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Dynamics of the Agricultural Water Footprint and the Decoupling Associations with Agricultural Economic Growth in Hangzhou, China

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Abstract: Understanding the relationship between the agricultural water footprint (AWF) and agricultural economic growth (AEG) is of great significance for promoting sustainable agriculture and regional economic development. In this study, we used agricultural statistics data from Hangzhou from 2010 to 2021 to calculate the AWF, predicted the decoupling relationship between the AWF and AEG, and explored the influencing factors of the decoupling relationship between the AWF and AEG. The results showed the following: (1) The AWF in Hangzhou exhibited a decreasing trend, with a reduction from 58.88×10^8 m^3 in 2010 to 37.80×10^8 m^3 in 2021; this was mainly related to the decline in the water footprints of grain, pork, and egg production. (2) The strong decoupling accounted for 63.64% of the decoupling between the AWF and AEG in Hangzhou during the study period. It was found that an agricultural structure adjustment was the main factor for achieving decoupling between the AWF and AEG. Under the guidance of policy, the decoupling between them could be changed by regulating the output of agricultural products with different water footprint contents per unit. (3) From 2022 to 2026, the AWF in Hangzhou is expected to decrease to 28.21×10^8 m^3, while the agricultural economy is projected to increase to CNY 40.008 billion. There will continue to be a strong decoupling status between the AWF and AEG in Hangzhou.

Keywords: agriculture; water footprint; economic growth; decoupling; prediction; Hangzhou

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1. Introduction

Water is an indispensable resource for social and economic development [1]. It is an important agricultural production component, and it is also one of the restrictive and strategic resources supporting sustainable agricultural development [2]. China is not only a major agricultural country, it also ranks among the countries with the most limited water resources globally [3]. Agriculture is the sector with the highest demand for water resources, accounting for more than half of the total water supply in China [4]. With the continuous growth of the economy, the demand for agricultural water resources is increasing, thus leading to ecological and environmental issues such as the decline of lake, river, and groundwater levels [5]. Additionally, the process of agricultural water use is accompanied by the emission of greenhouse gases; thus, it also contributes to accelerating global warming [6]. Climate change, since it is driven by greenhouse gas emissions and human activities, exacerbates water resource shortages through altered precipitation patterns and increased evaporation rates [7,8], thereby putting additional stress on regional agricultural economies [9,10]. How to make informed decisions that reduce agricultural water use while maintaining agricultural economic growth and achieving sustainable agriculture goals is an urgent problem that needs to be addressed.

Sustainable agriculture is an agricultural system that involves the rational use of natural resources and the implementation of technological innovations to ensure the sustainable development of agricultural product demand [11]. In terms of agricultural water resource management, addressing water scarcity involves a combination of measures including the implementation of water conservation policies [12,13] and the establishment of reasonable water allocation frameworks [14,15]. To enhance the socio-economic benefits of water resources, it is crucial to clarify the decoupling relationship between agricultural water use and agricultural economic growth (AEG), as well as the influencing factors, which are of significance for regional agricultural water resource management and sustainable development.

In 2002, Hoekstra, a Dutch scholar, proposed the concept of the water footprint, which is a measure of humanity's appropriation of fresh water, calculated in volumes of water consumed [16]. Early studies on the water footprint mainly accounted for water consumption at the national level. For example, Hoekstra et al. [17] calculated the water footprint of multiple countries globally from 1997 to 2001, and they advised that the size of the water footprint in a country is influenced by consumption level, consumption patterns, climate conditions, and water efficiency. Since then, the accounting of water footprints has gradually expanded to different scales [18–22] and perspectives (such as product-based [23], agriculture [10], and industry [24]). For example, Mekonnen et al. [25] calculated global water consumption based on the water footprint, and they found that it will grow by 22% by 2090. Furthermore, approximately 57% of the blue water footprint in the world violates environmental flow requirements. Based on the theory of the water footprint, research on water resource assessment and its association with human activities has also been further developed. Many studies have used indicators such as the water footprint economic value [26] and the water poverty index [27], which are based on the water footprint, in terms of evaluating regional water resources security [28]. Certain scholars have used water footprints to explore the sustainable utilization of regional water resources [29], as well as water usage coordination and its association with economic development [30] and urbanization [31].

Decoupling was first proposed by the Organization for Economic Co-operation and Development (OECD) [32], and this concept has been widely applied in research on the relationship between resources, environmental consumption, and economic growth. For instance, Dagher et al. [33,34] analyzed the relationship between resource (energy) consumption and economic growth from different perspectives using various methods. They found that energy was a limiting factor for economic growth and that government policies restricting resource imports and exports could either promote or inhibit economic growth [35,36]. Tapio [37] subsequently developed the Tapio model, which is based on the decoupling theory. Many studies have focused on the decoupling status between carbon emissions [38], water use [39], energy [40], and economic growth via the Tapio model. Certain studies have also predicted the decoupling status between carbon emissions [41], ecological footprints [42], and economic growth. Kong et al. [42] used the Tapio model to analyze the decoupling status between the water footprint of the marine fisheries industry and economic growth in China; as such, they predicted the ecological footprint of the fisheries sector by utilizing prediction models such as the autoregressive integrated moving average (ARIMA) model and the gray forecasting model (GM(1, 1)). However, few studies have deeply investigated the synergistic mechanisms between water resource management policies and economic growth.

The decoupling relationship between the agricultural water footprint (AWF) and the AEG is influenced by a variety of factors, such as agricultural structure, agricultural technology, and policy. For instance, Aldaya et al. [43] found that agricultural policies influence AWF and agricultural economics by directing changes in crop structure. Sun et al. [44] stated that changes in crop water footprints are controlled by agricultural management and agricultural water use efficiency. This provides a basis for the anthropogenic regulation of the decoupling relationship between crop water footprints and the AEG. Davis et al. [45] proposed that the current distribution of crops around the world is neither maximizing yields nor minimizing water use, and also that it is possible to increase crop yields while reducing agricultural water use by reshaping the global crop distribution within rain-fed and irrigated farmland, based on total water use. However, most of the previous studies have analyzed the effects of factors such as agricultural structure or of a single factor on the decoupling relationship between the AWF and AEG by regulating agricultural structure. Few studies have systematically analyzed the effects of multiple factors, such as epidemics and policies, on the decoupling relationship between the AWF and AEG by regulating agricultural structure, nor have they investigated the mechanism of their effects.

In terms of agricultural water use, integrated water resource management plays a crucial role in achieving sustainable agriculture. Measures such as technological innovations are employed to minimize agricultural water use and to ensure agricultural economic growth. The agricultural economy in Hangzhou is well developed; however, with continuous population growth, the demand for agricultural water use has been increasing, which has brought tremendous pressure on the utilization of agricultural water resources. Analyzing the relationship between agricultural water use and agricultural economic growth in Hangzhou from the perspective of the water footprint is crucial for water resource management and sustainable agricultural development.

This paper investigated and predicted the decoupling status between the AWF and AEG in Hangzhou. The objectives of this research are as follows: (1) to investigate the dynamics of the AWF in Hangzhou, (2) to analyze the decoupling relationship between the AWF and AEG in Hangzhou, (3) to predict the AWF and agricultural economy, as well as their decoupling status between 2022 and 2026, and (4) to reveal the impact mechanisms of government policies on the decoupling relationship between the AWF and AEG.

The innovations of this study are as follows: (1) analyzing the effects of multiple factors, such as epidemics and policies, on the decoupling relationship between the AWF and AEG, (2) exploring the mechanism of action of multiple factors indirectly by regulating the uncoupling of the AWF and AEG through agricultural structures, and (3) enumerating the timeline of the agricultural policy implemented in Hangzhou, as well as investigating the impacts of agricultural policy on the decoupling relationship between the AWF and AEG from an empirical perspective.

2. Materials and Methods

2.1. Study Region

Located on the southeast coast of China, Hangzhou (118°21′–120°30′ E, 29°11′–30°33′ N), is located in the north of Zhejiang Province, which is adjacent to Hangzhou Bay in the east, connected to Shaoxing, and bordering Quzhou in the southwest. In addition, it is adjacent to Huzhou and Jiaxing in the north, as well as being bordered by Huangshan in Anhui Province in the southwest and Xuancheng in Anhui Province in the northwest. Hangzhou is the political, economic, cultural, educational, transport, and financial center of Zhejiang Province. It covers ten districts, including Shangcheng District, Gongshu District, Xihu District, etc., as well as two counties and one county-level city. In 2021, the gross domestic product (GDP) in Hangzhou was CNY 1810.90 billion, which accounted for 24.63% of the total economic output of the province. Moreover, the agricultural GDP of Hangzhou was CNY 33.35 billion (ranked second in Zhejiang Province). Hangzhou is abundant in water resources, and the total water consumption in 2021 was 2.98 billion m^3, with agricultural water consumption accounting for 37.45% (1.11 billion m^3) of the total water consumption.

The crops grown in Hangzhou are mainly grain, cotton, oil plants, fruits, tea, vegetables, and sugar; furthermore, the animal products are mainly pork, beef, mutton, poultry, eggs, aquatic products, and milk.

