sustainability

MDPI

Article

Evolution in Patterns of Urban Water Consumption Accompanying Socio-Economic Development

Sizhong He [1,2], Zhenzhen Ma [2,*], Huashan Wang [3] and Yuqin Gao [4]

1 College of Hydrology and Water Resources, Hohai University, Nanjing 210098, China; hesizhong@hhu.edu.cn
2 State Key Laboratory of Simulation and Regulation of Water Cycle in River Basin, China Institute of Water Resources and Hydropower Research, Beijing 100038, China
3 Zhengzhou Water Conservancy Bureau, Zhengzhou 450000, China; ssljygc2024@163.com
4 College of Water Conservancy and Hydropower Engineering, Hohai University, Nanjing 210098, China; yqgao@hhu.edu.cn
* Correspondence: mazz@iwhr.com

Abstract: To explore the evolution in patterns of urban water consumption (UWC) accompanying socio-economic development, historical data on socio-economic conditions and water consumption in developed cities worldwide were collected. stages of evolution and patterns in UWC were identified through Pettitt tests. Through correlation analysis, the main socio-economic indicators influencing UWC were identified, and their threshold values for different trends in the evolution of UWC were statistically analyzed. The use of these patterns of evolution for UWC prediction was explored taking Changsha, China as a case study. Results indicate the following: (1) UWC typically increases in the early stage of development and then stabilizes or decreases later; (2) when UWC stabilizes or decreases, socio-economic indicators, namely per capita GDP, tertiary industry's contribution to GDP, and urbanization rate, range from [USD 10,000, 60,000], [60%, 80%], and [85%, 95%], respectively, entering or approaching the developed economy stage. (3) Using patterns in this evolution, Changsha's UWC is predicted to increase until the turning point, which will occur between 2027 and 2035 (earlier than that predicted using genetic programming) and then decrease earlier than that of Hunan Province or the entirety of China. Predicted values are lower than those obtained using the quota method. This study provides a new perspective on relationships between UWC and socio-economic conditions, supporting water resources planning.

Keywords: urban water consumption; socio-economic indicator; evolution stages and patterns; water consumption prediction; Pettitt test method; statistical analysis

check for updates

Citation: He, S.; Ma, Z.; Wang, H.; Gao, Y. Evolution in Patterns of Urban Water Consumption Accompanying Socio-Economic Development. *Sustainability* **2024**, *16*, 3737. https://doi.org/10.3390/su16093737

Academic Editor: Vasilis Kanakoudis

Received: 6 November 2023
Revised: 25 April 2024
Accepted: 26 April 2024
Published: 29 April 2024

1. Introduction

Water resources serve as the material basis for human survival and the fundamental guarantee of sustainable social-economic development [1–3]. As they are an important component of research on the supply-demand relationship of water resources, an understanding of trends in the evolution of urban water consumption (UWC) accompanying socio-economic development is a key scientific basis for water resources planning and optimal utilization of limited water resources [4–6].

Generally, water consumption is related to social-economic development and is subject to the constraints associated with the state of exploitable local water resources [7,8]. The limits on regional water consumption may depend on natural conditions [9,10]. However, the evolution of water consumption in a region is inevitably driven by socio-economic development [11–13]. Before delving into the evolution of water consumption with socio-economic development, the relevant theories of development stages based on socio-economic development should be discussed. Several theories characterizing the development stages of economies and the corresponding division schemes have been introduced in previous studies [14–17]. Although different division schemes are used to characterize the stages of socio-economic development, they are all based on factors related to socio-economic production, i.e., gross domestic product (GDP) per capita, industrial structure, etc. Based on Chenery's Industrialization Stage Theory [15], certain scholars [18–21] have adopted a theory of industrialization and variation in urbanization patterns to establish a standard system of urban development stages with measurable characterizing factors, as outlined in Table 1. By comparing socio-economic data with the threshold values of the characteristic factors listed in Table 1, the developmental stages of an economy may be determined.

Table 1. Factors characterizing the different stages of the socio-economic development of an economy [15].

Stage	GDP per Capita (USD) [1]	Industrial Structure	Urbanization Rate	Ratio of Secondary Industry to Employment	Ratio of Non-Agricultural Industries to GDP
Primary product stage	676–1352	Ratio of 1st industry > Ratio of 2nd industry	<10%	<9%	<50%
Primary stage of industrialization	1352–2705	Ratio of 2nd industry is greater than those of the 1st and 2nd industries	10–70%	9–17%	50–70%
Intermediate stage of industrialization	2705–5410			17–39%	70–87%
Advanced stage of industrialization	5410–10,143			39–55%	87–98%
Primary stage of having a developed economy	10,143–16,229	Ratio of 3rd industry > Ratio of 2nd industry > Ratio of 1st industry	>70%	Obviously decreasing	Obviously increasing
Advanced stage of having a developed economy	16,229–24,343				

[1] The GDP per capita unit, dollars (USD), should be converted to the value in 2015 based on comparable prices.

Considering the relevant theories of divisions of development stages based on socio-economic development, many researchers have explored the correlation between water consumption and socio-economic development. Merrett [22] investigated the evolution of water-consumption patterns in Europe and found that water consumption increased rapidly in the early urbanization stage but tended to stabilize and gradually decrease as urbanization slowed in the later stage. Jia et al. [23] adopted the Kuznets curve to analyze the relationships between industrial water consumption and economic development, thereby offering valuable insights for collaborative research on these correlations. Zhao et al. [24] summarized key patterns in the regional evolution of water consumption with socio-economic development in China, suggesting that this evolution may conform to an adaptive increase curve responsive to resource constraints (AIR curve). Wang et al. [25] proposed a fixed-effect panel regression approach and three-panel threshold regression approaches using updated data from China's 31 provinces to study the correlation between urbanization and water consumption at national and subnational scales. The authors highlighted the significant negative non-linear correlation between urbanization changes and water consumption. Liu et al. [26] evaluated the spatial variation in the level of urbanization across provinces in China and analyzed the influences of urbanization on regional water consumption. Notably, most of these studies have focused on the national or regional scales [24,27,28], and the correlation between water consumption and socio-economic development on the urban scale remains relatively unexplored.

Nevertheless, urban water consumption is an important issue, especially in the context of climate change and expected water shortages. On the one hand, cities are constantly growing, with aging existing infrastructures and increasing numbers of people moving to urban areas, which leads to an increased demand for water, putting a strain on existing water resources. On the other hand, climate change is also playing a role, with more frequent droughts and erratic rainfall patterns putting additional stress on water supplies [29]. These socio-economic and environmental factors may act together to exacerbate the state of water resources and cause severe issues in urban areas. As indicated in the studies of Savelli et al. [30], unsustainable water consumption in cities can lead to water shortages, impacting everything from sanitation and hygiene to food production and economic activity. Therefore, understanding the urban evolution of water consumption is crucial for identifying areas at risk of water stress or scarcity and balancing socio-economic development and water resources in urban areas. Through studies on the evolution of water consumption on the urban scale, the ways in which factors like changing socio-economic conditions, technological advancement, and climate change are influencing water consumption patterns within cities can be revealed. For instance, studies could explore how socio-economic development drives changes in water consumption in urban areas. Furthermore, advanced research might explore the use of universal patterns in the evolution of urban water consumption to predict future water consumption in different urban contexts. This approach could be crucial for developing proactive water management plans that consider factors like socio-economic development and climate variability.

The present study aims to explore the universal patterns in the evolution of UWC accompanying socio-economic development on the city scale and demonstrate the application of these derived patterns to predicting future water consumption trends over the evolution of a city. Figure 1 is a schematic diagram of the research on patterns in the evolution of UWC accompanying socio-economic development and the application to prediction of these patterns. According to the research approach shown in Figure 1, historical data on the socio-economy and water consumption of developed cities worldwide were collected. The corresponding data preparation is presented in Section 2.1.1. Then, the urban evolution of the stages and patterns of water consumption accompanying socio-economic development were studied through statistical analyses. The corresponding method of identifying UWC stages and patterns and the method used for analysis of the correlation between socio-economic development and the evolution of UWC are introduced in Section 2.1.2. The prediction of the evolution of UWC based on the patterns in the evolution of UWC is introduced in a case study in Section 2.2. In Section 3, the identified stages in the evolution of UWC and characteristics and the main socio-economic indicators influencing the evolution of UWC are presented. The universal patterns in the evolution of UWC were derived. The correlations between the evolution of UWC and socio-economic development are discussed, and the threshold values of the main socio-economic indicators corresponding to trends in transitions between stages of UWC evolution were derived. Taking Changsha City as a case study, the application of the derived patterns in the evolution of urban water consumption to predicting the future water consumption of a city are demonstrated and discussed. Additionally, in Section 4, the following are discussed: comparisons among models of the evolution of water consumption on different scales; and comparisons between prediction-based patterns in the evolution of UWC and those derived using other methods. The feasibility and adaptability of UWC prediction based on patterns in the evolution of UWC accompanying socio-economic development were analyzed. The reliability and generalizability of the proposed approach for studying patterns in the evolution of UWC accompanying socio-economic development are also discussed. The concluding remarks are presented in Section 5.

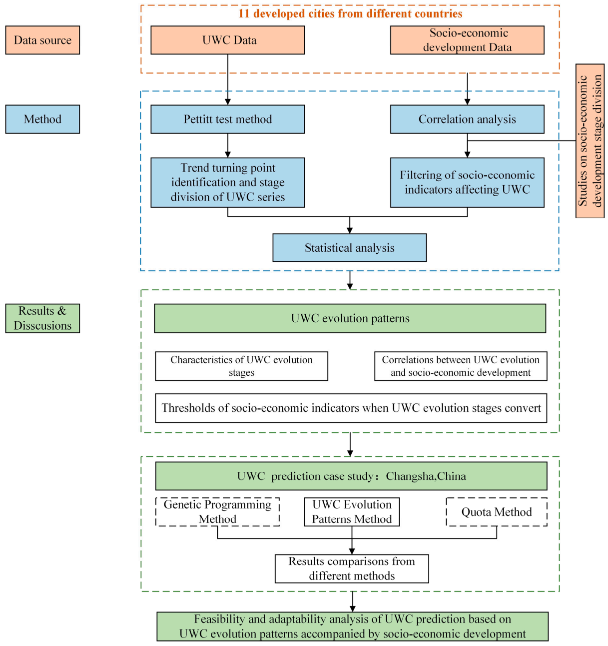


Figure 1. Schematic diagram of the research on patterns in the evolution of UWC accompanying socio-economic development and their application to prediction.

