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Fluctuations in Internal Water Footprint of Major Crops in Egypt: Implications for Sustainable Water Management

Mohannad Alobid [1],*, Okunlola Oluyemi Adewole [2] and István Szűcs [3]

[1] Institute of Agronomy and Crop Physiology, Justus-Liebig-University, 35392 Giessen, Germany

[2] Department of Mathematical and Computer Science, University of Medical Sciences, Ondo 351104, Nigeria; ookunlola@unimed.edu.ng (O.O.A.)

[3] Faculty of Economics and Business, Institute of Economics, Department of Agricultural Policy and Environmental Economics, University of Debrecen, Böszörményi St. 138, H-4032 Debrecen, Hungary; szucs.istvan@econ.unideb.hu (I.S.)

* Corresponding author. E-mail: mohannadalobid88@gmail.com (M.A.)

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ABSTRACT: The scarcity of water represents a significant obstacle to the advancement of agriculture in Egypt, requiring the implementation of inventive water policies and effective resource management practices. The notion of virtual water, which considers the water contained within things, is a possible remedy to mitigate the strain on water resources. This study examines the changes over time in the amount of water used internally and the amount of virtual water exported by rice, maize, and wheat crops in Egypt between 2000 and 2018. The assessment evaluates the impact of climate variables, crop productivity, and renewable water sources on the internal water footprint. The study uses data from several sources and applies a Nonlinear Autoregressive Distributed Lag (NARDL) model to analyse how productivity, renewable water supplies, temperature, and precipitation affect the internal water footprint. The EVIEWS software is utilised for conducting statistical analysis. The results demonstrate that the internal water footprint and productivity of the crops studied vary over time, and climate conditions and the availability of water control this variation. The maximum internal water footprint values for rice, maize, and wheat were recorded in 2008, 2011, and 2017, respectively, aligning with the highest temperatures and available renewable water resources. The analysis reveals complex connections between the independent factors and the internal water footprint of each crop. Precipitation has an inverse correlation with the internal water footprint of rice, but renewable water resources have a favourable impact on the internal water footprint of wheat. The study emphasizes improving crop choices to minimize water usage and boost water output. Given Egypt's expected water scarcity by 2025 and its reliance on Nile water for irrigation, implementing sustainable solutions for water resource management in agriculture is crucial. These findings give useful insights for policymakers and stakeholders in creating efficient water management policies and promoting food security in Egypt.

Keywords: Water scarcity; Virtual water; Internal water footprint; Crop productivity; Sustainable water management; Egypt

1. Introduction

Water scarcity is a serious issue in Egypt, a country that relies heavily on the Nile River for its water supply [1]. Water is regarded as one of the necessary and vital issues to accomplish economic development in general and agricultural development in particular, which has become increasingly demanding for Egyptian society due to its scarcity on the one hand and the expanding needs demanded of it on the other hand [2,3]. Therefore, it is imperative to develop new mechanisms for water policies, in addition to discovering mindful and effective strategies to enhance the efficiency of water resources [4]. Given that agriculture is the largest user of water resources in Egypt, absorbing over 80% of the country's available water, knowing water use efficiency, particularly in agricultural operations, is vital. Additionally, because the desire for food is fundamentally a demand for water in one form or another, this has led to the birth of the notion of virtual water, which is defined as the water included in a product, not in a realistic sense, but rather in the estimated meaning [5–7]. From this perspective, virtual water can be considered an alternative resource that can lower the demand for traditional water sources by reducing the production and exports of crops with high virtual water content while guaranteeing a sufficient degree of food security. Replacing such crops with others that have a lower percentage of virtual water and deliver a higher return becomes a strategic priority [8,9]. Relatively speaking, another key notion evolved, known as the water footprint, which indicates the total amount of water consumed to produce a good or service from the production stage to the ultimate customer [10]. The internal water footprint (IWF) refers to the volume of freshwater used within a country to create goods and services consumed by its residents [11].

The water footprint is generally divided into three primary components, each represented by a distinct color: the blue water footprint, the green water footprint, and the gray water footprint [12]. The blue water footprint represents the volume of surface and groundwater consumed during production processes, mainly through irrigation in agriculture [13]. The green water footprint accounts for rainwater stored in soil and used by plants, playing a crucial role in rainfed agriculture [14]. Lastly, the gray water footprint quantifies the volume of freshwater required to assimilate pollutants to meet water quality standards, reflecting the environmental impact of agricultural activities [15]. Together, these components provide a comprehensive assessment of water use, enabling policymakers to develop strategies that enhance sustainability and efficiency in water resource management [16].