2.2. Data Sources

This article takes Hangzhou as the study area and selects agriculture-related data from 2010 to 2021 for research. The required data include agricultural GDP and the agricultural output of 14 typical agricultural products, such as grain, cotton, oil plants, fruits, tea, vegetables, sugar, pork, beef, poultry, eggs, aquatic products, and milk. The data were obtained from the Hangzhou Statistical Yearbook, the Zhejiang Province Water Resources Bulletin, and the Hangzhou Municipal Bureau of Statistics (http://tjj.hangzhou.gov.cn/, accessed on 20 September 2023). Due to the complexity of calculating the water footprint per unit of both crops and animal products, the water footprint values per unit of most agricultural products were acquired from the existing literature on Zhejiang Province and Hangzhou [46,47]. As the local data were unobtainable, the water footprint values per unit of grain, oil plants, tea, etc., in this study were derived from the results of studies conducted in the surrounding cities of Hangzhou, which shares the same environmental background as Hangzhou [48–50]. The estimated results and method have been widely used in Chinese research [51,52], as shown in Tables 1 and 2. The data used for the comparison of the AWF and the water footprint content per unit were gathered from the work of Zheng et al. [53].

Table 1. Water footprint content per unit of crop products (m^3/kg) [46–50].

Products	Grain	Cotton	Oil Plants	Fruits	Tea	Vegetables	Sugar
Water footprint content	1.10	4.98	2.10	0.42	13.17	0.056	0.16

Table 2. Water footprint content per unit of animal products (m^3/kg) [46–50].

Products	Pork	Beef	Mutton	Poultry	Eggs	Aquatic Products	Milk
Water footprint content	3.70	19.99	18.01	3.50	8.65	5.00	2.20

2.3. Methods

2.3.1. Research Framework

We proposed a framework for the impact of policies and other factors on the decoupling relationship between the AWF and AEG, as shown in Figure 1. Firstly, agriculture-related statistics were collected to account for the agricultural water footprint in Hangzhou from 2010 to 2021. Then, the AWF and the agricultural economy from 2022 to 2026 were forecasted using the ARIMA model and GM(1,1), respectively. In addition, we investigated the decoupling relationship between the AWF and AEG in 2011–2026 using the Tapio model. On the above basis, we put forward a mechanism that can be used to analyze the decoupling between the AWF and AEG.

2.3.2. Accounting for the AWF

The AWF is the amount of water contained in agricultural products and services, and it is expressed as the product of the yield of each agricultural product and the corresponding water footprint content per unit [54]. The calculation formula is as follows [39]:

$$AWF = \sum_{i=1}^{n} AP_i \times VW_i \tag{1}$$

where AP_i represents the yield of the i-th agricultural product (10^8 kg), and VW_i represents the water footprint content of the i-th agricultural product per unit mass (m^3/kg).

The formula for calculating the crop water footprint per unit [46] is as follows:

$$CVW_i = \frac{W_i}{Y_i} \tag{2}$$

where CVW_i represents the water content of the i-th crop per unit mass (m^3/t); W_i represents the water requirement of the i-th crop per unit area (m^3/hm^2); and Y_i represents the i-th crop yield per unit area (t/hm^2).

$$W_i = ET_C = ET_0 \times K_C \tag{3}$$

Here, W_i is approximated as ET_C, which represents the cumulative evapotranspiration of the crop during the growing period; ET_0 represents the reference crop evapotranspiration, and K_C is the crop coefficient.

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}U_2(e_1 - e_2)}{\Delta + \gamma(1 + 0.34U_2)} \tag{4}$$

Here, R_n is the net radiation (MJ/m^2d); G is the soil heat flux $MJ/(m^2d)$; γ is the psychrometric constant (kPa/°C); T is the mean temperature (°C); U_2 is the wind speed at a height of 2 m above ground level (m/s); e_1 is the saturation vapor pressure (kPa); e_2 is the actual water vapor pressure (kPa); and Δ is the slope of the saturation vapor pressure versus temperature curve (kPa/°C).

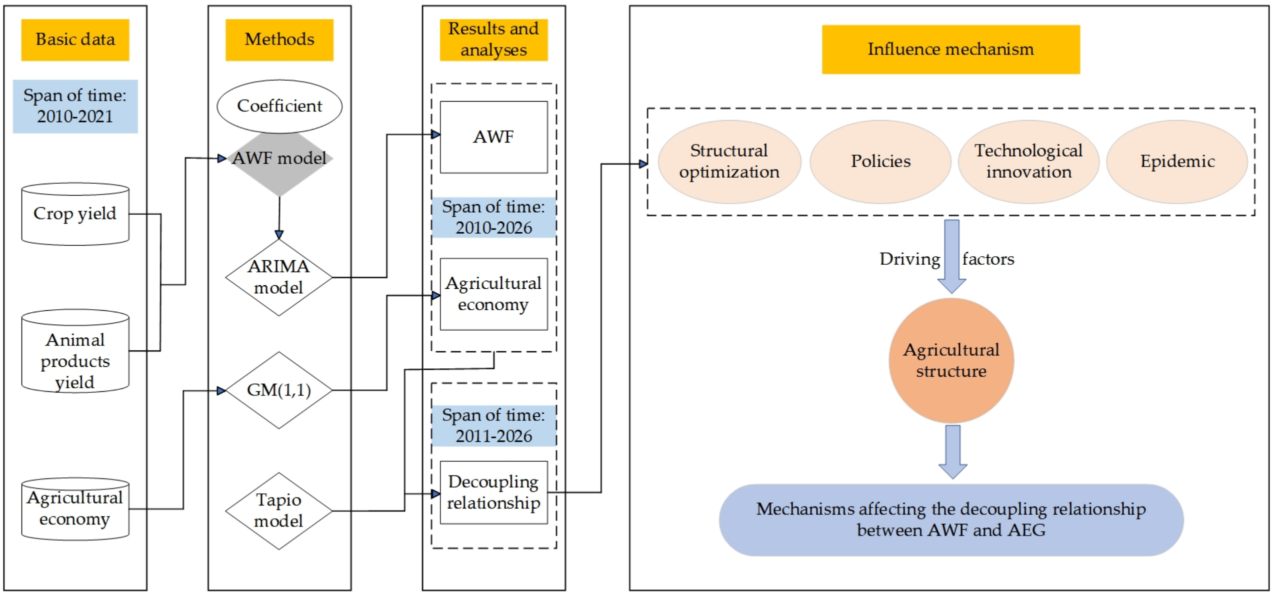

Figure 1. The flow chart of the methods.

Due to the complexity of the process and the data used to calculate the water footprint per unit of animal products, no specific formula is given in this paper. Detailed formulas can be found in the relevant literature [55].

2.3.3. Tapio Decoupling Model

The Tapio model, a statistical method, adopts the elastic analysis method to reflect the decoupling relationship between variables. It is not affected by statistical dimensions, and it effectively overcomes the dilemma of the OECD model in the selection of the base period. The expression for this [37] is as follows:

$$D = \frac{\Delta W / W}{\Delta G / G} = \frac{(W_t - W_{t-1}) / W_{t-1}}{(G_t - G_{t-1}) / G_{t-1}} \quad (5)$$

where D represents the decoupling index; ΔW indicates the rate of change in the agricultural water use (10^8 m^3); W_t and W_{t-1} represent the AWF in the area in year t and year $t-1$ (10^8 m^3), respectively; ΔG represents the rate of change in the agricultural GDP (CNY 10^8); and G_t and G_{t-1} represent the agricultural GDP in the region in year t and year $t-1$ (CNY 10^8), respectively. The Tapio decoupling index systems are shown in Table 3 [56].

Table 3. Tapio decoupling index systems.

Decoupling Type	ΔG	ΔW	D	Decoupling State
Decoupling	>0	<0	≤0	Strong decoupling
	>0	>0	(0, 0.8)	Weak decoupling
	<0	<0	≥1.2	Recessive decoupling
Negative decoupling	<0	>0	≤0	Strong negative decoupling
	<0	<0	(0, 0.8)	Weak negative decoupling
	>0	>0	≥1.2	Expansive negative decoupling
Coupling	>0	>0	(0.8, 1.2)	Expansive coupling
	<0	<0	(0.8, 1.2)	Recessive coupling

2.3.4. ARIMA Model

The ARIMA model is a time series forecasting statistical model that is widely used in economic, financial [57], and meteorological [58] fields. Furthermore, it can convert a non-stationary time series into a stationary time series for forecasting after differential processing. The ARIMA model can be expressed as ARIMA (p, d, q), where p represents the order of the autoregressive model, d represents the order of differentiation for the signal, and q represents the order of the moving average model. In this paper, SPSS 27 software was used to run the ARIMA model, which was based on the AWF data for Hangzhou from 2010 to 2021; this was then used to predict the AWF from 2022 to 2026. The specific steps were as follows: (1) the original time series was tested for smoothness, and if it was a non-smooth series, it was transformed into a smooth series by differentiation. By observing the autocorrelation function (ACF) coefficient plot and partial autocorrelation function (PACF) coefficient plot for the smoothness test, if the ACF coefficients and PACF coefficients were distributed within their respective confidence intervals and there was a trailing phenomenon, then the series was deemed smooth. The number of times that a different transformation of a non-stationary series into a stationary series occurred was referred to as the order of differentiation, denoted as d. (2) The parameters p and q were determined by the ACF, PACF coefficient plots, and the Bayesian information criterion. (3) The predictions were fitted using the determined parameters of p, d, and q. The model was then tested for residuals. (4) The above-determined most suitable model was used to predict the original time series, and the predicted data were counted.