2. Materials and Methods

2.1. Data Preparation and Research Methods

2.1.1. Data Preparation

This study is focused on analyzing the correlations between the evolution of UWC and socio-economic development. To this end, several representative developed cities considered to be in the advanced stage of economic development (as indicated in Table 1) before 2020 according to Chenery's Industrialization Stage Theory [15] were selected as research samples, including Beijing, Shanghai, Guangzhou, Shenzhen, Hong Kong, Macao, New York, Los Angeles, Paris, Tokyo, and Melbourne. Sources for historical UWC and socio-economic data for each city are listed in Table 2. In this study, UWC of a city was considered to include the residential, industrial, public, and environmental water consumption components.

Table 2. Data sources pertaining to each city.

City	Data Sources
Beijing Shanghai Guangzhou Shenzhen	Local water department websites, water resources bulletins, and statistical yearbooks
Hong Kong Macao	Local water department websites, local statistical yearbooks, and urbanization-rate statistics from World Bank
New York	NYC Open Data, New York State Department of Environmental Conservation, U.S. Department of Commerce, and U.S. Bureau of Economic Analysis
Los Angeles	Los Angeles Department of Water and Power, U.S. Department of Commerce, and U.S. Bureau of Economic Analysis
Paris	Eau de Paris and National Institute of Statistics and Economic Studies (INEE)
Tokyo	Local statistical yearbooks, Statistical Bureau of Japan, and Bureau of Waterworks Tokyo Metropolitan Government
Melbourne	Water in the World's Cities and other references and urbanization-rate statistics from World Bank

2.1.2. Research Methods

The stages in the evolution of UWC and patterns in these cities were identified through a trend analysis of time-series data using the Pettitt test method, through which the turning point in the time-series trend can be effectively identified [31,32]. Subsequently, the main socio-economic indicators influencing UWC were identified through a correlation analysis based on the Pearson product-moment correlation coefficient (PCC). The correlation between socio-economic development and the evolution of UWC was analyzed according to the socio-economic indicators across different stages in the evolution of UWC.

(1) Identification of stages and patterns in the evolution of UWC

The stages in the evolution of UWC were divided based on the turning point identified using a non-parametric test method, namely, the Pettitt test method. In this approach, given the time series of UWC, $X = (x_1, x_2, x_3, \ldots, x_n)$, the point x_t is taken as the potential turning point. The time series of UWC, X, can then be divided into two parts: $(x_1, x_2, x_3, \ldots, x_t)$ and $(x_{t+1}, x_{t+2}, x_{t+3}, \ldots, x_n)$. For a given turning point, x_t, a statistical variable ($U_{t,n}$) can be defined as follows [31]:

$$U_{t,n} = U_{t-1,n} + \sum_{j=1}^{n} \mathrm{sgn}\left(x_t - x_j\right) \quad t = 2, 3, \ldots, n-1 \tag{1}$$

where sgn is the sign function, defined as

$$\mathrm{sgn}\left(x_j - x_k\right) = \begin{pmatrix} -1 & \left(x_j - x_k\right) < 0 \\ 0 & \left(x_j - x_k\right) = 0 \\ 1 & \left(x_j - x_k\right) > 0 \end{pmatrix} \tag{2}$$

The statistical variable (K_t) for identifying the most likely turning point can be calculated as follows [31]:

$$K_t = \max_{2 \le t \le n-1} \left|U_{t,n}\right| \tag{3}$$

The rate of increase or decrease in the parts before and after the turning point of UWC time series, respectively, were calculated to analyze the patterns in the evolution of UWC.

(2) Analysis of correlation between socio-economic development and the evolution of UWC

Generally, water consumption is related to social-economic development and local water resource conditions. Factors influencing water consumption can be identified by analyzing historical data pertaining to the socio-economy and water consumption [7,8]. Representative studies focused on the factors influencing water consumption (listed in Table 3) suggest that socio-economic factors, including population structure, industry structure, economic development level, etc., may jointly impact water consumption [33–37]. Notably, the effects of these factors on water consumption are complex, and various correlations exist among them [24,38,39]. Therefore, it is essential to statistically analyze the socio-economic factors influencing UWC to identify the main socio-economic indicators.

Table 3. Representative studies focused on the socio-economic factors influencing water consumption.

Presenter	Study Area	Study Method	Indicated Main Influencing Socio-Economic Factors
Bithas and Stoforos [33]	Athens, Greece	Statistical analysis	Income, water price
Zhang et al. [37]	Zhuhai, China	Cobb-Douglas production function	GDP, industrial output, irrigated area
Wu et al. [36]	Heihe River Basin, China	Computable general equilibrium model	Industrial transformation
Romano et al. [35]	Italy	Statistical analysis	Applied tariff, income, population
Hao et al. [34]	China	Simultaneous equation model analysis	GDP per capita, trade openness, population density, economic growth

In this study, the factors influencing UWC were identified based on the data from several developed cities, i.e., Beijing, Shanghai, Guangzhou, Shenzhen, Hong Kong, Macao, New York, Los Angeles, Paris, Tokyo, and Melbourne. Data sources for the annual water consumption and socio-economic aspects of each city are summarized in Table 2. The PCC between UWC and socio-economic factors can be calculated as follows [40]:

$$\rho(W_c, F_{se}) = \frac{\text{cov}(W_c, F_{se})}{\sigma(W_c)\sigma(F_{se})} \quad (4)$$

where $\rho(W_c, F_{se})$ is the PCC between W_c, which is a vector containing water consumption data over several years, and F_{se}, which is a vector containing the data pertaining to a socio-economic factor in the city over the same time frame; $\text{cov}(W_c, F_{se})$ is the covariance between W_c and F_{se}; and $\sigma(W_c)$ and $\sigma(F_{se})$ are the variances of W_c and F_{se}, respectively. Generally, if the absolute value of the PCC approaches 1.0, UWC is considered to be strongly correlated with a socio-economic factor. The degree of correlation may be none, extremely weak, weak, medium, strong, or extremely strong depending on whether the PCC's value is in the range [0.0, 0.2), [0.2, 0.4), [0.4, 0.6), [0.6, 0.8), or [0.8, 1.0], respectively. Socio-economic factors exhibiting strong or extremely strong correlations with UWC may be identified as the potential socio-economic indicators and then used to analyze the evolution of UWC accompanying socio-economic development [40–42]. Besides the PCC, the correlations among different socio-economic factors and the development stage of the city were also considered as means of identifying the main socio-economic indicators influencing UWC. In the present study, the sensitivity of UWC to the variation in socio-economic indicators in each city was calculated as follows:

$$\begin{aligned} S_e &= \frac{(W_{a100\%} - W_{a90\%})/W_{a100\%}}{[x(W_a = W_{a100\%}) - x(W_a = W_{a90\%})]/x(W_a = W_{a100\%})} \\ &= \frac{0.1}{[x(W_a = W_{a100\%}) - x(W_a = W_{a90\%})]/x(W_a = W_{a100\%})} \end{aligned} \quad (5)$$

where S_e denotes the sensitivity, W_a denotes UWC in the city, $W_{a100\%}$ denotes UWC at the turning point, $W_{a90\%}$ denotes UWC equal to 90.0% of $W_{a100\%}$ in the year before the turning point, x denotes the socio-economic indicator (GDP_c, R_{tg}, or R_u). Furthermore, in the present study, data pertaining to the socio-economic indicators of developed cities that correspond to the evolutionary stages and the turning point of UWC were statistically analyzed to investigate the correlation between socio-economic development and UWC and identify the socio-economic threshold values associated with changes in UWC trends over the evolution of a city.

2.2. Case Study

In the present study, Changsha (Figure 2), located in the northeast region of Hunan Province, China, was used as the research case study to demonstrate the predictive value of the universal patterns in the evolution of UWC accompanying socio-economic development, as derived using the approaches in Section 2.1.2. The city of Changsha has a total area of 11,819 km^2, and the multi-year average precipitation is 1428 mm. Historical data from Changsha pertaining to UWC and socio-economy were obtained from local water department websites, water resources bulletins, and statistical yearbooks.

In such a case study, the socio-economic indicators identified as influencing UWC and their threshold values corresponding to trends in transitions between stages of UWC evolution were used to predict UWC in Changsha, China. The predicted data for Changsha pertaining to socio-economic indicators were compared with these threshold values to identify the potential turning point in the future series of annual UWC. According to the comparison of the historical socio-economic indicators and UWC data from Changsha and those from the research cities mentioned in Section 2.1.1, the annual rates of growth and decline in UWC before and after the corresponding UWC starts to decrease or stabilize can be approximately predicted. Based on the starting year of prediction and these predicted growth and decline rates, a predicted series of annual UWC can be obtained.

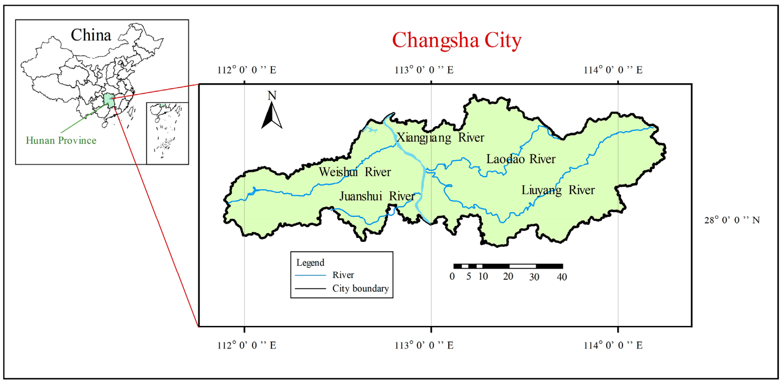


Figure 2. Location of Changsha city in China.