In Egypt, this water footprint varies substantially depending on the type of crop, geographical area, and agricultural practices practiced [17]. Staple crops like wheat and rice have very significant water footprints due to their extensive water requirements during the growing season. Similarly, crops such as maize and sugarcane also contribute significantly to the overall IWF due to their cultivation in water-intensive regions. Additionally, various factors influence the IWF of crops, including irrigation techniques, soil type, and meteorological circumstances [18]. Traditional irrigation technologies, such as flood irrigation, are still widely used in Egypt and are highly inefficient, resulting in significant water losses through evaporation and seepage [19]. Furthermore, the change in climatic conditions, particularly in Upper Egypt, where temperatures are higher, exacerbates water loss, hence raising the IWF. In contrast, current irrigation techniques like drip irrigation have been demonstrated to reduce the IWF by improving water use efficiency [20,21].

Without a doubt, there has been a significant quantity of scientific research conducted globally, including in Egypt, that predicts catastrophic climatic changes in the country. These changes are expected to result in reduced rainfall, higher temperatures, and more frequent droughts [22]. These changes pose significant challenges to agricultural productivity, particularly rainfed and specific irrigated crops [23,24].

In addition, the concept of virtual water exports (VWE) introduces intricacy to the scenario. For Egypt, exporting agricultural products is a mixed blessing since it brings in significant income but also puts a strain on essential water supplies. Significantly, the main agricultural products exported by Egypt, including cotton, oranges, and strawberries, have a considerable amount of virtual water [25,26]. The global demand for these items has intensified their cultivation, stressing Egypt's water resources further [27]. The virtual water trade concept underlines the world water supply interconnection [28]. By exporting water-intensive crops, Egypt indirectly participates in global water redistribution [29]. While this may increase the economy, issues arise over the sustainability of such activities in a water-scarce society [30]. Moreover, VWE should be thoroughly supervised and regulated to ensure domestic water demands are addressed instead of promoting international commerce. The repercussions of virtual water exports also affect food security [28]. An overwhelming focus on export-oriented crops may limit staple crop output vital for home consumption, thus risking food security. This issue is particularly pertinent to Egypt, where population increase, and urbanization escalate the demand for food and water resources. Consequently, internal water footprint (IWF) and virtual water export changes are vulnerable to different effects, such as meteorological variability, economic policies, and global market movements [1,31].

Climate change, characterized by rising temperatures and shifting precipitation patterns, directly influences crop water requirements and, subsequently, the IWF. For example, droughts or lower Nile flows may considerably increase the IWF due to higher water needs for agricultural expansion. Conversely, excellent weather conditions might lower the water footprint by enhancing agricultural water use efficiency [32].

Economic variables also considerably affect crop selection and amounts, which in turn affect both the IWF and VWE [33]. Government subsidies and market price variations can influence the type and volume of produced crops [34]. For instance, government incentives to develop specific export-oriented crops may enhance virtual water exports, diverting water resources from crops with high internal water footprints. This can result in unsustainable water resource distribution, aggravating water scarcity [9,35]. Additionally, worldwide market changes influence Egyptian agricultural product demand, affecting virtual water export volumes [36]. Changes in worldwide demand for certain crops might lead to alterations in the planted types, altering the IWF and VWE. For example, increased global demand for Egyptian strawberries has led to expanding cultivation, compromising water supplies and long-term sustainability [37–39].

Therefore, in this study, it will be seen if there is a fluctuation in the internal water footprint and, thus, a variation in the amount of water used in production, and this, in turn, leads to a change in the amount of virtual water exported from the crops (Rice, Maize, and Wheat) in Egypt during the period 2000–2018. This change will be studied statistically through a set of factors related to climate (annual average temperature and yearly average precipitation), crop productivity, and renewable water sources in Egypt. Specifically, the study focuses on the blue water footprint, which represents the volume of surface and groundwater consumed during crop production, and the green water footprint, which accounts for rainwater utilized by crops. The gray water footprint is not explicitly analyzed, as the primary emphasis is on the direct water consumption for agricultural activities and its implications for virtual water exports. Understanding these components enables a more precise assessment of how climate variability and water availability impact Egypt's internal water footprint, thereby guiding more effective water management strategies.

2. Materials and Methods

2.1. Data Collection

The research is based on published data from the Central Agency for Public Mobilization and Statistics (CAPMAS), the Ministry of Water Resources and Irrigation, the Ministry of Agriculture, and various issues of the Journal of Sustainable Agricultural Sciences (JSAS) published in Arabic in Egypt. These sources were used to assess the Internal Water Footprint [40,41]. The data from these references were utilized to calculate the internal water footprint. In addition, the data issued by the FAOSTAT were collected for the productivity of the crops and the FAO-AQUASTAT database for the renewable water resources, additionally for the Annual Average Temperature and Annual Average Precipitation were collected from the world bank database as well as the FAO-AQUASTAT database during the years 2000–2018. See Appendix Table A1, Table A2 and Table A3 for the Rice, Maize, and Wheat, respectively.

2.2. Reliability of the Data and the Methodology Used

The research relied on to achieve the objective of the study and answering the research questions by following:

- First, to check whether the time series data is suitable for scrutinizing the short and long-run effect of the set of covariates on the response variable measured at a time.
- Second, the method was used to analyse and to see the variation of the four variables (RWr, Productivity, Ta and Precipitation) on the response variable IWFP is the quantitative economic analysis through the use of Nonlinear Autoregressive Distributed Lag (NARDL) by using EVIEWS software.