2.3.5. GM (1, 1)

The GM (1, 1) is an evaluation model that combines qualitative and quantitative analysis; it uses fewer data and moderate calculations, it can solve the problem that evaluation indexes are difficult to quantify accurately, it can exclude the influence of human factors, and it can make the evaluation results more objective. For this paper, we constructed a GM (1, 1) model to forecast and analyze the agricultural economy in Hangzhou from 2022 to 2026, based on the agricultural economy data from 2010 to 2021. The specific steps [42] were as follows:

(1) Assuming that the original time series was $X^{(0)}$:

$$X^{(0)} = \left[X^{(0)}(1), X^{(0)}(2), \ldots X^{(0)}(n)\right] \tag{6}$$

The feasibility of the GM (1, 1) model was then determined by a cascade test:

$$\delta(k) = \frac{X^{(0)}(k-1)}{X^{(0)}(k)} \;\; (k = 2, 3, \ldots, n) \tag{7}$$

If the level ratio $\delta(k)$ was in the interval $(e^{-\frac{2}{n+1}}, e^{\frac{2}{n+1}})$, then the GM (1, 1) model was feasible. The new sequence $X^{(1)}$ was then formed by accumulating $X^{(0)}$:

$$X^{(1)} = \left[X^{(1)}(1), X^{(1)}(2), \ldots X^{(1)}(n)\right] \tag{8}$$

(2) Generators where the randomness was weakened were generated using discrete random numbers to develop a differential equation model.

Assuming that $Z^{(1)}$ is the sequence of means of $X^{(1)}$:

$$\begin{gathered} Z^{(1)} = \left[Z^{(1)}(2), Z^{(1)}(3), \ldots Z^{(1)}(n)\right] \\ Z^{(1)}(n) = 0.5\left[X^{(1)}(n) + X^{(1)}(n-1)\right] \end{gathered} \tag{9}$$

Then, we established the first-order differential whitening equation:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = u \tag{10}$$

where a denotes the development coefficient, u denotes the amount of gray activity, and t denotes time.

(3) Using the least squares method to solve the equation for the parameters a, u: $\hat{a} = (B^T B)^{-1} BY$.

$$\hat{a} = \begin{bmatrix} a \\ u \end{bmatrix} \qquad B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ \vdots & \vdots \\ -Z^{(1)}(n) & 1 \end{bmatrix} \qquad Y = \begin{bmatrix} X^{(0)}(2) \\ \vdots \\ X^{(0)}(n) \end{bmatrix} \tag{11}$$

(4) By substituting the parameters a, u into the first-order differential whitening equation, the whitening response equation of the GM (1, 1) prediction model was obtained as follows:

$$\hat{X}^{(1)}(k+1) = \left(X^{(0)}(1) - \frac{\hat{u}}{\hat{a}}\right) e^{-\hat{a}k} + \frac{\hat{u}}{\hat{a}} \;\; (k = 1,\ 2 \cdots, \mathrm{n}-1) \tag{12}$$

(5) The predicted value was obtained by calculating $X^{(1)}$ according to the above formula. The predicted data were counted, and residual tests were performed on the fitted data, as follows:

$$\varepsilon(k) = \frac{X^{(0)}(k) - \hat{X}^{(0)}(k)}{X^{(0)}(k)} \;\; (k = 1, 2, \ldots, n) \tag{13}$$

where $\hat{X}^{(0)}(1) = X^{(0)}(1)$, and the fit is satisfactory if the residual $\varepsilon(k) < 0.2$.

3. Results

3.1. Measurement of the AWF in Hangzhou

The AWF in Hangzhou significantly decreased from 2010 to 2021 (Figure 2), dropping from 58.88×10^8 m^3 in 2010 to 37.80×10^8 m^3 in 2021. The AWF experienced a slight upward trend from 2010 to 2013, which was contributed to jointly by crops and animal products. The significant reduction in grain, pork, and egg production from 2013 to 2014 resulted in a sharp decline in the AWF. From 2014 to 2020, the AWF continued to decrease, with the trend being dominated by the water footprint of animal products. Although there were occasional decreases in the crop water footprint during this period, it remained at a relatively low level. Overall, the decreasing trend of the AWF in Hangzhou was mainly dominated by grain, pork, and eggs. Among them, the water footprint of eggs decreased most strongly (6.23×10^8 m^3), followed by that of grain and pork—which decreased by 5.20×10^8 m^3 and 5.62×10^8 m^3, respectively—while the water footprint of other products such as fruits and vegetables remained at a stable level.

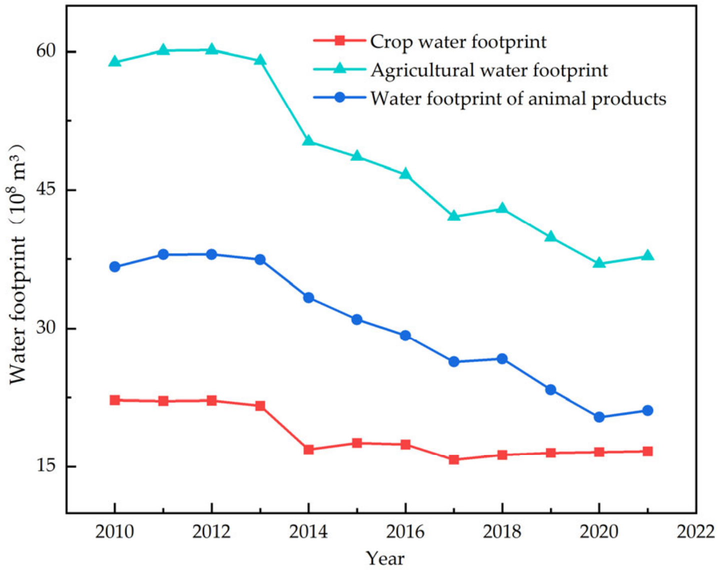

Figure 2. The AWF in Hangzhou from 2010 to 2021.

From the perspective of the crop water footprint (Figure 3), the temporal change trend of the crop water footprint was divided into four stages: "slightly declining–rapidly declining–rising and then falling–continuous increase". From 2010 to 2012, the water footprint of crops decreased slightly (from 22.24×10^8 m^3 to 22.18×10^8 m^3), and this was mainly related to the decrease in the water footprint of grain, sugar, and other crops. The crop water footprint decreased from 22.28×10^8 m^3 to 16.89×10^8 m^3 from 2012 to 2014, and this change was mainly dominated by the reduction in the water footprint of grain (which decreased from 10.66×10^8 m^3 to 6.88×10^8 m^3). This was closely related to the implementation of the strictest water resource management system, which was instituted in 2013, as well as due to the extensive drought conditions that occurred during the period. From 2014 to 2017, the crop water footprint showed a "convex" pattern of change, i.e., an initial increase followed by a decrease. The main reason for this trend was agricultural technology transformation and policy adjustments in 2015, which suppressed the growth of the water footprint. From 2017 to 2021, the crop water footprint showed a slight upward trend, and this was mainly attributed to the rapid population growth in Hangzhou, which led to an increasing demand for crops. However, during this period, the government implemented water price reform initiatives to drive the agricultural structure adjustment process. As a result, while the economy continued to grow, the growth of the water footprint slowed down and gradually stabilized during this stage.

There was a significant downward trend in the water footprint of animal products, wherein it decreased from 36.64×10^8 m^3 in 2010 to 21.13×10^8 m^3 in 2021 (Figure 4). This phenomenon was highly correlated with the decline in the water footprints of eggs and pork with their large-scale production and high water footprint content per unit. The livestock industry was supported from 2010 to 2013 and its production was increasing, thus leading to a rising water footprint for livestock products during this period. In addition, from 2013 to 2014, the water footprints of various types of products showed a decreasing trend due to the implementation of the most stringent water resource management system at the time. Since 2013, relevant policies have been introduced multiple times to vigorously develop high-quality animal husbandry. From the perspective of the water footprint and its changes regarding various types of animal husbandry, these policies have achieved positive results. From 2020 to 2021, the water footprint of animal products showed a noticeable upward trend. The production of animal products was suspended due to the COVID-19 pandemic in 2020. With the economy resuming in 2021, the water footprints of pork, eggs, and other products continued to increase on account of the increasing demand.

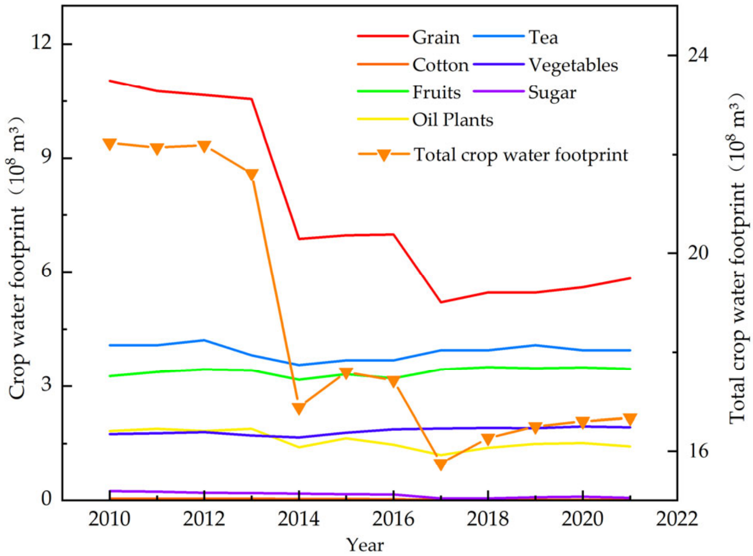

Figure 3. The water footprint of crops in Hangzhou from 2010 to 2021.