3. Results

3.1. Stages and Patterns in the Evolution of UWC in Cities

The general correlation between UWC and socio-economic development can be determined by referring to the historical evolution of UWC accompanying the stages of socio-economic development in the developed cities (Table 1). Annual UWC series data of the developed cities selected in Section 2.1.1 were used to clarify the temporal variation in UWC. Figure 3 plots the annual UWC series of different developed cities, spanning from 1985 to 2020. The stages of socio-economic development accompanying the evolution of UWC in each city were determined according to the threshold values of the characteristic factors for different stages of socio-economic development, as indicated in Table 1. These stages are marked as color backgrounds in each sub-figure in Figure 3. The turning point for the UWC time-series of each city was identified using the Pettitt test method introduced in Section 2.1.2, and the corresponding results are presented in Figure 3 using the dashed line in each sub-figure. The average annual rates of change in UWC before and behind the turning point in each city were compared to observe the common evolution of UWC characteristics.

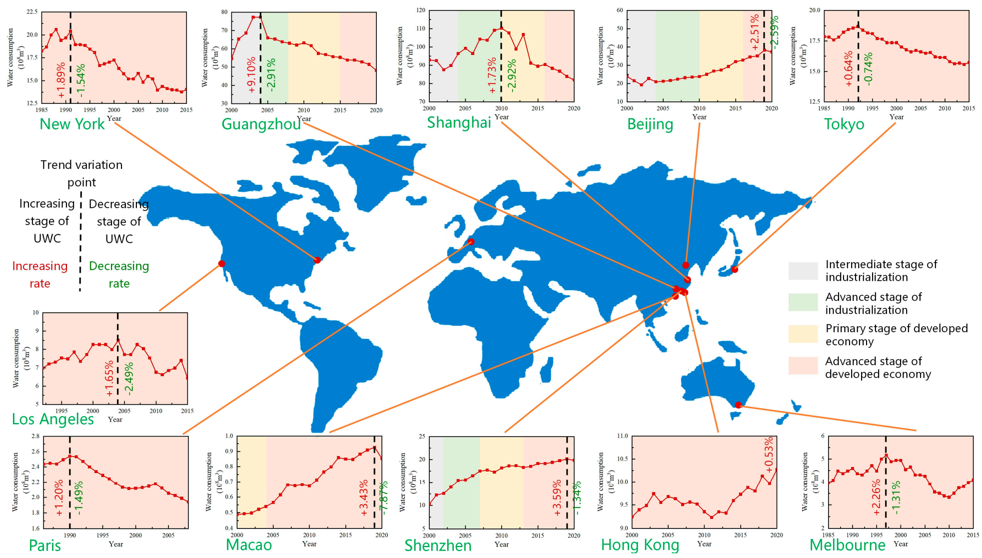


Figure 3. Evolution of UWC in cities with corresponding stages of socio-economic development.

As shown in Figure 3, a turning point was found in the UWC time-series of all cities except Hong Kong. It can be inferred that urban water consumption generally shows an increasing trend before such a point and then turns to decrease. The calculated average annual rates of change in UWC in these cities before the turning point were generally positive (ranging from 0.64% to 9.10%), but those after the turning point were generally negative (ranging from −7.87% to −0.74%). It is thus illustrated that there was generally an increasing trend in UWC in the initial period until it reached a peak value, after which UWC tended to decrease or remain stable. For example, annual water consumption in New York increased to approximately 2.04×10^9 m^3 in 1988 and then showed a decreasing trend between 1988 and 2015, with the annual water consumption being only 1.40×10^9 m^3 in 2015 (approximately 68.63% of that in 1988). The annual water consumption in Shanghai and Guangzhou increased to peak values in 2010 and 2004, respectively, and then decreased in the following years. The annual water consumption of Beijing and Macao maintained an increasing trend until 2019 and then decreased between 2019 and 2020. Owing to the short duration of declining UWC in the statistical series, it may be not definitive that UWC in Beijing and Macao will maintain steady decreasing trends in the future. UWC in Hong Kong entered a declining stage between 2003 and 2011 but reverted to an upward trend between 2011 and 2020. In Hong Kong, due to the extreme lack of local water resources, the water supply mostly came from water purchased from surrounding regions, a difference from the water supplies of the other research cities in the present study.

In the majority of the research cities, the turning point in the evolution of urban water consumption occurred in the context of developed economies, especially in the advanced stages of developed economies as defined by the socio-economic development stages based on Chenery's Industrialization Stage Theory, as indicated in Table 1. These representative cities include not only those located in characteristic developed countries, like New York, Tokyo, Los Angeles, Paris, and Melbourne, but also relatively developed cities located in developing countries, like Beijing, Shenzhen, and Macao. As for Shanghai, although the turning point did not occur in the context of a developed economy, the socio-economic indicators of GDP per capita and industrial structure corresponding to the year of the turning point were closer to the corresponding lower threshold values of a developed economy. Another city with an evolution of urban water consumption similar to that of Shanghai is Guangzhou. The turning point in the annual urban water consumption of Guangzhou occurred in the advanced stage of industrialization, before the developed economy stage. Only 4 years after the year of the turning point, the socio-economy of Guangzhou entered the developed economy stage. Compared with other cities like Beijing, Macao, Melbourne, etc., the available water resources of Shanghai and Guangzhou are relatively abundant. This factor may have driven the relatively extensive urban water consumption in the earlier stages in Guangzhou and Shanghai. The advances in water-saving policy-making after 2005 in China may also have had more obvious effects on decreasing UWC in these two cities. As indicated by Zhao and Li [43], the decreasing effects of the water-saving policies were generally significant in humid and large cities, which include Shanghai and Guangzhou. Nevertheless, it can be still concluded that when the urban water consumption of Guangzhou or Shanghai began to decrease, the corresponding socio-economy had reached the developed economy stage.

The aforementioned characteristics of the general patterns in the evolution of UWC illustrate that water resources may be consumed excessively in the initial stages due to rapid but extensive socio-economic development. As the socio-economy of a city develops to a high level and UWC approaches the limits of regional water-resource capacity, socio-economic development may tend to optimization and UWC can be decreased through water-saving measures.

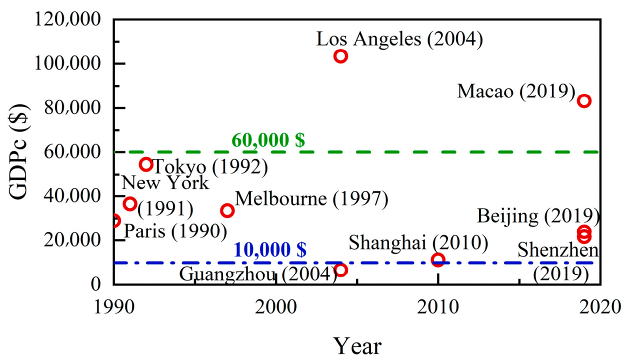
3.2. Correlation between Socio-Economic Development and UWC

In the present study, a correlation analysis was performed between UWC and selected representative socio-economic factors to identify the key factors influencing UWC. The selected socio-economic factors were the total population (P_t, million people), gross domestic production (GDP, USD), GDP per capita (GDP_c, USD), ratio of the annual added value of the tertiary industry to GDP (R_{tg}), ratio of the annual added value of the manufacturing industry to GDP (R_{mg}), and urbanization rate (R_u). P_t was defined as the permanent resident population within the administrative area under the jurisdiction of a city, which is the sum of the urban and rural populations. R_u was defined as the ratio of the urban population to the total population in a city. Additionally, the dollar (USD) amount associated with factors linked to the GDP is converted to 2015 values based on comparable prices. Table 4 lists the PCCs between the socio-economic factors and annual UWC in each city, as calculated through Equation (4). Generally, the socio-economic factors, including P_t, GDP, GDP_c, R_{tg}, Rmg, and R_u, are strongly correlated with water consumption in the developed cities, which means that these socio-economic factors significantly influence the water consumption of a developed city. Besides, it is also essential to consider the correlations among different socio-economic factors and the development stage of the city when identifying the factors influencing UWC. For example, GDP is the product of P_t and GDP_c, but identified influencing factors should be dependent. Several studies on the urban development stage have highlighted that the GDP per capita, urbanization rate, and tertiary industry tend to play more important roles in the socio-economy of a developed city [44–46]. Therefore, GDP_c, R_{tg}, and R_u were identified as the main factors influencing UWC in the present study.

Table 4. PCCs between the socio-economic factors and the total UWC in each city.

City	P_t	GDP	GDP_c	R_{tg}	R_{mg}	R_u
Beijing	0.484	0.268	0.332	0.577	0.645	0.667
Shanghai	0.833	0.604	0.606	0.532	0.477	0.252
Guangzhou	0.821	0.815	0.765	0.772	0.753	0.113
Shenzhen	0.878	0.812	0.861	0.624	0.602	/
Hong Kong	0.855	0.789	0.824	0.888	0.884	0.969
Macao	0.993	0.934	0.905	0.704	0.861	/
New York	0.946	0.833	0.824	0.835	0.925	0.723
Los Angeles	0.908	0.857	0.804	0.862	0.591	0.592
Paris	0.397	0.903	0.904	0.892	0.950	/
Tokyo	0.259	0.594	0.483	0.808	0.786	/
Melbourne	0.595	0.805	0.887	0.851	0.849	0.819

To further analyze the relationships between the evolution of UWC and the economic development of a city, three socio-economic indicators, including GDP_c, R_{tg}, and R_u, were selected based on the analysis of the factors influencing UWC. Based on the data sources indicated in Table 2, the socio-economic data (GDP_c, R_{tg}, and R_u) of some developed cities when the corresponding UWC began to decrease or stabilize were obtained, as shown in Figure 4. Because no turning point was observed in the annual UWC series from Hong Kong, the socio-economic indicator values of Hong Kong were not included in Figure 4. The sensitivity of UWC to variations in socio-economic indicators in each city were calculated using Equation (5). The sensitivity calculation results corresponding to the socio-economic indicators in the cities included in Figure 4 are shown in Table 5.