2.3. Assessment of the Internal Water Footprint

The estimation of the internal water footprint is based on the following data [42]:

1. The Quantity of Water Used in Production = The Quantity of Production per ton X Water Requirements of the Crop per ton.
2. The Quantity of Exported Virtual Water = The Quantity of Exported Crops per ton X the Water Requirement per ton.
3. The Internal Water Footprint = The Quantity of Water Used in Production—The Quantity of Exported Virtual Water.

Since the available data sources do not provide direct water footprint values but only water use data, the internal water footprint was derived using crop-specific water use estimates. The blue water footprint was estimated by considering the volume of irrigation water applied to each crop, while the green water footprint was determined based on rainwater contributions to crop growth. The water requirement per ton for each crop was obtained from established agricultural databases and literature. By applying these coefficients to production and export data, the study computed the internal water footprint for rice, maize, and wheat over the study period. This methodological approach ensures a reliable approximation of actual water use in Egypt's agricultural sector, allowing for an accurate assessment of the impact of climate and water resource availability on internal water footprint fluctuations.

2.4. NARDL Model Specification

The autoregressive distributed lag (ARDL) model is commonly used to investigate the short- and long-run effects of explanatory variables on a dependent variable, particularly when the variables exhibit a mixed order of integration of at most one [43]. However, the standard ARDL model assumes that the effects of increasing and decreasing values of covariates on the dependent variable are symmetric, which may not always hold in reality. To address this limitation, we employ the Nonlinear Autoregressive Distributed Lag (NARDL) model, as developed by [44], to examine the asymmetric effects of selected covariates on the Internal Water Footprint (IWFP) of three major crops: rice, maize, and wheat. In this study, the selection of explanatory variables—productivity, renewable water resources, temperature, and precipitation—is grounded in their direct and indirect influence on the water footprint of crops. The water footprint is largely determined by crop evapotranspiration, which is affected by climatic factors such as temperature and precipitation. Higher temperatures typically increase evapotranspiration rates, leading to a higher water footprint, whereas increased precipitation can reduce reliance on irrigation, potentially lowering the blue water footprint component [42]. Crop productivity is included as an essential variable, as a more water-efficient crop (higher yield per unit of water consumed) can influence the overall footprint. Renewable water resources serve as a proxy for water availability, which can impact irrigation practices and crop water consumption.

It is important to clarify that our model does not suggest an inverse relationship between water footprint and evapotranspiration, as this would contradict physical principles. Instead, we account for potential nonlinear effects, where changes in temperature and precipitation may lead to asymmetric responses in water consumption depending on local conditions, irrigation efficiency, and crop-specific factors. These considerations align with established frameworks for water footprint assessments, as discussed in Ansorge (2024) [45]. Considering the variables mentioned above, the long-run NARDL model specification is given as follow: Equation (1)

$$IWFP_t = \alpha_0 + \alpha_1 Prod_t + \alpha_2 RWr_t + \alpha_3 Ta_t + \alpha_4 Prep_t + \varepsilon_t \tag{1}$$

In Equation (1), α_0 = constant term, $\alpha_1 - \alpha_4$ are the parameters of the model to be estimated. The independent variables *Prod*, *RWr*, *Ta* and *Prep* are used to denote production, renewable water resource, temperature, and precipitation, respectively. *IWFP* is the internal water footprint for a particular crop.

In a situation in which the interest is to capture the possible asymmetry effect of each independent variable on the internal water footprint, each of the independent variables needed to be decomposed into a partial sum of positive and negative changes and included in the model as a separate variable [44]. For example, the partial sum of productivity is given as Equation (2).

$$\left.\begin{aligned} Prod_{t-1}^{+} &= \sum_{j=1}^{t} \Delta Prod_j^{+} = \sum_{j=1}^{t} \max(\Delta Prod_t, 0) \\ Prod_{t-1}^{-} &= \sum_{j=1}^{t} \Delta Prod_j^{-} = \sum_{j=1}^{t} \min(\Delta Prod_t, 0) \end{aligned}\right] \tag{2}$$

Specifically, the NARDL representation of Equation (3) has the following form:

$$\begin{gathered} \Delta IWFP_t = \alpha_0 + \alpha_1 IWFP_{t-1} + \alpha_2 Prod_{t-1}^{+} + \alpha_3 Prod_{t-1}^{-} + \alpha_4 Rwr_{t-1}^{+} + \alpha_5 Rwr_{t-1}^{-} + \alpha_6 Ta_{t-1}^{+} + \\ \alpha_7 Ta_{t-1}^{-} + \alpha_8 Prep_{t-1}^{+} + \alpha_9 Prep_{t-1}^{-} + \textstyle\sum_{i=1}^{m} \beta \Delta IWFP_{t-1} \end{gathered} \tag{3}$$

The long coefficients can be computed from the estimated model (3) by dividing the negative of the coefficient of the partial sum (*i.e.*, each of $\alpha_2 - \alpha_9$) by α_1, For example, the long coefficient of productivity is given as $(-\frac{\alpha_2}{\alpha_1})$ and $(-\frac{\alpha_3}{\alpha_1})$, respectively.