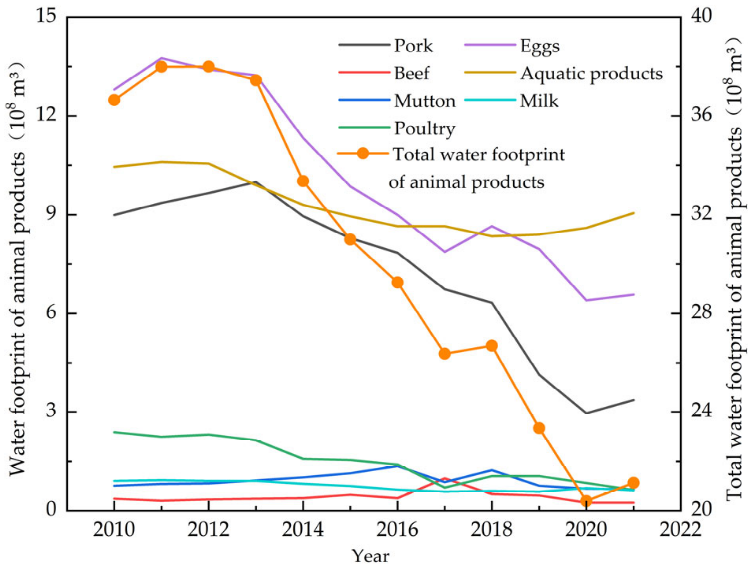

Figure 4. The water footprints of animal products in Hangzhou from 2010 to 2021.

The percentage of the AWF from 2010 to 2021 is shown in Figure 5. It can be seen that aquatic products shared the highest proportion (17–24%) among all types of agricultural products; in addition, their proportion has undergone the greatest changes. However, their water footprint remained relatively stable, and this has mainly been attributed to the changes in the production of agricultural products (such as grain, pork, and eggs) with their high production and high water footprint content. The water footprints of grain, eggs, aquatic products, and pork remained between 12% and 24%, and the water footprint of tea and fruits was below 15%, thus indicating that the water use for grain, eggs, aquatic products, and pork products should be sufficiently reduced with agricultural water resources management. In terms of temporal changes, the total proportion of the water footprint of grain, eggs, aquatic products, and pork decreased from 74% in 2010 to 65% in 2021, i.e., the center of gravity of the AWF shifted from grain, pork, and eggs to fruits, tea, and other products, thereby indicating the positive effects of agricultural water management in Hangzhou.

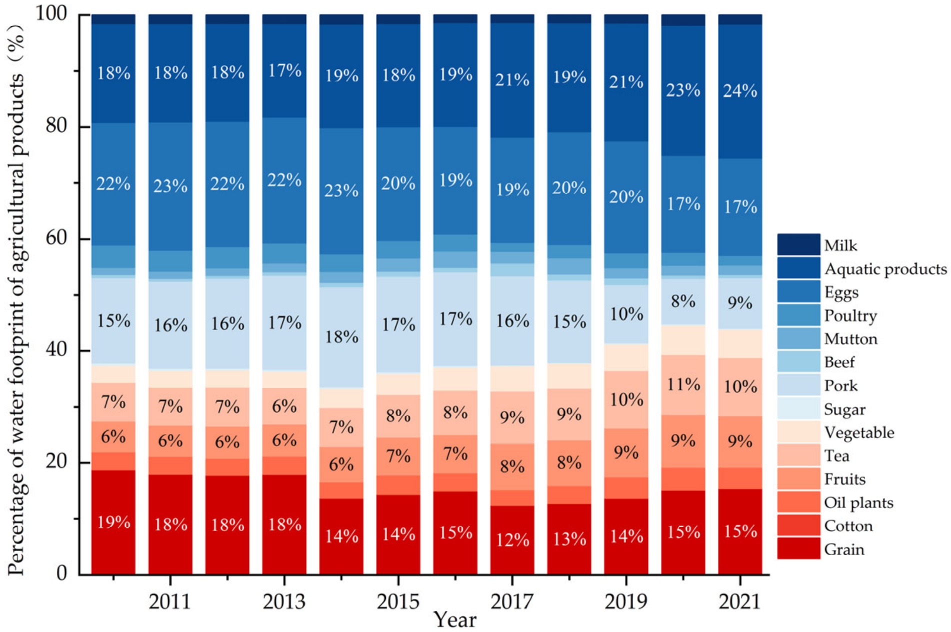

Figure 5. Percentage of the AWF in Hangzhou from 2010 to 2021.

3.2. The Decoupling Relationship between the AWF and AEG

Based on the water footprint accounting results and the agricultural economy data from Hangzhou for 2011–2021, the growth rate of the AWF (ΔW) and the AEG rate (ΔG), as well as the decoupling index (D) between them, were calculated (Table 4). As can be seen from Table 4, the decoupling between the AWF and AEG in Hangzhou was strong from 2013 to 2017, as well as from 2019 to 2020. It was weakly decoupled in 2011–2012 and strongly negatively decoupled in 2018, with expansive coupling in 2021. During the research period, strong decoupling accounted for 63.64% of the decoupling between the AWF and AEG in Hangzhou.

Table 4. The decoupling relationship between the AWF and AEG in Hangzhou from 2011 to 2021.

Year	ΔG	ΔW	D	Decoupling State
2011	28.36	1.25	0.16	Weak decoupling
2012	18.34	0.05	0.01	Weak decoupling
2013	10.31	−1.13	−0.46	Strong decoupling
2014	8.93	−8.82	−4.44	Strong decoupling
2015	13.60	−1.65	−0.66	Strong decoupling
2016	16.26	−1.91	−0.70	Strong decoupling
2017	6.87	−4.56	−4.32	Strong decoupling
2018	−5.57	0.83	−1.11	Strong negative decoupling
2019	20.19	−3.12	−1.10	Strong decoupling
2020	0.52	−2.85	−44.79	Strong decoupling
2021	7.27	0.81	0.98	Expansive coupling

In terms of the decoupling status, the decoupling between the AWF and AEG can be mainly divided into two stages: “the decoupling stage from 2011 to 2017 and the non-stationary decoupling stage from 2018 to 2021". During the decoupling phase, the relationship between the AWF and AEG transitioned from a weak decoupling state to a strong decoupling state (from 2012 to 2013). This shift was mainly attributed to a series of favorable agricultural policies that improved agricultural production. During the non-stationary decoupling stage, the decoupling state went through a process of "deterioration–improvement–deterioration". During 2017–2018, the decoupling status deteriorated from a strong decoupling to a strong negative decoupling. This was primarily caused by the increase in demand for the production of water-intensive agricultural products, which, thus, led to an increase in agricultural water use.

Specifically, in 2018, the outbreak of African swine fever resulted in a decrease in pork production. As a result, other animal products with a higher water footprint content per unit, such as mutton, contributed to an increase in the AWF. The shift from a strong negative decoupling state to a strong decoupling state in 2018–2020 was due to the government's pro-agricultural policies, which have solidified AEG. From 2019 to 2021, the decoupling status deteriorated from strong decoupling to growing coupling. In 2019, Hangzhou was not yet affected by the pandemic, and there was a strong decoupling between the AWF and AEG. In the early months of 2020, the pandemic led to a slow increase in residents' demand for agricultural products. In the mid-term of 2020, the pandemic caused a significant increase in resident demand for agricultural products [59–61]. Despite the impact of the pandemic for over six months, it only changed the decoupling index and did not completely alter the decoupling status. The AWF and the AEG still exhibited a strong decoupling status. In 2021, the impact of the pandemic still continued, resulting in a change in the decoupling status. There was a sharp increase in agricultural products, thereby leading to a simultaneous rise in the AWF and the agricultural economy. They also exhibited a connected growth status.

3.3. Decoupling State Prediction of the AWF and AEG

3.3.1. Model Test

The AWF from 2010 to 2021 showed a downward trend and was a non-stationary series; as such, it should be converted into a stationary series by a first-order differentiation process. The ACF and PACF coefficients after first-order differentiation were within the confidence interval and showed signs of trailing (Figure 6), thus indicating that an ARIMA (0, 1, 0) model could be built. In addition, a residual series test was used to calculate the ACF and PACF of the model residuals. It can be seen that the autocorrelation coefficient and partial autocorrelation coefficient of the residual series were within the confidence interval; moreover, the *p*-value of the Q-statistic information of the model was greater than 0.1, thus indicating that the residual series was a white noise series. There were similar trends between the predicted curve of the AWF and the actual curve (shown in Figure 7, R^2 = 0.89), and the residuals were all within the confidence interval. Therefore, the results were reliable enough that the ARIMA (0, 1, 0) model could be used to predict the AWF in Hangzhou.

The GM (1, 1) model test is shown in Table 5, and the results indicate that the residuals of the 2010–2021 time series, $\varepsilon(k) < 0.2$, and the model accuracy level were qualified.

3.3.2. Prediction of the Decoupling Relationship between the AWF and AEG

Considering the AWF and agricultural GDP data in Hangzhou from 2010 to 2021 as the original time series, the ARIMA (0, 1, 0) model and the GM (1, 1) model were used to predict the AWF and agricultural GDP in Hangzhou from 2022 to 2026, respectively. Under the current conditions of high-intensity control of agricultural water use and a reasonable agricultural structure, the AWF in Hangzhou will most likely drop to 35.88×10^8 m^3 in 2022 (Figure 8) and it will continue to drop at a high rate in the next four years. The upper and lower limits of the predicted AWF indicate that if there is a relaxation of control on agricultural water use in the future, the water footprint will continue to rise significantly.