(**a**)

Figure 4. *Cont.*

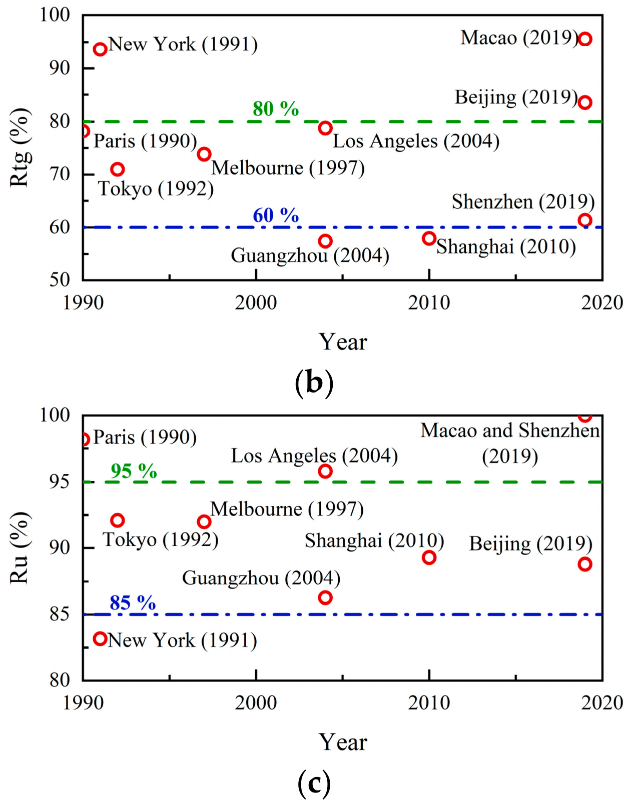


Figure 4. Socio-economic indicator values of cities when the corresponding UWC started to decrease or stabilize: (**a**) GDP_c; (**b**) R_{tg}; (**c**) R_u.

Table 5. Sensitivity of UWC to socio-economic indicators in each city.

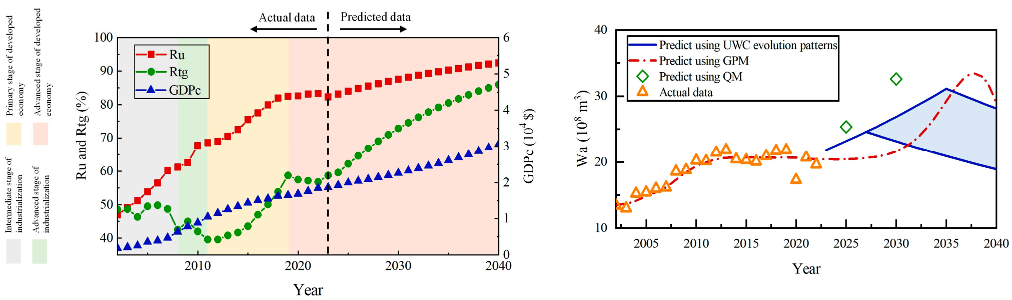
City	S_e		
	GDP_c	R_{tg}	R_u
Beijing	0.473	2.879	10.005
Shanghai	0.267	1.003	44.650
Guangzhou	0.301	−3.190	1.915
Shenzhen	0.260	0.732	/
Macao	0.835	2.780	/
New York	1.682	9.776	0.874
Los Angeles	1.103	39.966	1.116
Paris	0.289	1.536	/
Tokyo	0.390	2.630	/
Melbourne	1.075	12.300	5.111

Using the patterns in the evolution of UWC with the economic development of a city (derived in Section 3.1), it can be illustrated from Figure 4 that when UWC starts to decrease or stabilize, the socio-economic indicators of a city have typically approached or exceeded the lower threshold values associated with the developed economy stage (indicated in Table 1). At such a turning point in the evolution of UWC, the GDP_c, R_{tg}, and R_u values of the majority of cities are in the ranges [USD 10,000, USD 60,000], [60%, 80%], and [85%, 95%], respectively. In particular, cities like Beijing, Melbourne, and Tokyo can be considered to have entered the advanced stage of a developed economy. Besides, as shown in Table 5, UWC was more sensitive to R_{tg} or R_u than to GDP_c in most cities. The average S_e of UWC to GDP_c, R_{tg} and R_u of the cities in Table 5 are 0.71, 7.65, and 10.61, respectively. This phenomenon of sensitivity may illustrate that the effect of the increase in R_{tg} or R_u on the increase in UWC is more obvious than the effect of the increase in GDP_c. Moreover, the socio-economic indicators of cities with inferior water resources may exhibit higher values than those of cities with more abundant water resources. For example, the multi-year average precipitation (Pma) of Melbourne (650 mm) is approximately one-third that of Guangzhou (1801.2 mm), but the GDP_c when the UWC started to decrease or stabilize in Melbourne (USD 33,467) is more than five times the corresponding value for Guangzhou (USD 6677).

3.3. UWC Predictions for Changsha Based on Patterns in the Evolution of UWC

The socio-economic indicators identified as influencing UWC and their threshold values for the stages in the evolution of UWC derived in Section 3.2 were used to predict UWC in Changsha, China.

Historical data regarding the socio-economic indicators and UWC in Changsha are shown in Figure 5a. As shown in Figure 5a, the R_u and GDP_c of Changsha generally maintained steady growth between 2002 and 2022. The R_{tg} of Changsha exhibited fluctuations between 40–50% from 2002 to 2012 but maintained steady growth from 2012 to 2019. From 2019 to 2022, the R_{tg} of Changsha decreased slightly, which may have been caused by the COVID-19 outbreak and corresponding domestic quarantine policies in China. The R_u and R_{tg} of Changsha from 2023 to 2030 were predicted according to Equation (A1), as illustrated in Appendix A, in which the coefficients are fitted using the corresponding historical R_u and R_{tg} data (Figure 5a). Due to the impacts of the COVID-19 outbreak and corresponding domestic quarantine policies on the R_{tg} of Changsha between 2019 and 2022, the equation for predicting R_{tg} of Changsha was fitted only according to the historical data from before 2019. Considering the socio-economic recovery and the adjustment of quarantine policies, the prediction of R_{tg} of Changsha after 2022 was continued directly from the historical data before 2019. According to planning targets specified in "The 14th Five-Year Plan for the National Economic and Social Development of Changsha City and the Outline of the Long-Term Goals for 2035", Changsha's GDP was predicted to grow annually by 6.62% from 2023 to 2025 and by 5.41% after 2025. The population of Changsha after 2023 was predicted by substituting the historical population data from 2002 to 2022 into Equation (A2), as illustrated in Appendix A. The predicted R_u, R_{tg}, and GDP_c values are shown in Figure 5a.



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

Figure 5. Socio-economic indicators and UWC in Changsha: (**a**) Actual and predicted data pertaining to the socio-economic indicators of Changsha; (**b**) Comparison between the actual annual UWC of Changsha from 2023 to 2040 and the values predicted using the patterns in the evolution of UWC, GPM, and QM.

As shown in Figure 5a, the R_u, R_{tg}, and GDP_c of Changsha in 2027 were predicted to be 85.52%, 66.90%, and USD 20,911, respectively, exceeding the lower socio-economic indicator threshold values derived in Section 3.2 (85%, 60%, and USD 10,000), respectively. In 2035, R_{tg} of Changsha were predicted to 80.48%, exceeding the upper R_{tg} threshold derived in Section 3.2 (80%). Accordingly, Changsha's UWC was predicted to start declining or stabilizing in one of the years between 2027 and 2035.

The average annual rates of growth and decline in water consumption in different developed cities before their corresponding UWC started to decrease or stabilize are presented in Figure 3. According to a comparison of the historical socio-economic indicators and UWC data of Changsha and those of the cities provided in Figure 3, the patterns in the evolution of UWC in Changsha before it starts to decrease or stabilize are similar to those of Guangzhou or Shanghai in the initial stage. In this period, GDP_c was approximately USD 10,000, with R_u and R_{tg} approaching, respectively, 85% and 60%. The average annual growth rate of UWC in Changsha from 2002 to 2010 was 5.29%. Considering the abundant transitory water resources and the water-conservation measures adopted in Changsha, the annual growth rate of UWC before UWC starts to decrease or stabilize was predicted to be 3.0% and that after the corresponding UWC starts to decrease or stabilize was predicted to be about 2.0%.

Compared with the actual UWC of Changsha in 2019, the predicted UWC of Changsha decreased between 2020 and 2022 (especially in 2020). Meanwhile, the socio-economic activities of Changsha were strongly impacted by the COVID-19 outbreak and quarantine policies between 2020 and 2022. Accompanying socio-economic recovery and the adjustment of quarantine policies after 2022, UWC in Changsha may recover rapidly and return to following the normal trend. Accordingly, the predicted values for UWC of Changsha after 2022 continued directly from the historical UWC data from before 2019. The predicted annual total water consumption of Changsha from 2023 to 2040, based on patterns in the evolution of UWC, was plotted in Figure 5b using the blue envelope. The annual UWC of Changsha was predicted to increase from 2.184×10^9 m^3 in 2023 until its value reached the turning point in one of the years between 2027 and 2035. The UWC value in the turning point was predicted to range from 2.458×10^9 m^3 to 3.114×10^9 m^3. Thereafter, the annual UWC was predicted to gradually decrease from the turning point to 2040. The annual UWC of Changsha in 2040 was predicted to range from 1.545×10^9 m^3 to 2.300×10^9 m^3.

In contrast, Zhao et al. [24] predicted that water consumption in Hunan Province or China may reach a peak value between 2035 and 2040, as the R_u, R_{tg}, and GDP_c exceed 70%, 60%, and USD 10,000, respectively. As it is a relatively developed city, the socio-economic development of Changsha is more advanced than the average level of Hunan Province or China. Hence, it is reasonable to predict that Changsha's UWC will start declining or stabilizing earlier than that of Hunan Province or China.