To investigate the existence of long-run relationships or cointegration, a joint null hypothesis of $(-\frac{\alpha_2}{\alpha_1} = -\frac{\alpha_3}{\alpha_1})$ was tested. The rejection of the hypothesis will indicate sufficient evidence for long-run asymmetry.

2.5. Statistical Analysis

The model described above was estimated to use EVIEWS statistical software version 9. Prior to the model estimation, preliminary time series testing was carried out. The steps involved are summarized below;

(1) Unit root test was carried out on each of the variables to ascertain their order of integration;
(2) A partial sum of all independent variables was computed;
(3) The NARDL model was estimated for each crop (rice, maize, and wheat);
(4) Wald *F*-test was conducted for nonlinear cointegration;
(5) Asymmetries were checked in each of the estimated models.

3. Results

3.1. Descriptive Statistics of the Variables

The descriptive features of the variables under investigation were examined and summarized in terms of their minimum, mean and maximum values (Table 1). Precisely, the highest value of internal water footprint for rice, maize and wheat were recorded in the year 2008, 2011 and 2017, respectively. Also, the productivity of rice, maize, and wheat during the period under investigation was maximum in the years 2006, 2011, and 2017, respectively. It was noted that the internal water footprint and productivity were at their highest in the same year. However, this was not the pattern in the case of crops considered. Further, the peak value of temperature, renewable water resources and precipitation were recorded for the period under investigation in 2009, 2012 and 2017, respectively.

Table 1. Variable's summary statistics and determination of order of integration.

Denomination	Variables	Minimum	Mean	Maximum	Integration
Internal Water Footprint	Rice (IWFPRC)	5.32	7.39	10.56	I(0)
	Maize (IWFPMZ)	5.00	6.36	7.60	I(1)
	Wheat (IWFPWT)	3.80	5.58	7.60	I(1)
Productivity	Rice (ProdRC)	8826.50	9514.29	10,075.00	I(0)
	Maize (ProdMZ)	6979.80	7751.47	8370.50	I(1)
	Wheat (ProdWT)	5574.10	6462.25	6859.70	I(0)
Temperature	Ta (Celsius)	22.35	23.28	24.73	I(0)
Renewable water resource	RWr (billion m^3)	51.80	54.35	57.12	I(1)
Precipitation (mm)	Prep (mm)	1.45	2.34	3.22	I(1)

Source: Own calculation.

As a custom in the analysis of time series data, the first statistical property tested is stationarity. This is important to determine the level of the integration of the variables under study and to avoid spurious regression. This study used the augmented Dickey Fuller (ADF) Test to establish the order of integration of the variables considered in the study. As shown in the last column of Table 1, the variables are a mix of stationery and integrated variables. For instance, IWFPRC, ProdRC, and Ta were stationary at level I(0), while RWr and Prep were integrated into order one, I(1). Also, IWFPMZ, ProdMZ, RWr and Prep were integrated into order one I(1), while Ta was a level stationary variable. Equally, IWFPWT, RWr and Prep were I(1) variables, while ProdWT and Ta were integrated into order zero.

Due to the mixed order of integration among the variables, a nonlinear autoregressive distributed lag (NARDL) model was adopted, as it effectively handles such variables while capturing asymmetries. As discussed in the methodology section, the partial sum of each covariate was computed prior to the model estimation. For example, the partial sum of productivity was computed using the EVIEWS code below:

- genr dprod = prod-prod(-1)
- genr ros = dprod >= 0
- genr dprod_p = ros*dprod
- genr dprod_n = (1-ros)*dprod
- genr prod_p = @cumsum(dprod_p)
- genr prod_n = @cumsum(dprod_n).

The prod_p and prod_n are the positive and negative values of productivity, respectively. This code was modified to compute the partial sum of other covariates included in the model. The result of three separate NARDL using the internal water footprint of each of rice, maize, and wheat the dependent variables were discussed in the next section.

3.2. Analysis of Internal Water Footprint of Rice

Table 2 shows the correlation analysis of water footprint with the independent variables. It was noted that each of the independent variables has a negative and insignificant relationship with the internal water footprint of rice (see column 1 of Table 2). The implication of this result is that there is an inverse relationship between these variables and internal water footprint. This implies that an increase in any of these variables will produce a decrease in the response variables (IWFPRC).

Table 2. Correlation analysis of internal water footprint of Rice and Covariates.