In a future state with intensive water resource management, the above forecast results are conducive to supporting agricultural water resource allocation.

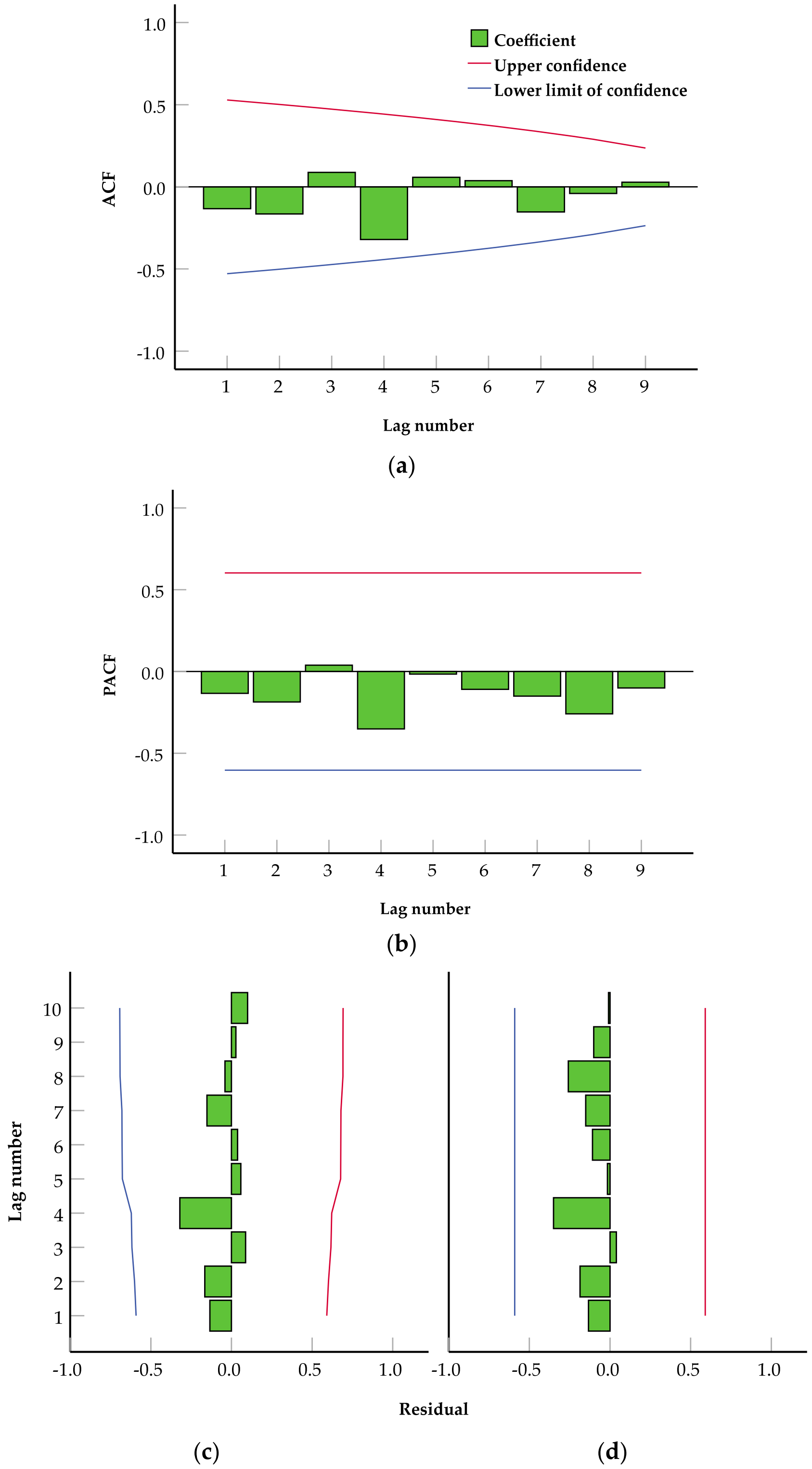

Figure 6. (**a**) Autocorrelation function chart. (**b**) Partial autocorrelation function chart. (**c**) Autocorrelation coefficients of the residual model. (**d**) Partial autocorrelation coefficients of the residual model.

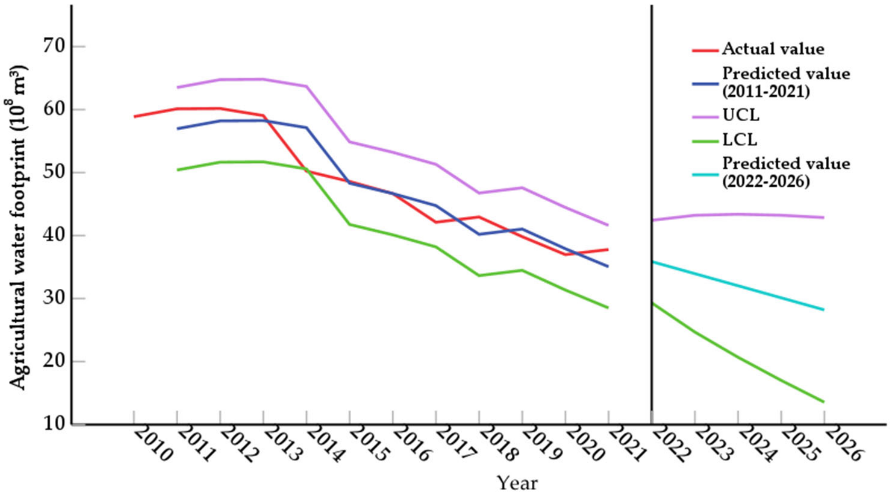

Figure 7. Forecasting of the AWF in Hangzhou from 2010 to 2026. UCL represents the upper control limit and LCL represents the lower control limit.

Table 5. The GM (1, 1) model test.

Year	Residuals	Relative Error	Stage Ratio
2010	0.000	0.00	—
2011	0.053	5.27	0.880
2012	0.008	0.83	0.928
2013	0.001	0.02	0.961
2014	0.001	0.13	0.967
2015	0.018	1.80	0.953
2016	0.041	4.07	0.947
2017	0.032	3.18	0.978
2018	0.017	1.75	1.018
2019	0.015	1.50	0.938
2020	0.015	1.49	0.998
2021	0.025	2.46	0.978

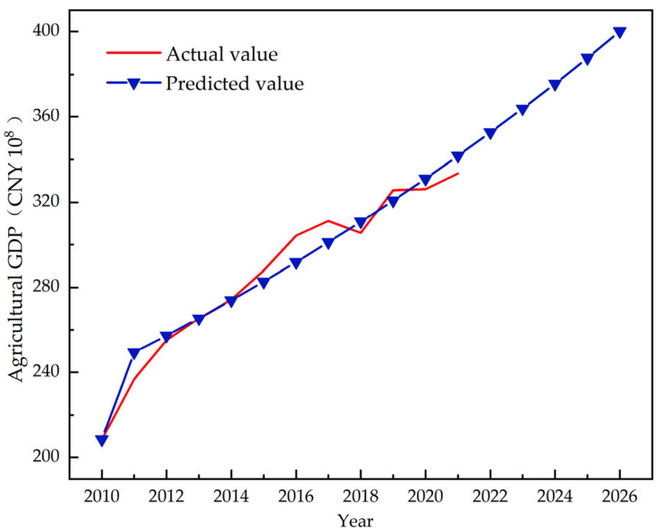

Figure 8. Agriculture economy forecast for Hangzhou from 2022 to 2026.

The trend of the predicted curve from 2010 to 2021 was consistent with the actual curve (shown in Figure 8). The agricultural economy in Hangzhou from 2022 to 2026 will grow from CNY 35.27 billion in 2022 to CNY 40.01 billion in 2026, without the influence of external factors. This growth will probably be related to the improvement of agricultural production technology, the increase in demand for agricultural products, the increase in the agricultural economy, and the implementation of beneficial agriculture policies. With an increasing population in Hangzhou in the future, the demand for agricultural products will continue to grow, which will bring about the sustained growth of the agricultural economy. The agricultural GDP in Hangzhou in 2022 was CNY 34.60 billion, which is close to the predicted value, thus demonstrating that the prediction was reliable.

The decoupling forecast of the AWF and AEG in Hangzhou from 2022 to 2026 is shown in Table 6. The results showed that there would be a strong decoupling between the AWF and AEG in Hangzhou from 2022 to 2026. This means that Hangzhou will achieve the coordinated development of agricultural water use and the agricultural economy in the future, thus providing for the long-term sustainability of Hangzhou's agricultural practices.

Table 6. Prediction of the decoupling state between the AWF and AEG in Hangzhou from 2022 to 2026.

Year	ΔG	ΔW	D	Decoupling State
2022	19.16	−1.92	−0.88	Strong decoupling
2023	11.30	−1.92	−1.67	Strong decoupling
2024	11.67	−1.91	−1.75	Strong decoupling
2025	12.04	−1.92	−1.87	Strong decoupling
2026	12.42	−1.92	−1.99	Strong decoupling

3.4. Mechanisms of the Decoupling Relationship between the AWF and AEG

Based on the above analyses, we proposed the potential mechanism determining the decoupling relationship between the AWF and AEG (Figure 9), thus providing a decision-making basis for the integrated management of agricultural water resources and sustainable agricultural development. The factors that impact the decoupling relationship between the AWF and AEG consist of agricultural structure, technological advancements, and public emergencies. In terms of agricultural structure, through policy guidance, increasing the yields of agricultural products with a lower water footprint per unit can reduce the AWF while increasing the agricultural economy. In terms of technological effects, by enhancing the level of agricultural mechanization and promoting agricultural production efficiency, agricultural product yields can be increased, thereby improving the agricultural economy. Outbreaks such as epidemics can lead to an increased demand for certain agricultural products with high water consumption, a dampening decline in the AWF, and increases in the agricultural economy. Policies can further influence the AWF and the agricultural economy by changing the agricultural structure and technological effects. This means that policies can guide the agricultural sector to enhance mechanization levels and adjust local agricultural structure, thus maintaining a decoupling relationship between AWF and AEG. Moreover, certain policies could also mitigate the impact of unforeseen events on the decoupling relationship between them, which can be achieved by properly adjusting the agricultural structure to reduce the AWF. It is worth noting that government policies influence the decoupling relationship between the AWF and AEG through the synergistic effects of multiple factors.