4. Discussion

4.1. Comparisons among Evolution of Water Consumptions on Different Scales

The evolution of water consumption on the city scale can be compared with that on the state or regional scale. The evolution of water consumption in different states or regions is plotted in Figure 6a, for which the data source is AQUASTAT, a product of the Food and Agriculture Organization (FAO). As shown in Figure 6a, the state or regional water consumption increased in the initial period but decreased or stabilized after reaching its peak value, which was similar to the general patterns in the evolution of UWC on the city scale derived in Section 3.1. By analyzing the driving mechanisms of state or regional water consumption, Zhao et al. [24] highlighted that the state or regional evolution of water consumption typically follows an AIR curve, as indicated in Figure 6b. Depending on the availability of water resources, the AIR curve can be divided into three types: naturally growing, development-constrained, and severely stressed. It can be inferred from the comparisons between the evolutions of UWC in different cities (Figure 3) and the AIR curve layout (Figure 6b) that the evolution of water consumption in a city may resemble an AIR curve. For instance, given the relatively abundant water resources in Guangzhou, the evolution of UWC may resemble the natural-growth type of AIR curve, in which water consumption increases and decreases rapidly before and after it reaches the peak value, respectively. In contrast, the increase and decrease rates of Tokyo are considerably lower, consistent with the development-constrained type or severely stressed type of AIR curve.

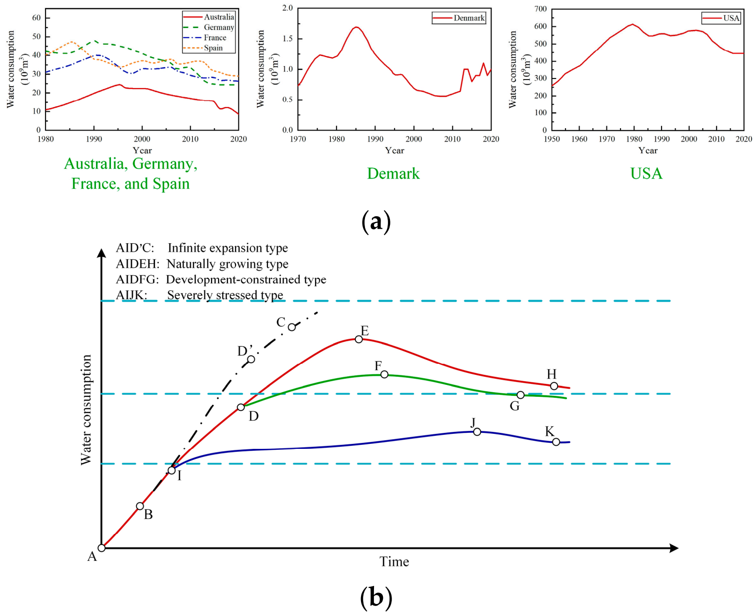


Figure 6. Evolution of water consumption on state or regional and river-basin scales with variation in socio-economic indicators: (**a**) Evolution of water consumption in different states or regions based on AQUASTAT data from the Food and Agriculture Organization (FAO); (**b**) Layout of the AIR curve [24].

Moreover, to compare the correlations between the patterns in the evolution of water consumption on the city scale and those on the state or regional scale, data on the GDP_c, R_{tg}, and R_u (derived from the works of Zhao et al. [24]) of several states and regions when the corresponding UWC began to decrease or stabilize (derived from World Bank Open Data) are presented in Figure 7. The relationships between the evolution of water consumption and the socio-economic development characteristics of a city, as derived in Section 3.2, were similar to those in a state or region, as shown in Figure 7. However, certain differences exist. Zhao et al. [24] summarized the relationships between the evolution of water consumption and socio-economic development in a developed country or region and indicated that when water consumption of a country or region reaches its peak value, the GDP_c, R_{tg}, and R_u of the developed state or region generally exceed USD 10,000, 60%, and 70%, respectively. A comparison of Figures 4 and 7 indicates that the distributions of GDP_c and R_{tg} of cities when the corresponding UWC started to decrease or stabilize are more discrete than those of states and regions. However, the distribution of the R_u of states and regions when the corresponding UWC started to decrease or stabilize is more discrete than those of cities. The standard deviations of GDP_c, R_{tg}, and R_u of the cities are USD 32,888.68, 14.41%, and 6.23% respectively, but those of states and regions are USD 4878.49, 4.06%, and 9.85%, respectively. This discrepancy may be attributable to the fact that the socio-economic development patterns of cities are more varied than those of states or regions.

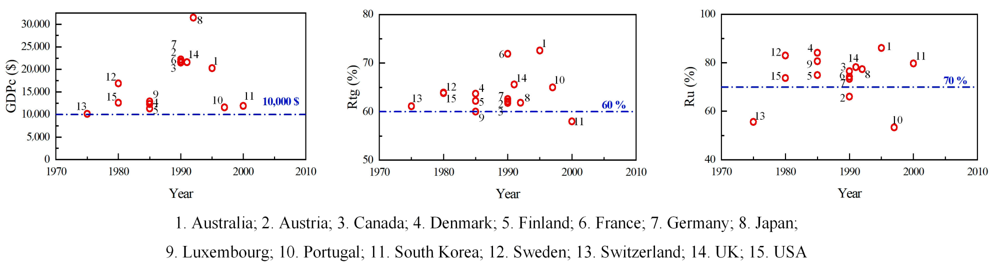


Figure 7. GDP_c, R_{tg}, and R_u of states or regions when the corresponding water consumption started to decrease or stabilize.

Accordingly, a city, as a constitutional element of a region or state, may not synchronize with the state or region to which it belongs, in terms of the socio-economic development process and the accompanying evolution of UWC. Even in the same state or region, the socio-economic development processes, water resources conditions, and urban functions of different cities may vary significantly. In the case of developed cities, like Beijing, Shanghai, Guangzhou, Tokyo, and Melbourne, the city's socio-economic development is generally more advanced than the state or region average. In addition, differences in water resource conditions between the city and the broader state or region can result in the distinct evolution of water-consumption patterns.

4.2. Comparisons between UWC Prediction Based on Patterns in the Evolution of UWC with Those Using Other Methods

For reference and comparison with the UWC prediction based on the patterns in the evolution of UWC, UWC in Changsha was also predicted using the genetic programming model (GPM) and quota method (QM). Technical details of UWC predictions for Changsha using the GPM and QM can be found in Appendices B and C, respectively.

Using historical data pertaining to the annual UWC and socio-economic indicators from 2002 to 2015 (Figure 5a) as the input data, an urban water demand prediction model for Changsha was established based on the GPM (introduced in Appendix B). The parameters of the GPM model are listed in Figure A1c. As the final result of the GPM model, the equation for predicting the annual urban water demand (consumption) of Changsha is given in Equation (A4). The comparison between the annual water consumption values obtained from the actual data and those obtained using the GPM can be seen in Figure 5b. To assess the imitative performance of the formula obtained using the GPM model, the Nash-Sutcliffe efficiency coefficient (NSE) between the predicted and the actual data was calculated as follows:

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Q_i - q_i)^2}{\sum_{i=1}^{n} \left(q_i - \sum_{i=1}^{n} \frac{q_i}{n} \right)^2} \tag{6}$$

where Q is the predicted annual UWC; q is the actual annual UWC; and n is the number of years. According to Equation (6), the NSE between the predicted and actual UWC data (from 2002 to 2015) is 0.956. In addition, the relative error between the predicted and actual annual UWC from 2016 to 2019 is approximately 5.0% or less. By substituting the predicted values for the socio-economic indicators from 2020 to 2030 into Equation (A4), UWC in Changsha can be predicted, as shown in Figure 5b. According to the GPM model results, the annual UWC of Changsha was predicted to remain stable from 2023 to 2030. The annual UWC of Changsha was predicted to be only 2.160×10^9 m^3 in 2030, close to the value 2.073×10^9 m^3 from 2019. After 2030, the annual UWC was predicted to maintain an increasing trend until 2038 and thereafter to decrease. The annual UWC value was predicted to be 3.370×10^9 m^3 in 2038.

According to the UWC predictions for Changsha generated using the QM (Appendix C), the domestic, industrial, public, and ecological water consumption values will increase to, respectively, 6.89×10^8, 11.52×10^8, 4.92×10^8, and 2.01×10^8 m^3 by 2025, and further to, respectively, 8.30×10^8, 15.47×10^8, 6.24×10^8, and 2.61×10^8 m^3 by 2030. UWC in Changsha is predicted to increase to 2.535×10^9 m^3 in 2025 and 3.261×10^9 m^3 in 2030.

The comparison between the predicted annual UWC of Changsha from 2021–2030 obtained using the patterns in the evolution of UWC, GPM, and QM can be seen in Figure 5b. The differences between the data predicted using the patterns in the evolution of UWC and those predicted using the GPM in 2023 are minimal. However, these differences gradually increase between 2023 and 2027. The annual UWC predicted using the patterns in the evolution of UWC is only 1.42×10^8 m^3 greater than that obtained using the GPM in 2023 but 3.96×10^8 m^3 more than that obtained using the GPM in 2027. UWC in Changsha remains stable from 2023 to 2030 in the prediction produced using the GPM. After 2027, there are turning points in both the UWC predicted using the evolutionary patterns and in that predicted using the GPM, whereas the rates of increase before and decrease after the turning point predicted using the GPM are much larger than those predicted using the evolutionary patterns. Besides, the turning point predicted using the GPM (being 2038) is later than that predicted using the evolutionary patterns (ranging from 2027 to 2035). These differences suggest that the GPM may not be able to predict the general patterns in the evolution in the UWC of a city despite its ability to provide a formula for calculating UWC based on three socio-economic factors (R_u, R_{tg}, and GDP_c) with reasonable imitative performance. This approach may be able to only approximate the trend in the evolution based on limited existing data. UWC in Changsha appears to be stable from 2013 to 2019, which may be the reason that the GPM-predicted UWC is stable from 2020 to 2030. However, Zhao et al. [24] indicated that the stable or decreasing trend in water consumption in China since 2013 may be deceptive, attributable to factors such as water-resource constraints, changes in development mode, statistical patterns, etc. They highlight that water consumption in China may tend to increase until the socio-economic indicators exceed the threshold values. As recommended by Anele et al. [4], intelligent algorithms may be suitable for short-term UWC predictions but not long-term ones. Moreover, the annual UWC predicted using the patterns in the evolution of UWC is close to that predicted using the QM in 2025 but is much smaller than that predicted using the QM in 2030. According to the technical details of the QM (Appendix B), UWC values predicted using the QM may increase with the expanding urban socio-economy. Thus, the QM may be more suitably used to predict the UWC of a city on a relatively short timescale. Considering the universal patterns in the evolution of UWC derived from the historical data on socio-economic conditions and UWC in several developed cities, these patterns may be more suitable for predicting UWC on a longer timescale compared with GPM or QM.