Variables	IWFPRC	ProdRC	RWr	Ta	Prep
IWFPRC	1				
ProdRC	−0.013	1			
RWr	−0.022	−0.240	1		
Ta	−0.110	−0.242	0.598 **	1	
Prep	−0.085	−0.358	−0.011	0.319	1

Source: Own calculation. (**) The correlation coefficient between rainwater requirement (RWr) and temperature (Ta) is statistically significant at a specific confidence level 95%. This means the observed correlation (0.598) is unlikely to have occurred by chance, and there is a meaningful relationship between these two variables.

The estimated coefficient of the NARDL model presented in Table 3 indicates that the lagged negative change of precipitation has a statistically significant effect on internal water footprint, while the lagged positive change is statistically insignificant. In this case, it can be deduced from the long-run coefficient that a unit negative change of precipitation leads to a 1.22 decrease in the internal water footprint. However, the asymmetry test failed to reject the hypothesis that the negative and the positive change of precipitation are statistically different in the long run. In terms of productivity, the lagged positive change is found to be significantly related to the internal water footprint at a 5% level with a long-run coefficient of 0.01. However, the long-run asymmetry of the lagged negative and the positive change in productivity was also not rejected. The renewable water resource produced a different result with a long-run coefficient of 1.54 and −3.74 for lagged negative and positive change, respectively. This indicates that a unit negative change in the RWr will lead to a 1.54 increase in the footprint of rice, while a unit point increase will reduce the footprint by 3.74. This implies that the impact of renewable water resources on the internal water footprint is asymmetric. Also, the impact of temperature on the internal water footprint is negative and asymmetric.

Table 3. NARDL Model Estimate for Rice.

Variables	NARDL Coefficient	*p*-Value	Long Run Coefficient	Long Run Asymmetry Test
IWFP(−1)	−0.84875	0.7961		
PREP_N(−1)	−1.03591	0.0146	−1.22052	F = 0.098293 (0.7645)
PREP_P(−1)	−0.13394	0.6677	−0.15781	DF = (1, 6)
PROD_N(−1)	−0.01274	0.9273	−0.01501	F = 0.098293 (0.1211)
PROD_P(−1)	0.009528	0.0227	0.011226	DF = (1, 6)
RWR_N(−1)	1.308942	0.1597	1.542207	F = 6.799207 (0.0403)
RWR_P(−1)	−3.17963	0.2344	−3.74627	DF = (1, 6)
TA_N(−1)	−5.96533	0.0279	−7.02841	F = 1.633715 (0.2484)
TA_P(−1)	−4.46399	0.0188	−5.25951	DF = (1, 6)

Source: Own calculation.

3.3. Analysis of Internal Water Footprint of Maize

The correlation analysis result presented in Table 4 indicates that renewable water resources, temperature and precipitation have a positive relationship with the internal water footprint of maize. However, only the renewable water resource exhibited a statistically significant relationship at the 1% level. Whereas productivity has a negative and insignificant relationship with the dependent variable.

Table 4. Correlation analysis of internal water footprint of Maize and Covariates.

Variables	IWFPMZ	ProdMZ	RWr	Ta	Prep
IWFPMZ	1				
ProdMZ	−0.135	1			
RWr	0.752 **	−0.051	1		
Ta	0.236	−0.177	0.598 **	1	
Prep	0.089	−0.121	−0.011	0.319	1

Source: Own calculation. (**) The correlation coefficient between rainwater requirement (RWr) and temperature (Ta) is statistically significant at a specific confidence level 95%. This means the observed correlation (0.598) is unlikely to have occurred by chance, and there is a meaningful relationship between these two variables.

The NARDL estimated coefficient presented in Table 5 showed that only precipitation has an asymmetry impact on the internal footprint in relation to maize. The impact of the negative and positive change of other variables on the internal water footprint appeared to be the same. In the case of precipitation, the estimated long-run coefficient for the lagged negative and positive change were found to be −0.6265 and 0.6242, respectively. This implies that a unit point increase will lead to a reduction of 0.6265, while a unit point increase will lead to a corresponding increase of 0.6242 in the long run.

Table 5. Estimation of Long-Run Coefficient for Maize Crop.

Variables	NARDL Coefficient	*p*-Value	Long-Run Coefficient	Long Run Asymmetry Test
IWFP(−1)	−1.560684	0.0170		
PREP_N(−1)	−0.977838	0.1338	−0.6265	F = 10.83628 (0.0133)
PREP_P(−1)	0.974150	0.0754	0.6242	DF = (1, 7)
PROD_N(−1)	−0.001016	0.3044	−0.0007	F = 0.008120 (0.9307)
PROD_P(−1)	−0.001143	0.1666	−0.0007	DF= (1, 7)
RWR_N(−1)	0.545360	0.1001	0.3494	F = 1.969594 (0.2033)
RWR_P(−1)	−0.336282	0.3772	−0.2155	DF = (1, 6)
TA_N(−1)	−0.260960	0.5345	−0.1672	F = 0.256986 (0.6278)
TA_P(−1)	−0.450594	0.4773	−0.2887	DF = (1, 7)

Source: Own calculation.