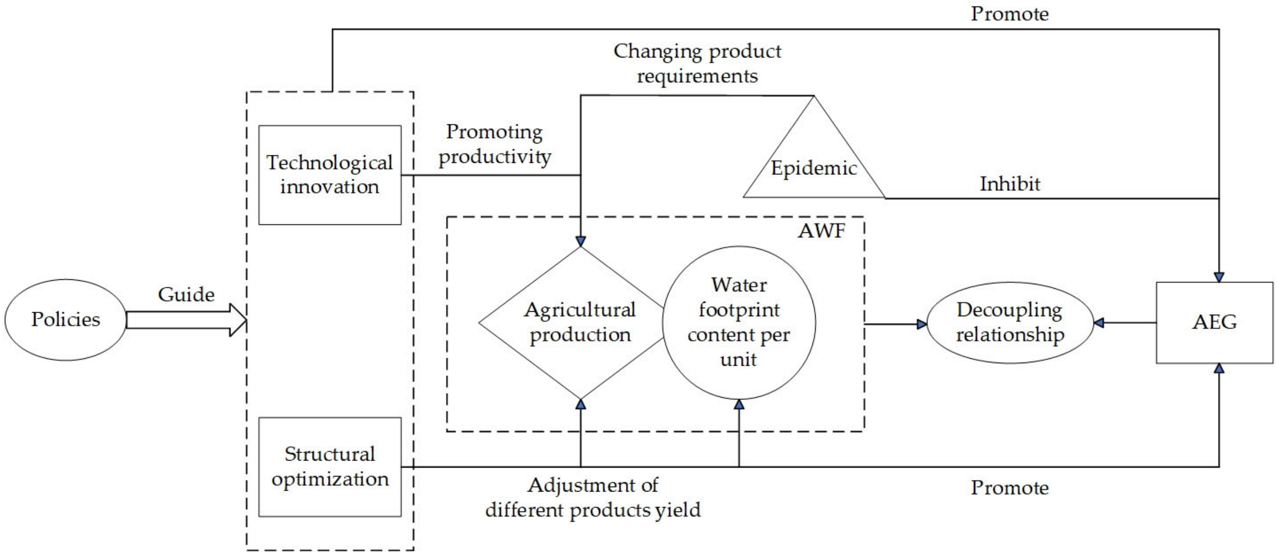

Figure 9. The mechanisms of the decoupling relationship between the AWF and AEG.

4. Discussion

4.1. Comparison of the Water Footprint Results and Analyses of the Limitations

The AWF in Hangzhou from 2010 to 2021 showed a decreasing trend, which was consistent with the results of Zheng et al. [53]. Both studies adopted the same calculation methods and shared the same data sources regarding agricultural products. However, there was a narrow difference in the total amount of water footprint determined (Table 7). The main cause for the disparity can be attributed to the differences in the water footprint content per unit that was selected when calculating the water footprint. The water footprint content per unit, as adopted by Zhang et al., came from the results published by Mekonnen et al. [62,63], who measured the mean global water footprints of agricultural products. The values for water footprint content per unit in the current study were taken from the results published by Zhao et al. [46], Zhang et al. [47], Liu et al. [48], Li et al. [49], and Sun et al. [50], who all measured the water footprint content of agricultural products in the cities near Hangzhou, Zhejiang Province, and Hangzhou itself. The water footprint content per unit depends largely on regional environmental background conditions, such as evapotranspiration, climate, and soil. As these conditions vary across different regions, the water footprint content per unit for crops also differs [64]. In this paper, the values of water footprint content per unit of the cities near Hangzhou, Zhejiang Province, and Hangzhou itself were selected to provide a more accurate estimation of AWF consumption in Hangzhou. As a result, the AWF calculated in this paper provided a closer approximation to the actual utilization of agricultural water within Hangzhou. Furthermore, the difference in crop categorization also plays a role in the discrepancies seen in the calculation results of the water footprint. For instance, Zheng et al. [53] implemented a more detailed subdivision of grain crops, while this study calculated the water footprint of grain crops as a whole.

Table 7. Comparison of the agricultural water footprint in Hangzhou from 2010 to 2016 (unit 10^8 m^3).

Years	2010	2011	2012	2013	2014	2015	2016
This study	58.88	60.12	60.18	59.06	50.25	48.60	46.70
Zheng et al. [53]	58.08	58.91	59.21	52.86	48.99	48.45	47.12

The results of the water footprint calculations in this study also have certain limitations. Due to the difficulty in obtaining the values of the local water footprint content per unit, the water footprint content per unit of a few indicators was selected from cities near Hangzhou instead. Despite their sharing a similar climatic background and exhibiting only a relatively small variation from the actual water footprint content per unit in Hangzhou, this still has a certain impact on the results of the water footprint. Moreover, this study did not calculate the water footprint for all agricultural products in Hangzhou. While this method is often employed in AWF assessments and produces quantitative results that are close to the actual AWF, it still leads to an underestimation of the AWF. Furthermore, blue water footprints and green water footprints were not distinguished in the AWF analysis in this study, which might result in a lack of clarity regarding which water footprint played a predominant role in the decoupling relationship between the AWF and AEG. Hence, the assumptions made in this study will have introduced errors in terms of the selection of the water footprint content per unit, the subdivision of grain crops, and the adoption of agricultural products, which can lead to a deviation between the calculated AWF and the actual agricultural water consumption.

4.2. The Impact of Government Policies on the Decoupling Relationship between the AWF and AEG

The decoupling relationship between the AWF and AEG is closely related to government policies. A series of policies were implemented by the Hangzhou Municipal Government from 2011 to 2021, as shown in Figure 10. In 2011, significant initiatives were undertaken to promote the high-quality and sustainable development of animal husbandry. The structure of the livestock industry was adjusted by boosting the production of agricultural products such as pork, eggs, and dairy, which have a relatively lower water footprint per unit. Consequently, although the agricultural economy continued to expand, there was only a marginal increase in the AWF. In 2012, an increase in the production of products with lower water footprint content per unit, such as fruits, vegetables, and grain, helped mitigate the increase in the water footprint. Additionally, an improvement in agricultural technology promoted the AEG. In 2013, strict water management systems drove down the yields of crops with a high water footprint content per unit, thereby reducing the AWF. In 2014, dedicated efforts were undertaken to bolster the production area and yield of drought-resistant crops, thereby resulting in an enhanced agricultural structure and a subsequent decrease in the AWF. In 2016, significant attention was devoted to the advancement of agricultural technology to amplify agricultural production efficiency. This endeavor encouraged higher yields of grain and vegetables. Nonetheless, a decline in egg production dominated the contributions to the reduction in the AWF. In 2018, the outbreak of African swine fever and other factors triggered a substantial drop in pork production, thus leading to an agricultural economic downturn. Conversely, the production of high water-consumption products such as mutton experienced an increase, thereby resulting in a rise in the AWF. However, the implementation of policies aimed at enhancing technological advancements and promoting drought-resistant grain production in the year 2018 helped to partially inhibit the increase in the water footprint.

In addition, similar conclusions regarding the impact of government policies on the water footprint and the economy can also be drawn from research conducted in Europe [43] and the United States [65]. For example, farmers tend to cultivate irrigated cereals that offer high economic returns. Furthermore, they are encouraged to cultivate crops using rainfed systems by the implementation of policy subsidies, thus achieving a reduction in the AWF and an increase in the agricultural economy at the same time. Therefore, the impact mechanism of government policies on the AWF and the agricultural economy is also applicable in other countries or regions.

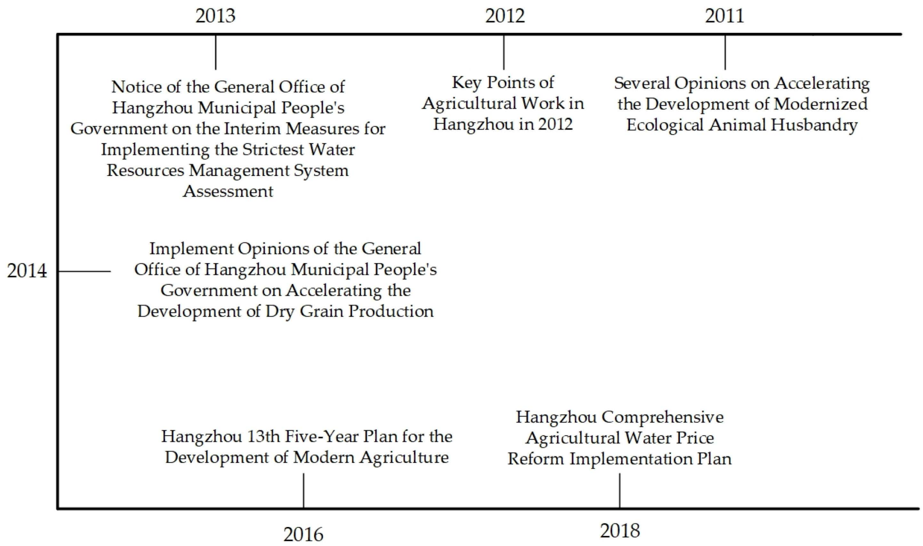

Figure 10. Agricultural policies issued by the government from 2011 to 2021.