4.3. Reliability and Generalization of the Proposed Approach for Studying Patterns in the Evolution of UWC Accompanying Socio-Economic Development

The reliability of the proposed approach for studying patterns in the evolution of UWC accompanying socio-economic development may be evaluated through comparisons between the patterns in the evolution of UWC accompanying socio-economic development derived in Sections 3.1 and 3.2 with the evolution of UWC in cities that were not included in among the research cities in the present study. For instance, the evolution of UWC in Toronto and Barcelona with socio-economic indicator values corresponding to the turning point is shown in Figure 8. The sources of the data shown in Figures 8a and 8b, respectively, were a. the Chief Financial Officer and Treasurer and General Manager, Toronto Water, and Statistics Canada and b. the data sets constructed by Rasilla et al. [47] and Idescat. Statistical Institute of Catalonia (IDESCAT).

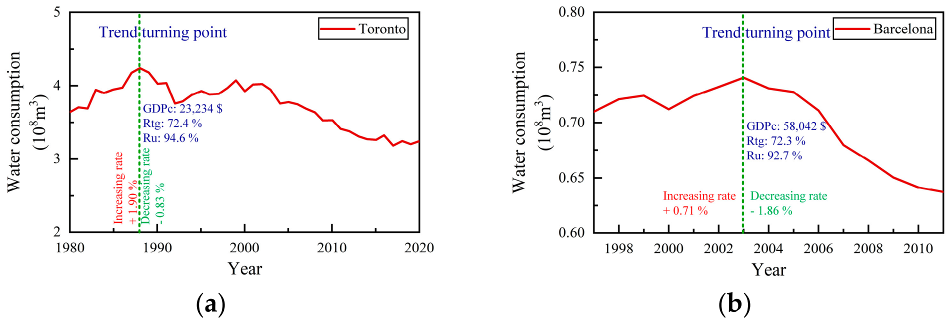


Figure 8. Evolution of UWC with socio-economic indicator values corresponding to the turning point in Toronto and Barcelona: (**a**) Toronto; data sources were the Chief Financial Officer and Treasurer and General Manager, Toronto Water, and Statistics Canada; (**b**) Barcelona; data sources were the data sets constructed by Rasilla et al. [47] and Idescat. Statistical Institute of Catalonia (IDESCAT).

As shown in Figure 8, the evolutionary patterns of UWC in Toronto or Barcelona were similar to the general patterns in the evolution of UWC derived in Section 3.1. There also existed a turning point in the annual UWC series from 1980 to 2020 in Toronto and in the annual UWC series from 1997 to 2011 in Barcelona, which was observed through the Pettitt test method, as illustrated in Section 2.1.2. The annual UWC showed an increasing trend before the turning points and then began to decrease in these two cities. The annual rates of increase and decrease before and after the turning point in Toronto were +1.90% and −0.83%, respectively, and those in Barcelona were +0.71% and −1.86%, respectively. The socio-economic indicators, including GDP_c, R_{tg}, and R_u, at the turning point were USD 23,234, 72.4%, and 94.6%, respectively, in Toronto, and USD 58,042, 72.3%, and 92.7%, respectively, in Barcelona. These values were between the lower and upper threshold values of the socio-economic indicators driving trends in UWC, as derived in Section 3.2. These similarities may support the reliability of the general patterns in the evolution of UWC that accompany socio-economic development derived in Sections 3.1 and 3.2. Additionally, if any other cities can be substituted as research cases into the proposed approach in the present study, the lower and upper threshold values of the socio-economic indicators driving trends in UWC may be updated more accurately.

Moreover, the proposed approach to studying patterns in the evolution of UWC accompanying socio-economic development on the city scale may be generalized for application to studying such patterns on other scales, like city groups, river basins, etc. For instance, as indicated in Figure 9, the annual water consumption in the Colorado River Basin showed an increasing trend before reaching the peak value and then changed to a decreasing trend, a pattern similar to the patterns in UWC on the city scale, as derived in Section 3.1. Therefore, the turning point in the annual water-consumption series on another scale may be also identified through the Pettitt test method, as illustrated in Section 2.1.1. The main socio-economic indicators impacting the evolution of water consumption may be similarly identified through the correlation analysis based on the PCC. Then, the lower and upper threshold values of the socio-economic indicators driving trends in UWC on this scale may be also derived through the statistical analysis method, as illustrated in Section 3.2. Through these generalized applications, novel findings on the patterns of water consumption on other scales, like city groups and river basins, may be attained.

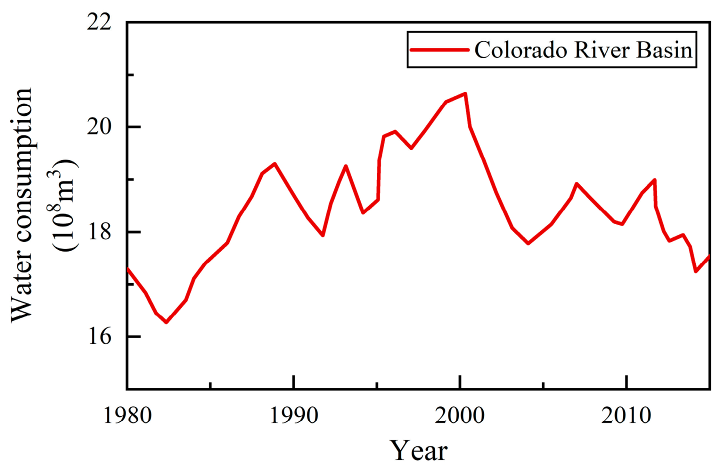


Figure 9. Evolution of water consumption in the Colorado River Basin from the data source of US Bureau of Reclamation.

5. Conclusions

The patterns in the evolution of UWC accompanying socio-economic development were statically analyzed, and the application of this approach to UWC prediction was discussed using Changsha, China as a case study.

The patterns in the evolution of UWC derived from the historical data from developed cities indicate that UWC in a city typically shows an increasing trend in the initial stage and then tends to decrease or stabilize in the following years. According to the correlation analysis between the socio-economic factors and UWC, three socio-economic factors, including the urbanization rate (R_u), GDP per capita (GDP_c), and ratio of annual added value of tertiary industry to GDP (R_{tg}) can be identified as the main socio-economic indicators influencing UWC. When UWC begins to decrease or stabilize, the values of the socio-economic indicators (GDP_c, R_{tg}, and R_u) are approximately in the ranges [USD 10,000, USD 60,000], [60%, 80%], and [85%, 95%], respectively. Thus, when UWC in a city begins to decrease or stabilize, the city can be considered to have approached or entered the stage of having a developed economy.

According to the prediction based on the patterns in the evolution of UWC, UWC in Changsha will continue to increase until the turning point (between 2027 and 2035) and then gradually decrease over the next few years. The value of UWC at the turning point was predicted to range from 2.458×10^9 m^3 to 3.114×10^9 m^3. This transition for Changsha will occur earlier than those for Hunan Province and China. Moreover, the value of UWC predicted using the evolutionary patterns is lower than that predicted using the quota method. The turning point of UWC predicted using the evolutionary patterns occurs earlier than that predicted using genetic programming. This difference suggests that for longer-term UWC predictions, patterns in the evolution of UWC might be a more suitable approach for a city compared with the genetic programming or quota method.

As further research prospects, future work on the patterns in the evolution of UWC can be aimed at improving on the limitations of the present study. Firstly, the effects of conditions related to water resources, regional cultures, policy-based regulations, etc., on patterns in UWC are insufficiently considered in the present study. In further research works, the research cities may be categorized using these influencing factors and the patterns in the evolution of UWC belonging to different city categories may be derived accordingly. On the other hand, the derived patterns in UWC can be applied to general situations, but their applications to unexpected situations, i.e., war, natural hazards, etc. need to be further studied. Moreover, the patterns in the evolution of UWC derived using historical data for long-term annual series of UWC may be suitable for medium- and long-term urban water resources planning on the annual scale, but the applications of these patterns in the evolution of UWC to short-term UWC predictions also need to be further studied.

Author Contributions: Conceptualization, Z.M.; Methodology, Z.M. and S.H.; Computer programming, S.H.; Data collection and preparation, S.H. and H.W.; Investigation, S.H.; Visualization, S.H.; Writing—original draft, S.H.; Writing—review and editing, Z.M., H.W. and Y.G.; Supervision, Z.M.; Funding, Z.M. All authors have read and agreed to the published version of the manuscript.