3.4. Analysis of Internal Water Footprint of Wheat

The correlation analysis table presented in Table 6 showed that all the independent variables have positive and insignificant relationships with the exemption of renewable water resources, which is positive and statistically related to the internal water footprint of wheat crops. It is also noted that the relationship between a pair of independent variables is moderate, indicating multicollinearity.

Table 6. Correlation analysis of internal water footprint of rice and Covariates.

Variables	IWFPWT	ProdWT	RWr	Ta	Prep
IWFPWT	1				
ProdWT	0.317	1			
RWr	0.715 **	0.090	1		
Ta	0.364	0.041	0.598 **	1	
Prep	0.254	0.130	−0.011	0.319	1

Source: Own calculation. (**) The correlation coefficient between rainwater requirement (RWr) and temperature (Ta) is statistically significant at a specific confidence level 95%. This means the observed correlation (0.598) is unlikely to have occurred by chance, and there is a meaningful relationship between these two variables.

The estimated NARDL coefficient for wheat crop internal water footprint is presented in Table 7. It is noted that the negative and positive change in each of the independent variables produces a similar impact on the response variable with the exemption of temperature, in which the asymmetric impact of the negative and positive change was noticed.

Table 7. Estimation of Long-Run Coefficient for Wheat Crop.

Variables	NARDL Coefficient	*p*-Value	Long-Run Coefficient	Long Run Asymmetry Test
IWFP(−1)	−0.935225	0.0337		
PREP_N(−1)	0.168774	0.6985	0.1805	F = 0.549912 (0.4825)
PREP_P(−1)	0.466101	0.1570	0.4984	DF = (1, 7)
PROD_N(−1)	0.000901	0.0823	0.0010	F = 0.521211 (0.4937)
PROD_P(−1)	0.000450	0.3944	0.0005	DF = (1, 7)
RWR_N(−1)	0.350629	0.1798	0.3749	F = 0.549806 (0.4825)
RWR_P(−1)	0.025536	0.9176	0.0273	DF = (1, 7)
TA_N(−1)	−0.186522	0.6037	−0.1994	F = 10.17358 (0.0153)
TA_P(−1)	0.800662	0.0399	0.8561	DF = (1, 7)

Source: Own calculation.

Summarily, the asymmetrical impact of renewable water resources, precipitation and temperature was established in the rice, maize, and wheat models, respectively.

4. Discussion

The results of this study reveal important insights into the internal water footprint (IWF) of rice, maize, and wheat, and how these are influenced by climatic and agricultural variables such as renewable water resources, precipitation, temperature, and productivity. The findings highlight both the complexity and the asymmetry of these relationships, providing a foundation for understanding how water use in agriculture can be managed more sustainably under varying climatic conditions. One of the key findings is the relationship between crop productivity and internal water footprint. For all three crops, peak productivity and peak IWF were observed in specific years, with rice and wheat showing alignment between these peaks. For example, rice productivity and IWF were highest in 2006 and 2008, respectively, while wheat showed peak values for both in 2017. This suggests that higher agricultural output in certain years is associated with increased water use, emphasizing the trade-off between productivity and water resource utilization. This finding is particularly relevant for regions facing water scarcity, as it underscores the need for strategies that optimize water use efficiency without compromising crop yields.

The study also uncovered significant asymmetric effects of climatic variables on the IWF of the crops. For rice, renewable water resources (RWr) and temperature had notable asymmetric impacts. A unit increase in RWr led to a substantial reduction in IWF (by 3.74), while a unit decrease resulted in a smaller increase (by 1.54). This indicates that the availability of renewable water resources plays a critical role in determining the water footprint of rice, with water scarcity disproportionately increasing IWF. Similarly, temperature had a negative and asymmetric impact on rice, with a unit increase reducing IWF by 5.26. This suggests that higher temperatures may reduce water use for rice, possibly due to accelerated growth cycles or changes in evapotranspiration rates. However, this finding also raises concerns about the potential trade-offs between water use and crop stress under warming conditions.

The findings of this study underscore the intricate relationship between available water resources, irrigation practices, and crop water consumption, particularly in a controlled irrigation system such as Egypt's. While renewable water resources are included as a key explanatory variable in our model, it is important to demonstrate their direct and indirect effects on irrigation and crop water consumption.

Previous research highlights that fluctuations in water availability influence irrigation intensity and cropping patterns. For example, Mekonnen and Hoekstra (2016) found that declining water availability in water-scarce regions leads to shifts in irrigation strategies, including the reduction of high water-consuming crops like rice [46]. Similarly, El-Sadek (2014) and Alobid (2022) noted that when the Nile water supply diminishes, Egyptian farmers often adjust irrigation frequencies and volumes, which directly affects crop water consumption [47,48].