4.3. Research Insights and Policy Recommendations

In terms of changes in the AWF and the agricultural economy, changes in the structure of agricultural products (Figure 5) reduced the water footprint of agriculture while promoting the AEG in Hangzhou. According to the water footprint proportion of agricultural products, we believe that a reduction in the water footprint proportion of aquatic products will further reduce the agricultural water footprint in Hangzhou. In different regions, it is necessary to develop a planting structure pattern that is compatible with local agricultural water resources, as well as reduce the area planted with high water-consumption crops and increase the areas planted with low water-consumption crops, in accordance with the objectives of local water conservation and economic development. At the same time, by drawing on successful policies implemented in Europe and the United States in terms of regulating agricultural structures by subsidizing farmers, there could be the creation of further incentives for farmers to reduce water use in agricultural practices. Although this article does not address the impact of water-saving technologies on changes in the agricultural water footprint, the reduction in the agricultural water footprint through the active development of water-saving agricultural technologies cannot be ignored. In epidemics and other emergencies (e.g., swine fever), the government may consider products with a low water footprint (e.g., poultry) as substitute products through which they can minimize the production of products with a high water footprint.

5. Conclusions

In this paper, we analyzed the decoupling relationship between the AWF and AEG from 2011 to 2021, based on an estimation of the AWF from 2010 to 2022, as well as predicting the decoupling state of the AWF and AEG from 2022 to 2026. The main conclusions are as follows:

(1) The water footprint of agriculture in Hangzhou decreased from 60.14×10^8 m^3 in 2010 to 38.42×10^8 m^3 in 2021, and this decreasing trend was dominated by the water footprint of animal products. The temporal trend of the crop water footprint was divided into four stages: "small decline–rapid decline–rising and then falling–continuous rise", while the water footprint of animal products mainly showed the trend of a rise and then a fall, which was highly correlated with the change in the egg production water footprint. The main factor driving this reduction in the AWF was the change in agricultural structure.

(2) From 2011 to 2021, there was a strong decoupling between the AWF and AEG in Hangzhou. Overall, there were seven strong decouplings, two weak decouplings, one expansive coupling, and one strong negative decoupling. The decoupling state

between the AWF and AEG was mainly divided into two stages: "the decoupling stage and the non-smooth decoupling stage". The main factor promoting the decoupling between the AWF and AEG was determined by the agricultural structure adjustment, while the main factors inhibiting the decoupling were external factors such as COVID-19.

(3) There will be a continuing strong decoupling between the AWF and AEG in Hangzhou in the future.

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References

1. Lu, N.; Zhu, J.; Tang, Z.; Zhang, J.; Chi, H. Decreasing water dependency for economic growth in water-scarce regions by focusing on water footprint and physical water: A case study of Xi'an, China. *Sustain. Cities Soc.* **2022**, *85*, 104092. [CrossRef]
2. Zhao, D.; Tang, Y.; Liu, J.; Tillotson, M.R. Water footprint of Jing-Jin-Ji urban agglomeration in China. *J. Clean. Prod.* **2017**, *167*, 919–928. [CrossRef]
3. Sun, S.; Zhou, X.; Liu, H.; Jiang, Y.; Zhou, H.; Zhang, C.; Fu, G. Unraveling the effect of inter-basin water transfer on reducing water scarcity and its inequality in China. *Water Res.* **2021**, *194*, 116931. [CrossRef]
4. Xue-bing, W.; Fang, G.; Yun, Y. Regional Differences and Convergence of Green Efficiency of Agricultural Water Use in China. *China Rural Water Hydropower* **2023**, *6*, 196–201+208. (In Chinese)
5. Niu, G.; Zheng, Y.; Han, F.; Qin, H. The nexus of water, ecosystems and agriculture in arid areas: A multiobjective optimization study on system efficiencies. *Agric. Water Manag.* **2019**, *223*, 105697. [CrossRef]
6. Huang, X.; Xu, X.; Wang, Q.; Zhang, L.; Gao, X.; Chen, L. Assessment of Agricultural Carbon Emissions and Their Spatiotemporal Changes in China, 1997–2016. *Int. J. Environ. Res. Public Health* **2019**, *16*, 3105. [CrossRef]
7. Cammarano, D.; Jamshidi, S.; Hoogenboom, G.; Ruane, A.C.; Niyogi, D.; Ronga, D. Processing tomato production is expected to decrease by 2050 due to the projected increase in temperature. *Nat. Food* **2022**, *3*, 437–444. [CrossRef]
8. Abbaszadeh, M.; Bazrafshan, O.; Mahdavi, R.; Sardooi, E.R.; Jamshidi, S. Modeling Future Hydrological Characteristics Based on Land Use/Land Cover and Climate Changes Using the SWAT Model. *Water Resour. Manag.* **2023**, *37*, 4177–4194. [CrossRef]
9. Jamshidi, S.; Zand-parsa, S.; Pakparvar, M.; Niyogi, D. Evaluation of Evapotranspiration over a Semiarid Region Using Multiresolution Data Sources. *J. Hydrometeorol.* **2019**, *20*, 947–964. [CrossRef]
10. Feng, B.; Zhuo, L.; Xie, D.; Mao, Y.; Gao, J.; Xie, P.; Wu, P. A quantitative review of water footprint accounting and simulation for crop production based on publications during 2002–2018. *Ecol. Indic.* **2021**, *120*, 106962. [CrossRef]
11. Robertson, G.P. A Sustainable Agriculture? *Daedalus* **2015**, *144*, 76–89. [CrossRef]
12. van Leeuwen, C.C.E.; Cammeraat, E.L.H.; de Vente, J.; Boix-Fayos, C. The evolution of soil conservation policies targeting land abandonment and soil erosion in Spain: A review. *Land Use Policy* **2019**, *83*, 174–186. [CrossRef]
13. Jamshidi, S.; Zand-Parsa, S.; Niyogi, D. Assessing Crop Water Stress Index of Citrus Using In-Situ Measurements, Landsat, and Sentinel-2 Data. *Int. J. Remote Sens.* **2020**, *42*, 1893–1916. [CrossRef]
14. Zhang, L.; Dong, H.; Geng, Y.; Francisco, M.J. China's provincial grey water footprint characteristic and driving forces. *Sci. Total Environ.* **2019**, *677*, 427–435. [CrossRef]

