water demand. The predictions indicate higher population growth and increased residential water use without corresponding GDP growth, suggesting insufficient financial resources to address the increased demand. These findings have significant implications for developing water management strategies in Al-Madinah, guiding local authorities to review and adjust measures and policies to mitigate potential adverse effects of water shortages.This study also contributes to enriching the water management research field. By applying the modified IPAT model, the methodology presented could assist arid countries to improve water management policies and strategies to face the scarcity of water resources and increased demand in the context of socioeconomic changes. The proposed model could be applied accordance the countries' conditions by accommodating any number of extra variables. Further research is needed to evaluate water demand in Saudi Arabia using improved and more comprehensive socioeconomic data.

Appendix I

The VIP is expressed as follows:

$$VIP_j = \sqrt{P\sum_{h=1}^{m} r_h^2(Y;t_h)\,w_{h_j}^2 / \sum_{h=1}^{m} r_h^2(Y;t_h)} \tag{8}$$

where p is the number of independent input variables; $w_{h_j}^2$ is the component of the j_{th} variable on the latent variable t_h, which is used to evaluate the marginal contribution of X_j to the construction of t_h latent variable; $r_h^2(Y;t_h)$ indicates the explanatory of all extracted components to Y (Liu et al. 2020; Li et al. 2015).

Appendix II

The Fig. 5 shows the output of the correlation test by XLSTAT software. The histogram was displayed for each variable (diagonal), and a scatter plot was used for all combinations of variables. The red colour of the data points in the scatter plots revealed a positive correlation, and the grey colour is a negative one.

Appendix III

As shown in the Fig. 6 of t1/u1 scatter plot, the PLS results presented that the relationship is almost linear, indicating such findings could be accepted for addressing issues such as water consumption (Li et al. 2015). Moreover, the correlation between t1/t2 as displayed in Fig. 6, revealed that the variables used have distributed within the oval plot where no points were outside the shape, which evidence that the PLS results were consistent and reliable utilising. Accordingly, the regression equation that extracted using the partial least squares and could be employed in prediction scenarios.

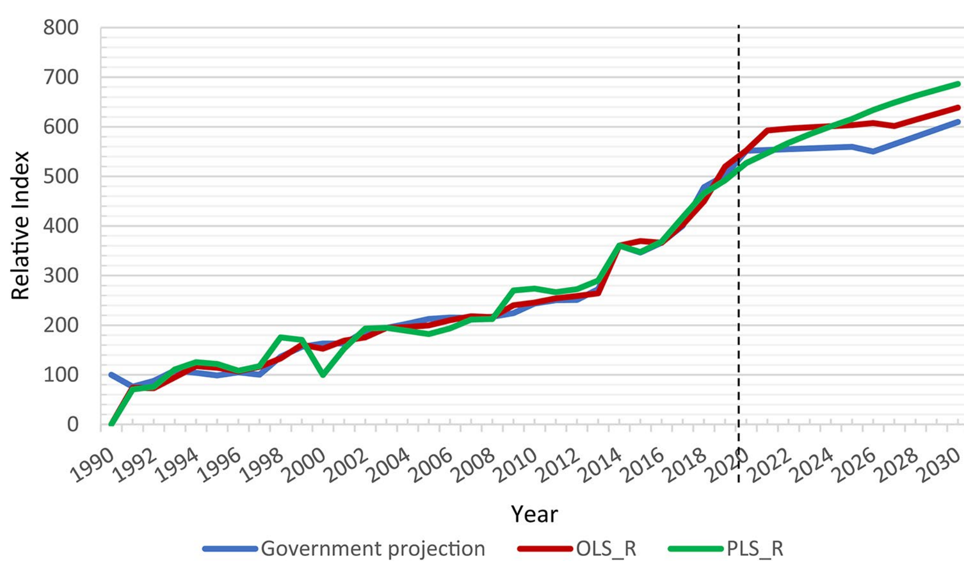

Fig. 5 The water consumption scenarios in Al-Madinah under OLS and PLS regression

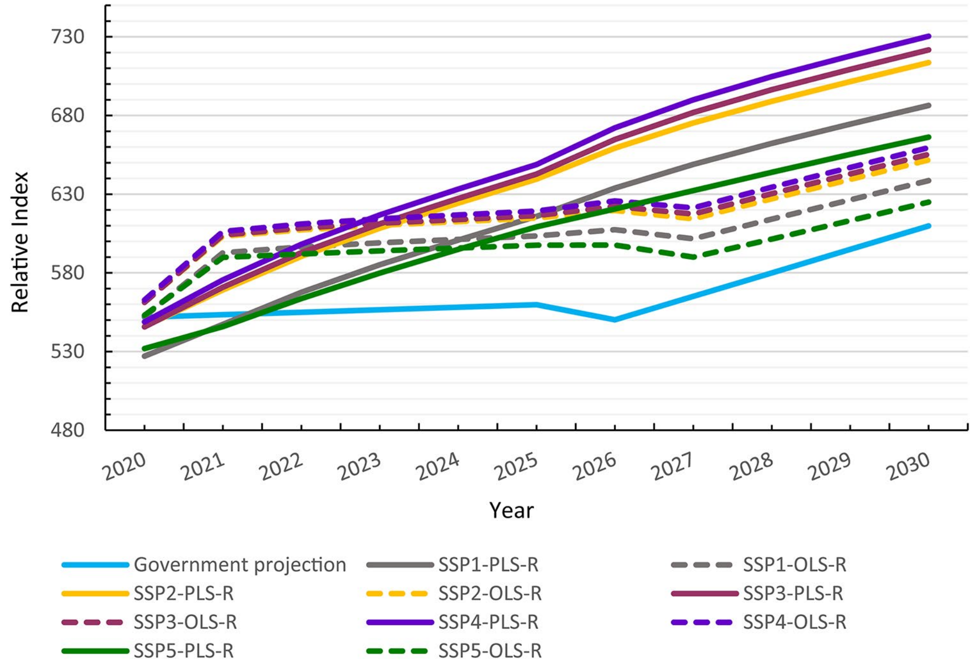

Fig. 6 t1(x)/t2(y) oval plot. X = predictor variables, Y = dependent variables (left) and scatter plot of t1 (x)/u1 (y) (right)

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Authors contributions Ohood Alharbi developed the methodology and data curation of the study, formal analysis and writing of original draft preparation. Marco Sakai and Colin McClean supervised and wrote the review and editing.

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Availability of data and materials The authors declare that the data sources supporting the findings of this study are cited within the paper. The Land Use/Land Cover (1990–2020) data in this manuscript is also used in other ongoing research; thus, this data is not applicable.

Declarations

Conflict of interest The authors declare no conflict of interest.

Consent to participate All authors have provided their consent to participate.

Consent to publish All authors have given consent for publication.

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