Our study extends these findings by applying the NARDL approach, which reveals that changes in available renewable water resources do not have a symmetric effect on IWFP. For instance, an increase in renewable water resources is associated with a significant decrease in the IWFP of rice, maize, and wheat, indicating that greater water availability leads to more efficient irrigation and reduced water stress. However, a decline in water resources results in a less pronounced increase in IWFP, suggesting that farmers implement adaptive strategies such as deficit irrigation to mitigate water shortages.

For maize, precipitation emerged as the most influential variable, exhibiting a significant asymmetric effect. A unit increase in precipitation reduced the IWF by 0.63, while a unit decrease increased it by 0.62. This highlights the sensitivity of maize to changes in rainfall patterns, making it particularly vulnerable in regions with erratic or declining precipitation. These results emphasize the importance of irrigation management and water storage solutions for maize cultivation, especially in areas prone to drought.

In the case of wheat, temperature was the only variable with a significant asymmetric effect. A unit increase in temperature led to a 0.86 rise in IWF, indicating that wheat production becomes more water-intensive under warmer conditions. This finding is concerning in the context of climate change, as rising temperatures could exacerbate water use in wheat cultivation, particularly in arid and semi-arid regions. The results suggest that developing heat-tolerant wheat varieties and optimizing planting schedules may be crucial for reducing water use in the face of global warming.

Furthermore, while irrigation is the dominant water use sector in Egypt, it does not account for 100% of renewable water resources. Water is also allocated to domestic, industrial, and environmental uses, which may influence the observed relationship between water availability and agricultural consumption [49]. Despite this, agriculture remains the largest consumer, with irrigation efficiency improvements playing a critical role in mitigating the impact of water shortages [3]. According to FAO (2020), irrigation efficiency in Egypt has improved in recent years through technological advancements, yet the system remains vulnerable to fluctuations in Nile water inflows [50].

The correlation analysis further enriched our understanding of these relationships. For rice, all independent variables had negative but insignificant relationships with IWF, suggesting a weak inverse association. In contrast, maize and wheat showed positive relationships with renewable water resources, with maize exhibiting a statistically significant correlation. These findings highlight the differential impacts of climatic and agricultural factors on the water footprint of each crop, reinforcing the need for crop-specific water management strategies.

The implications of these findings are significant for sustainable water management in agriculture. The asymmetric effects of climatic variables on IWF suggest that policymakers and farmers need to adopt tailored strategies to mitigate the impacts of climate variability. For rice, improving irrigation efficiency and promoting water-saving technologies could help reduce IWF, particularly in years of high productivity. For maize, enhancing rainwater harvesting and storage systems could mitigate the adverse effects of precipitation variability. For wheat, developing heat-tolerant varieties and optimizing planting schedules could help reduce water use under rising temperatures.

Furthermore, the study underscores the importance of integrating climate resilience into agricultural planning. By understanding the asymmetric impacts of climatic variables, stakeholders can design more effective adaptation strategies to ensure food security and water sustainability in the face of climate change. For instance, policymakers could prioritize investments in water infrastructure, such as reservoirs and drip irrigation systems, to buffer against variability in renewable water resources and precipitation. Similarly, agricultural extension services could promote best practices for water use efficiency, such as precision agriculture and soil moisture conservation techniques.

5. Conclusions and Recommendations

Agriculture is a substantial contributor to water scarcity in Egypt, accounting for 76.7 percent of all water withdrawal activities. However, improvements can be made in water use for food production, such as picking legume crops with smaller water footprints. Egypt is anticipated to experience water scarcity by 2025, and it cannot meet food demand by relying on Nile water for agriculture due to population increase, desert land reclamation programs, and imported grain. Lake Nasser's surface water evaporation rate is estimated to be higher than originally predicted, leading to a deficit in the national water budget of nearly 19.5 billion cubic meters.

Climate change has also affected Egypt's water resources pressure, with economic changes in upstream countries increasing water resources demand. The Nile is vulnerable to fluctuations in temperature and precipitation, especially due to its low runoff/precipitation rate. This study investigated the internal water footprint of three critical crops in Egypt (rice, maize, and wheat) for 19 years, assessing average annual temperatures, precipitation, renewable water resources, and crop yield.

The study indicated that rice, maize, and wheat had the highest internal water footprint values in 2008, 2011, and 2017, respectively. The productivity of these crops was highest in 2006, 2011, and 2017, with the largest internal water footprint and productivity seen in the same year. The influence of temperature on the interior water footprint was negative and asymmetric. For maize, renewable water resources, temperature, and precipitation had positive associations with the internal water footprint, but only precipitation had an asymmetric impact.

Appendix 1. (Table A1, Table A2 and Table A3) for the Rice, Maize, and Wheat Crops Respectively

Table A1. The Data Were Used in the Model to Analyse the IWFP Variation for the Rice Crop.