Funding: The National Keypoint Research and Invention Program of the Fourteenth (No. 2021YFC3000204) and the National Natural Science Foundation of China (No. 51609261; No. 52079039).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be available upon request.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

In the present study, the future R_u and R_{tg} of the research city employed in UWC prediction were predicted according to the following equation:

$$R = 1 - \exp[-a(t-b)] \quad \text{(A1)}$$

where R is the R_u or R_{tg}; t is the time, year; and coefficients, a and b, are fitted using the corresponding historical data. The future population was predicted based on the following equation [48,49]:

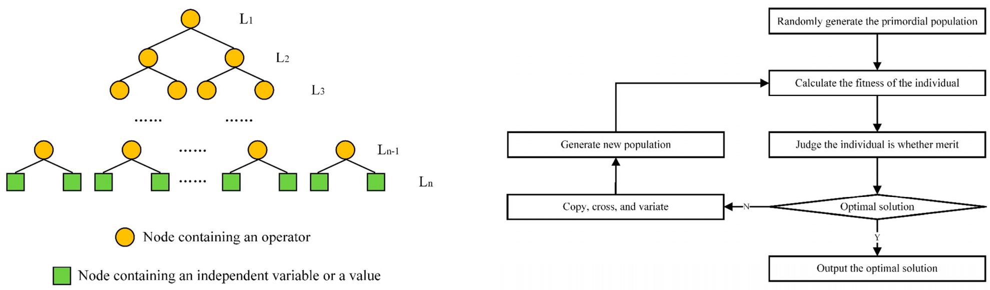
$$P_t = \frac{P_{t\max}}{1 + \left(\frac{P_{t\max}}{P_{t0}} - 1\right)e^{-r(t-t_0)}} \tag{A2}$$

where P_t is the total population; t is the time, year; and coefficient, $P_{t\max}$, P_{t0}, r, and t_0, are fitted using the historical population data.

Appendix B

Genetic programming is a bionics algorithm based on genetic principles that is typically used for solving optimization problems [50]. Unlike the genetic algorithm, genetic programming focuses on determining the optimal regression function by allowing regression fitting of operators and optimization of the parameters and structures of the function [51]. Therefore, the regression equation for UWC predictions can be determined based on the genetic programming model (GPM) incorporating the factors influencing water demand as identified from UWC data [52–54].

In the present study, a UWC prediction model based on genetic programming was established. According to the basic principle of genetic programming [50], each individual participating in the genetic programming can be considered to have a tree structure consisting of nodes and connectors, as shown in Figure A1a. The bottom layer of the tree structure includes the nodes, each of which contains an independent variable or a value. Layers L1 to Ln-1 include the nodes, with each hosting an operator. Based on the identification results provided in Section 3.2, the basic independent variables in the tree structure include GDP_c, R_{tg}, and R_u. The basic operators incorporated into the tree structure are listed in Figure A1c. Technical details pertaining to the generation of initial individuals and mechanisms of copy, cross, and variation of offspring individuals are given in Koza [50].



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

Parameter	Configuration
Maximum iteration step number	10,000
Termination condition	Meeting the maximum iteration step number
Primordial individual number	200,000
Offspring individual number	500,000
Layer number of the tree structure of an individual	10
Operators	+, -, *, /, ^, and sin
Variation probability	0.05
Cross probability	0.4
Copy probability	0.05
Fitness function	Root-mean-square deviation

(**c**)

Figure A1. Layout of the tree structure of an individual and technical progress of genetic programming: (**a**) tree structure of an individual; (**b**) technical progress; (**c**) modeling parameters.

In the process of genetic programming for predicting UWC, the fitness of each individual can be calculated as follows [51]:

$$RMS = \sqrt{\frac{\sum_{i=1}^{n}(Q_i - q_i)^2}{n-1}} \tag{A3}$$

where *RMS* is the root-mean-square deviation, indicating the fitness of the individual; Q is the predicted annual UWC obtained using the equation corresponding to the tree structure of the individual; q is the actual annual UWC; and n is the number of years. Individuals with lower RMS are preferred in the GPM.

As shown in Figure A1b, the genetic programming process for UWC prediction includes the following steps:

(1) The initial population is randomly generated.
(2) The fitness of each individual is calculated using Equation (A3).
(3) The most fit individuals are selected, and the assessment of whether the equation corresponding to each individual is the optimal solution is performed.
(4) If the optimal solution is obtained, it is output. If not, the offspring population is generated through the copy, cross, and variation processes and step (2) is repeated.

Using historical data pertaining to the annual UWC and socio-economic indicators from 2002 to 2015 (Figure 5a) as the input data, an urban water demand prediction model for Changsha was established based on the aforementioned GPM model. The parameters of the GPM model are listed in Figure A1c. According to the final iteration result of the GPM model, the equation for predicting the annual UWC of Changsha is derived as follows:

$$\begin{aligned} W_a = {} & ((((R_{\mathrm{tg}})/\sin((GDP_c)\hat{}\sin((R_u)\times\sin((GDP_c\times\sin((GDP_c) \\ & +\sin(R_u))))))/\sin(R_{\mathrm{tg}}))+\sin((GDP_c)\times\sin(GDP_c)))\times 10 \end{aligned} \tag{A4}$$

where W_a is the annual UWC of Changsha, 10^8 m^3; R_u is the urbanization rate; R_{tg} is the ratio of the annual added value of the tertiary industry to GDP; and GDP_c is the GDP per capita, USD 10^4.

Appendix C

Using the quota method for UWC prediction of Changsha, UWC is divided into four parts, domestic, public, ecological, and industrial water consumption, which can be calculated as follows:

$$W_d = P \times [R_u \times q_{du} + (1 - R_u) \times q_{dr}] \times 0.365 \times 10^{-4} \tag{A5}$$

$$W_p = P \times q_p \times 0.365 \times 10^{-4} \tag{A6}$$

$$W_e = P \times q_e \times 0.365 \times 10^{-4} \tag{A7}$$

$$W_i = I \times q_i \times 10^{-4} \tag{A8}$$

where W_d, W_p, W_e, and W_i represent the domestic, public, ecological, and industrial annual water consumption, respectively, in units of 10^8 m^3; q_{du}, q_{dr}, q_p, q_e, and q_i represent, respectively, the urban and rural domestic, public, ecological, and industrial quotas of water consumption, as shown in Table A1; P is the population, 10^4 people; I is the annual industrial added value, CNY 10^8.

The urban and rural quota values corresponding to domestic water consumption can be referred to as "Hunan: Norm of water intake (DB43/T 388-2020)" [55], as outlined in Table A1. Quota values for public, ecological, and industrial water consumption can be evaluated based on the trend analysis of the data pertaining to the historical water consumption and socio-economy of Changsha from 2002 to 2019, the results of which are shown in Table A1. The methods used to predict the population and R_u of Changsha are those introduced in Section 3.3. The average growth rate of the annual industrial added value of Changsha from 2018 to 2022 (7%) is used to predict the future industrial added values, with 2022 as the base year. The predicted P, R_u, and I of Changsha in 2025 and 2030 are listed in Table A1. Substituting the predicted P, R_u, and I into Equations (A5)–(A8), UWC in Changsha in 2025 and 2030 can be predicted, as indicated in Table A1.

Table A1. Predicted data pertaining to quota, socio-economy, and water consumption in Changsha in 2025 and 2030.

Year	Quota Type					Socio-Economic Factors			Water Consumption				
	Domestic ($L \cdot People^{-1} \cdot d^{-1}$)		Public	Ecological	Industrial	P (10^4 People)	R_u (%)	I (CNY 10^4)	W_d	W_i	W_p	W_e	Summary
	Urban	Rural	($L \cdot People^{-1} \cdot d^{-1}$)						(10^8 m^3)				
2025	160	120	110	45	23	1226	84.77	5010	6.89	11.52	4.92	2.01	25.35
2030	150	120	110	46	22	1553	88.20	7030	8.30	15.47	6.24	2.61	32.61

References

1. Sediqi, M.N.; Komori, D. Assessing water resource sustainability in the Kabul River Basin: A standardized runoff index and reliability, resilience, and vulnerability framework approach. *Sustainability* **2024**, *16*, 246. [CrossRef]
2. Zhao, J.; Fang, G.; Wang, X.; Zhong, H. Joint optimization of urban water quantity and quality allocation in the plain river network area. *Sustainability* **2024**, *16*, 1368. [CrossRef]
3. Torres López, S.; Barrionuevo, M.D.L.A.; Rodríguez-Labajos, B. A new operational approach for understanding water-related interactions to achieve water sustainability in growing cities. *Environ. Dev. Sustain.* **2021**, *25*, 122–137. [CrossRef]
4. Anele, A.O.; Hamam, Y.; Abu-Mahfouz, A.M.; Todini, E. Overview, Comparative Assessment and Recommendations of Forecasting Models for Short-Term Water Demand Prediction. *Water* **2017**, *9*, 887. [CrossRef]
5. Fu, G.; Jin, Y.; Sun, S.; Yuan, Z.; Butler, D. The role of deep learning in urban water management: A critical review. *Water Res.* **2022**, *223*, 118973. [CrossRef] [PubMed]
6. Surendra, H.J.; Deka, P.C. Municipal Residential Water Consumption Estimation Techniques Using Traditional and Soft Computing Approach: A Review. *Water Conserv. Sci. Eng.* **2022**, *7*, 77–85. [CrossRef]
7. Mosleh, L.; Negahban-Azar, M. Role of Models in the Decision-Making Process in Integrated Urban Water Management: A Review. *Water* **2021**, *13*, 1252. [CrossRef]
8. Sivagurunathan, V.; Elsawah, S.; Khan, S.J. Scenarios for urban water management futures: A systematic review. *Water Res.* **2022**, *211*, 118079. [CrossRef]
9. Chen, M.; Luo, Y.; Shen, Y.; Han, Z.; Cui, Y. Driving force analysis of irrigation water consumption using principal component regression analysis. *Agric. Water Manag.* **2020**, *234*, 106089. [CrossRef]
10. Lu, S.; Gao, X.; Li, W.; Jiang, S.; Huang, L. A study on the spatial and temporal variability of the urban residential water consumption and its influencing factors in the major cities of China. *Habitat Int.* **2018**, *78*, 29–40. [CrossRef]
11. Anríquez, G.; Melo, O. The Socio-Economic Context of Chilean Water Consumption and Water Markets Growth: 1985–2015. In *Water Policy in Chile*; Donoso, G., Ed.; Springer International Publishing: Cham, Switzerland, 2018; pp. 53–63.
12. Sant'Ana, D.; Mazzega, P. Socioeconomic analysis of domestic water end-use consumption in the Federal District, Brazil. *Sustain. Water Resour. Manag.* **2018**, *4*, 921–936. [CrossRef]
13. Sun, S.; Bao, C.; Tang, Z. Tele-connecting water consumption in Tibet: Patterns and socio-economic driving factors for virtual water trades. *J. Clean. Prod.* **2019**, *233*, 1250–1258. [CrossRef]
14. Bell, D. *The Coming of Post Industrial Society*; Harper: New York, NY, USA, 1973; pp. 12–33.
15. Chenery, H.; Robinson, S.; Syrquin, M. *Industrialization and Growth: A Comparative Study*; Oxford University Press: Oxford, UK, 1986; pp. 309–355.
16. Hoover, E.M.; Fisher, J.L. Research in Regional Economic Growth. In *Problems in the Study of Economic Growth*; National Bureau of Economic Research, Inc.: Cambridge, MA, USA, 1949; pp. 173–250.
17. Rostow, W.W. *The Stages of Economic Growth: A Non-Communist Manifesto*; Cambridge University Press: Cambridge, UK, 1960; pp. 4–16.
18. Syrquin, M. Quantifying Economic Development: Kuznets, Chenery, and the Quantitative Approach to Development Economics. *Hist. Polit. Econ.* **2018**, *50*, 211–230. [CrossRef]
19. Emako, E.; Nuru, S.; Menza, M. The effect of foreign direct investment on structural transformation in developing countries. *Cogent Econ. Financ.* **2022**, *10*, 2125658. [CrossRef]
20. Sen, K. Structural Transformation around the World: Patterns and Drivers. *Asian Dev. Rev.* **2019**, *36*, 1–31. [CrossRef]
21. Dohrn, R.; Heilemann, U. The Chenery hypothesis and structural change in Eastern Europe. *Econ. Transit.* **1996**, *4*, 411–425. [CrossRef]
22. Merrett, S. *Introduction to the Economics of Water Resources: An International Perspective*; Routledge: London, UK, 1997; pp. 140–160.