15. Fathian, M.; Bazrafshan, O.; Jamshidi, S.; Jafari, L. Impacts of climate change on water footprint components of rainfed and irrigated wheat in a semi-arid environment. *Environ. Monit. Assess.* **2023**, *195*, 324. [CrossRef]
16. Hoekstra, A.; Hung, P.Q. Virtual water trade: A quantification of virtual water flows between nations in relation to international crop trade. *Water Sci. Technol.* **2002**, *49*, 203–209.
17. Hoekstra, A.Y.; Chapagain, A.K. Water footprints of nations: Water use by people as a function of their consumption pattern. *Water Resour. Manag.* **2007**, *21*, 35–48. [CrossRef]
18. Kampman, D.A.; Hoekstra, A.Y.; Krol, M.S. The water footprint of India. *Value Water Res. Rep. Ser.* **2008**, *32*, 1–152.
19. Gerbens-Leenes, P.; Hoekstra, A. *Business Water Footprint Accounting*; UNESCO-IHE Institute for Water Education: Delft, The Netherland, 2008.
20. Yin, J.; Wang, H.X.; Cai, Y. Water Footprint Calculation on the Basis of Input-Output Analysis and a Biproportional Algorithm: A Case Study for the Yellow River Basin, China. *Water* **2016**, *8*, 363. [CrossRef]
21. Manzardo, A.; Loss, A.; Fialkiewicz, W.; Rauch, W.; Scipioni, A. Methodological proposal to assess the water footprint accounting of direct water use at an urban level: A case study of the Municipality of Vicenza. *Ecol. Indic.* **2016**, *69*, 165–175. [CrossRef]
22. Cazcarro, I.; Hoekstra, A.Y.; Sánchez Chóliz, J. The water footprint of tourism in Spain. *Tour. Manag.* **2014**, *40*, 90–101. [CrossRef]
23. Mekonnen, M.M.; Hoekstra, A.Y. A Global Assessment of the Water Footprint of Farm Animal Products. *Ecosystems* **2012**, *15*, 401–415. [CrossRef]
24. Xu, M.; Li, C.H.; Wang, X.; Cai, Y.P.; Yue, W.C. Optimal water utilization and allocation in industrial sectors based on water footprint accounting in Dalian City, China. *J. Clean. Prod.* **2018**, *176*, 1283–1291. [CrossRef]
25. Mekonnen, M.M.; Gerbens-Leenes, W. The Water Footprint of Global Food Production. *Water* **2020**, *12*, 2696. [CrossRef]
26. Bazarfshan, O.; Yahyazadeh, M.; Jamshidi, S.; Zamani, H. Spatial prioritization of tomato cultivation based on water footprint, land productivity, and economic indices. *Irrig. Drain.* **2022**, *71*, 1363–1378. [CrossRef]
27. Sullivan, C.A.; Meigh, J.R.; Giacomello, A.M. The Water Poverty Index: Development and application at the community scale. *Nat. Resour. Forum* **2003**, *27*, 189–199. [CrossRef]
28. Jing, M.; Jian, P. Research progress on water footprint. *Acta Ecol. Sin.* **2013**, *33*, 5458–5466. (In Chinese) [CrossRef]
29. Wang, H.; Huang, J.; Zhou, H.; Deng, C.; Fang, C. Analysis of sustainable utilization of water resources based on the improved water resources ecological footprint model: A case study of Hubei Province, China. *J. Environ. Manag.* **2020**, *262*, 110331. [CrossRef]
30. Shi, C.; Yuan, H.; Pang, Q.; Zhang, Y. Research on the Decoupling of Water Resources Utilization and Agricultural Economic Development in Gansu Province from the Perspective of Water Footprint. *Int. J. Environ. Res. Public Health* **2020**, *17*, 5758. [CrossRef]
31. Shen, R.; Yao, L. Exploring the Regional Coordination Relationship between Water Utilization and Urbanization Based on Decoupling Analysis: A Case Study of the Beijing-Tianjin-Hebei Region. *Int. J. Environ. Res Public Health* **2022**, *19*, 6793. [CrossRef]
32. Lipeng, H.; Lin, W.; Yao, Q.; Lina, T. Decoupling status and driving mechanisms of carbon emissions in the Golden Triangle of Southern Fujian uner "carbon peaking and neutrality" goals. *Acta Ecol. Sin.* **2022**, *42*, 9663–9676. (In Chinese)
33. Belaid, F.; Dagher, L.; Filis, G. Revisiting the resource curse in the MENA region. *Resour. Policy* **2021**, *73*, 102225. [CrossRef]
34. Dagher, L.; Fattouh, B.; Jamali, I. Oil price dynamics and energy transitions in the Middle East and North Africa: Economic implications and structural reforms. *Energy Policy* **2020**, *139*, 111329. [CrossRef]
35. Dagher, L.; Yacoubian, T. The causal relationship between energy consumption and economic growth in Lebanon. *Energy Policy* **2012**, *50*, 795–801. [CrossRef]
36. Dagher, L. Natural gas demand at the utility level: An application of dynamic elasticities. *Energy Econ.* **2012**, *34*, 961–969. [CrossRef]
37. Tapio, P. Towards a theory of decoupling: Degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001. *Transp. Policy* **2005**, *12*, 137–151. [CrossRef]
38. Zhang, Y.-J.; Da, Y.-B. The decomposition of energy-related carbon emission and its decoupling with economic growth in China. *Renew. Sustain. Energy Rev.* **2015**, *41*, 1255–1266. [CrossRef]
39. Kong, Y.; He, W.; Yuan, L.; Shen, J.; An, M.; Degefu, D.M.; Gao, X.; Zhang, Z.; Sun, F.; Wan, Z. Decoupling Analysis of Water Footprint and Economic Growth: A Case Study of Beijing-Tianjin-Hebei Region from 2004 to 2017. *Int. J. Environ. Res. Public Health* **2019**, *16*, 4873. [CrossRef]
40. Csereklyei, Z.; Stern, D.I. Global energy use: Decoupling or convergence? *Energy Econ.* **2015**, *51*, 633–641. [CrossRef]
41. Hao, J.; Gao, F.; Fang, X.; Nong, X.; Zhang, Y.; Hong, F. Multi-factor decomposition and multi-scenario prediction decoupling analysis of China's carbon emission under dual carbon goal. *Sci. Total Environ.* **2022**, *841*, 156788. [CrossRef]
42. Kong, F.; Cui, W.; Xi, H. Spatial–temporal variation, decoupling effects and prediction of marine fishery based on modified ecological footprint model: Case study of 11 coastal provinces in China. *Ecol. Indic.* **2021**, *132*, 108271. [CrossRef]
43. Aldaya, M.M.; Martínez-Santos, P.; Llamas, M.R. Incorporating the Water Footprint and Virtual Water into Policy: Reflections from the Mancha Occidental Region, Spain. *Water Resour. Manag.* **2009**, *24*, 941–958. [CrossRef]
44. Sun, S.; Wu, P.; Wang, Y.; Zhao, X.; Liu, J.; Zhang, X. The impacts of interannual climate variability and agricultural inputs on water footprint of crop production in an irrigation district of China. *Sci. Total Environ.* **2013**, *444*, 498–507. [CrossRef] [PubMed]
45. Davis, K.F.; Rulli, M.C.; Seveso, A.; D'Odorico, P. Increased food production and reduced water use through optimized crop distribution. *Nat. Geosci.* **2017**, *10*, 919–924. [CrossRef]

46. Chunfang, Z. Research on Water Resource Sustainable Utilization Based on Water Footprint Theory in Zhejiang Province. Master's Thesis, Ningbo University, Ningbo, China, 2017. (In Chinese).
47. Lei, Z. Study on the Regional Differences of the Efficiency of the Virtual Water and Water Footprint in China. Master's Thesis, Liaoning Normal University, Dalian, China, 2009. (In Chinese).
48. Can-hui, L.; Wen-long, J.; Ying-jie, S.; Kang-li, C. Evaluation of Water Resources Utilization in the Taihu Basin from the Perspective of Water Footprint. *China Rural Water Hydropower* **2022**, *8*, 70–77. (In Chinese)
49. Ning, L.; Jian-qing, Z.; Lei, W. Decoupling and water footprint analysis of the coordinated development between water utilization and the economy in urban agglomeration in the middle reaches of the Yangtze River. *China Popul. Resour. Environ.* **2017**, *27*, 202–208. (In Chinese)
50. Caizhi, S.; Yuyu, L.; Lixin, C.; Lei, Z. The spatial-temporal disparitise of water footprints intensity based on Gini coefficient and Theil index in China. *Acta Ecol. Sin.* **2010**, *30*, 1312–1321. (In Chinese)
51. Ji-xin, T.; Qing, L. Spatio-temporal Correlation Pattern and Driving Factors Between Water Footprint and Provincial Scale in Yangtze River Economic Belt. *Resour. Environ. Yangtze Basin* **2023**, *32*, 961–972. (In Chinese)
52. Chun, F.; Junhan, L. Evaluation of water resources utilization of Poyang Lake in Jiangxi Province from the perspective of water footprint. *J. Nanchang Univ. (Eng. Technol.)* **2021**, *43*, 52–56+61. (In Chinese) [CrossRef]
53. Heng, Z.; Hailong, D.; Jing, H. Analysis of Water Footprint in Hangzhou in 2010–2016. *Pearl River* **2019**, *40*, 69–75. (In Chinese)
54. Zhao, C.; Chen, B. Driving force analysis of the agricultural water footprint in China based on the LMDI method. *Environ. Sci. Technol.* **2014**, *48*, 12723–12731. [CrossRef] [PubMed]
55. Chapagain, A.K.; Hoekstra, A.Y. *Virtual Water Flows between Nations in Relation to Trade in Livestock and Livestock Products*; Value of Water Research Report Series No.13; UNESCO-IHE: Delft, The Netherlands, 2003.
56. Zhang, Y.; Liu, W.; Cai, Y.; Khan, S.U.; Zhao, M. Decoupling analysis of water use and economic development in arid region of China—Based on quantity and quality of water use. *Sci. Total Environ.* **2021**, *761*, 143275. [CrossRef] [PubMed]
57. Ariyo, A.A.; Adewumi, A.O.; Ayo, C.K. Stock Price Prediction Using the ARIMA Model. In Proceedings of the 2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation, Cambridge, UK, 26–28 March 2014; pp. 106–112.
58. Yang, S.; Liu, S.; Li, X.; Zhong, Y.; He, X.; Wu, C. The short-term forecasting of evaporation duct height (EDH) based on ARIMA model. *Multimed. Tools Appl.* **2016**, *76*, 24903–24916. [CrossRef]
59. Abid, A.; Jie, S. Impact of COVID-19 on agricultural food: A Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis. *Food Front.* **2021**, *2*, 396–406. [CrossRef]
60. Huang, J.-K. Impacts of COVID-19 on agriculture and rural poverty in China. *J. Integr. Agric.* **2020**, *19*, 2849–2853. [CrossRef]
61. Wang, H.H.; Hao, N. Panic buying? Food hoarding during the pandemic period with city lockdown. *J. Integr. Agric.* **2020**, *19*, 2916–2925. [CrossRef]
62. Mekonnen, M.M.; Hoekstra, A.Y. The green, blue and grey water footprint of crops and derived crop products. *Hydrol. Earth Syst. Sci.* **2011**, *15*, 1577–1600. [CrossRef]
63. Mekonnen, M.; Hoekstra, A.Y. *The Green, Blue and Grey Water Footprint of Farm Animals and Animal Products. Volume 2: Appendices*; Daugherty Water for Food Global Institute: Lincoln, NE, USA, 2010.
64. Fader, M.; Rost, S.; Müller, C.; Bondeau, A.; Gerten, D. Virtual water content of temperate cereals and maize: Present and potential future patterns. *J. Hydrol.* **2010**, *384*, 218–231. [CrossRef]
65. Fulton, J.; Cooley, H.; Gleick, P.H. Water Footprint Outcomes and Policy Relevance Change with Scale Considered: Evidence from California. *Water Resour. Manag.* **2014**, *28*, 3637–3649. [CrossRef]