Year	Rice Crop				
	IWFP	RWr	Productivity	Ta	Precipitation
	Billion m^3	Billion m^3 $year^{-1}$	Kg/Ha	Celsius	mm
2000	7.89	52.08	9102.50	23.1285	3.21577
2001	7.21	51.80	9283.30	23.1901	1.89678
2002	6.43	52.26	9388.90	22.3457	2.3418
2003	7.49	52.66	9748.40	23.0467	1.45347
2004	6.86	52.17	9838.40	23.1941	2.59356
2005	6.85	53.09	9987.40	23.0280	1.96633
2006	5.80	53.38	10,075.00	23.0661	2.19336
2007	7.46	53.21	9767.50	23.0779	2.71153
2008	10.56	54.17	9734.90	22.9806	1.91344
2009	9.99	55.10	9593.00	23.1440	2.02872
2010	6.86	55.42	9421.70	23.5117	2.33414
2011	7.19	56.29	9567.00	23.4048	1.94263

2012	5.93	57.12	9529.60	24.7271	2.69287
2013	5.32	56.63	9586.50	22.8719	1.96707
2014	9.04	56.17	9530.00	23.5320	2.1495
2015	8.63	55.11	9431.20	23.3878	3.02228
2016	6.71	54.29	9335.30	23.6309	3.16321
2017	7.32	55.66	9024.50	23.5347	2.83109
2018	6.85	56.12	8826.50	23.5437	2.11474

Table A2. The Data Were Used in the Model to Analyse the IWFP Variation for the Maize Crop.

Year	**Maize Crop**				
	IWFP	**RWr**	**Productivity**	**Ta**	**Precipitation**
	Billion m^3	**Billion m^3 year^{-1}**	**Kg/Ha**	**Celsius**	**mm**
2000	5.00	52.08	7680.00	23.1285	3.21577
2001	5.40	51.80	6979.80	23.1901	1.89678
2002	5.60	52.26	7765.60	22.3457	2.3418
2003	5.30	52.66	7829.30	23.0467	1.45347
2004	5.60	52.17	7908.70	23.1941	2.59356
2005	5.80	53.09	8160.70	23.0280	1.96633
2006	5.80	53.38	8370.50	23.0661	2.19336
2007	6.20	53.21	8046.30	23.0779	2.71153
2008	6.60	54.17	7905.30	22.9806	1.91344
2009	7.00	55.10	7818.40	23.1440	2.02872
2010	6.70	55.42	7270.00	23.5117	2.33414
2011	7.60	56.29	7740.90	23.4048	1.94263
2012	5.90	57.12	7772.30	24.7271	2.69287
2013	7.00	56.63	7722.30	22.8719	1.96707
2014	7.20	56.17	7755.60	23.5320	2.1495
2015	7.40	55.11	7354.60	23.3878	3.02228
2016	7.10	54.29	7607.10	23.6309	3.16321
2017	7.30	55.66	7789.50	23.5347	2.83109
2018	6.40	56.12	7801.00	23.5437	2.11474

Table A3. The Data Were Used in the Model to Analyse the IWFP Variation for the Wheat Crop.

Year	**Wheat Crop**				
	IWFP	**RWr**	**Productivity**	**Ta**	**Precipitation**
	Billion m^3	**Billion m^3 year^{-1}**	**Kg/Ha**	**Celsius**	**mm**
2000	3.90	52.08	6342.20	23.1285	3.21577
2001	3.80	51.80	6358.00	23.1901	1.89678
2002	3.90	52.26	6434.50	22.3457	2.3418
2003	4.20	52.66	6500.10	23.0467	1.45347
2004	4.40	52.17	6556.70	23.1941	2.59356
2005	4.70	53.09	6492.90	23.0280	1.96633
2006	5.60	53.38	6430.30	23.0661	2.19336
2007	5.10	53.21	6467.30	23.0779	2.71153
2008	5.40	54.17	6503.10	22.9806	1.91344
2009	5.30	55.10	6382.90	23.1440	2.02872
2010	5.30	55.42	5574.10	23.5117	2.33414
2011	5.10	56.29	6542.80	23.4048	1.94263
2012	5.40	57.12	6582.30	24.7271	2.69287
2013	7.10	56.63	6668.20	22.8719	1.96707
2014	7.30	56.17	6175.20	23.5320	2.1495
2015	7.10	55.11	6591.90	23.3878	3.02228
2016	7.50	54.29	6631.10	23.6309	3.16321
2017	7.60	55.66	6859.70	23.5347	2.83109
2018	7.40	56.12	6689.50	23.5437	2.11474

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Author Contributions

Conceptualization, M.A. and I.S.; methodology, M.A. and O.O.A.; software, M.A. and O.O.A.; validation, M.A.; formal analysis, M.A. and O.O.A.; investigation, M.A. and I.S.; resources, M.A.; data curation, M.A. and O.O.A.; writing—original draft preparation, M.A.; writing—review and editing, I.S. and O.O.A.; visualization, I.S. and M.A.; supervision, I.S. project administration, M.A. and I.S. funding acquisition, I.S. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement

Not applicable.

Data Availability Statement

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Declaration of Competing Interest

The authors declare no conflicts of interest.

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