23. Jia, S.; Zhang, S.; Yang, H.; Xia, J. Relation of industrial water use and economic development: Water use Kuznets Curve. *J. Nat. Resour.* **2004**, *19*, 279–284.
24. Zhao, Y.; Li, H.; Liu, H.; Wang, L.; He, G.; Wang, H. The law of growth: Prediction of peak water consumption in china. *J. Hydraul. Eng.* **2021**, *52*, 129–141.
25. Wang, Q.; Wang, X.; Liu, Y.; Li, R. Urbanization and water consumption at national- and subnational-scale: The roles of structural changes in economy, population, and resources. *Sustain. Cities Soc.* **2021**, *75*, 103272. [CrossRef]
26. Liu, J.; Xuan, K.; Xie, N.; Zhang, J.; Wang, X.; Yu, Z.; Wang, W. Effects of urbanisation on regional water consumption in China. *J. Hydrol.* **2022**, *609*, 127721. [CrossRef]
27. Ito, Y.; Kobayashi, Y.; Yokomichi, H.; Malla, S.S.; Kiem, A.S.; Nishida, K. Physical and non-physical factors associated with water consumption at the household level in a region using multiple water sources. *J. Hydrol. Reg. Stud.* **2021**, *37*, 100928. [CrossRef]
28. Ou, Z.; He, F.; Zhu, Y.; Lu, P.; Wang, L. Analysis of driving factors of water demand based on explainable artificial intelligence. *J. Hydrol. Reg. Stud.* **2023**, *47*, 101396. [CrossRef]
29. Dias, T.F.; Ghisi, E. Urban water consumption: A systematic literature review. *Water* **2024**, *16*, 838. [CrossRef]
30. Savelli, E.; Mazzoleni, M.; Di Baldassarre, G.; Cloke, H.; Rusca, M. Urban water crises driven by elites' unsustainable consumption. *Nat. Sustain.* **2023**, *6*, 929–940. [CrossRef]
31. Conte, L.C.; Bayer, D.M.; Bayer, F.M. Bootstrap Pettitt test for detecting change points in hydroclimatological data: Case study of Itaipu Hydroelectric Plant, Brazil. *Hydrol. Sci. J.* **2019**, *64*, 1312–1326. [CrossRef]
32. Li, J.; Tan, S.; Wei, Z.; Chen, F.; Feng, P. A New Method of Change Point Detection Using Variable Fuzzy Sets Under Environmental Change. *Water Resour. Manag.* **2014**, *28*, 5125–5138. [CrossRef]
33. Bithas, K.; Stoforos, C. Estimating urban residential water demand determinants and forecasting water demand for athens metropolitan area, 2000–2010. *South-East. Eur. J. Econ.* **2006**, *4*, 47–59.
34. Hao, Y.; Hu, X.; Chen, H. On the relationship between water use and economic growth in China: New evidence from simultaneous equation model analysis. *J. Clean. Prod.* **2019**, *235*, 953–965. [CrossRef]
35. Romano, G.; Salvati, N.; Guerrini, A. An empirical analysis of the determinants of water demand in Italy. *J. Clean. Prod.* **2016**, *130*, 74–81. [CrossRef]
36. Wu, F.; Zhan, J.; Zhang, Q.; Sun, Z.; Wang, Z. Evaluating Impacts of Industrial Transformation on Water Consumption in the Heihe River Basin of Northwest China. *Sustainability* **2014**, *6*, 8283–8296. [CrossRef]
37. Zhang, Q.; Diao, Y.; Dong, J. Regional Water Demand Prediction and Analysis Based on Cobb-Douglas Model. *Water Resour. Manag.* **2013**, *27*, 3103–3113. [CrossRef]
38. Mankad, A.; Tapsuwan, S. Review of socio-economic drivers of community acceptance and adoption of decentralised water systems. *J. Environ. Manag.* **2011**, *92*, 380–391. [CrossRef] [PubMed]
39. Sun, S.; Wang, Y.; Liu, J.; Cai, H.; Wu, P.; Geng, Q.; Xu, L. Sustainability assessment of regional water resources under the DPSIR framework. *J. Hydrol.* **2016**, *532*, 140–148. [CrossRef]
40. Zhu, B.; Yuan, J. Pressure transfer modeling for an urban water supply system based on Pearson correlation analysis. *J. Hydroinformatics* **2014**, *17*, 90–98. [CrossRef]
41. Omer, A.; Elagib, N.A.; Zhuguo, M.; Saleem, F.; Mohammed, A. Water scarcity in the Yellow River Basin under future climate change and human activities. *Sci. Total Environ.* **2020**, *749*, 141446. [CrossRef]
42. Yang, S.; Zhang, J.; Zhang, S.; Wang, J.; Bai, Y.; Yao, F.; Guo, H. The potential of remote sensing-based models on global water-use efficiency estimation: An evaluation and intercomparison of an ecosystem model (BESS) and algorithm (MODIS) using site level and upscaled eddy covariance data. *Agric. For. Meteorol.* **2020**, *287*, 107959. [CrossRef]
43. Zhao, Y.; Li, M. Effect of water-saving society policy on water consumption in the cities of China: A propensity score matching analysis. *Int. J. Environ. Res. Public Health* **2020**, *17*, 8171. [CrossRef] [PubMed]
44. Arvianto, A.; Sopha, B.M.; Asih, A.M.S.; Imron, M.A. City logistics challenges and innovative solutions in developed and developing economies: A systematic literature review. *Int. J. Eng. Bus. Manag.* **2021**, *13*, 18479790211039723. [CrossRef]
45. Muhammad, S.; Pan, Y.; Agha, M.H.; Umar, M.; Chen, S. Industrial structure, energy intensity and environmental efficiency across developed and developing economies: The intermediary role of primary, secondary and tertiary industry. *Energy* **2022**, *247*, 123576. [CrossRef]
46. Yang, L.; Luo, X.; Ding, Z.; Liu, X.; Gu, Z. Restructuring for Growth in Development Zones, China: A Systematic Literature and Policy Review (1984–2022). *Land* **2022**, *11*, 972. [CrossRef]
47. Rasilla, D.F.; Garmendia, C.; García-Codron, J.C. Climate change projections of streamflow in the Iberian peninsula. *Int. J. Water Resour. Dev.* **2013**, *29*, 184–200. [CrossRef]
48. Mulligan, G.F. Logistic Population Growth in the World's Largest Cities. *Geogr. Anal.* **2006**, *38*, 344–370. [CrossRef]
49. Tsoularis, A.; Wallace, J. Analysis of logistic growth models. *Math. Biosci.* **2002**, *179*, 21–55. [CrossRef] [PubMed]
50. Koza, J. *Genetic Programming: On the Programming of Computers by Means of Natural Selection*; MIT Press: Cambridge, MA, USA, 1992; Volume 1, pp. 9–16.
51. Affenzeller, M.; Winkler, S.; Wagner, S.; Beham, A. *Genetic Algorithms and Genetic Programming: Modern Concepts and Practical Applications*; CRC Press: Boca Raton, FL, USA, 2009; pp. 25–62.
52. Danandeh Mehr, A.; Nourani, V.; Kahya, E.; Hrnjica, B.; Sattar, A.M.A.; Yaseen, Z.M. Genetic programming in water resources engineering: A state-of-the-art review. *J. Hydrol.* **2018**, *566*, 643–667. [CrossRef]

53. Liu, Y. *Study on Reservoir Operation Hedging Rules for Economic and Ecologic Objectives*; Tsinghua University: Beijing, China, 2014; pp. 31–48.
54. Nasseri, M.; Moeini, A.; Tabesh, M. Forecasting monthly urban water demand using Extended Kalman Filter and Genetic Programming. *Expert Syst. Appl.* **2011**, *38*, 7387–7395. [CrossRef]
55. DB43/T 388-2020. Available online: http://www.jsgg.com.cn/Files/PictureDocument/20200907123602251828652069.pdf (accessed on 5 November 2023).