Water Resources and Economics 47 (2024) 100248

Contents lists available at ScienceDirect

Water Resources and Economics

journal homepage: www.elsevier.com/locate/wre

Capturing the drivers of crop water footprints in Africa and its spatial patterns

Pilar Gracia-de-Rentería [a,b,*], Victor Nechifor [c], Emanuele Ferrari [c]

[a] University of Zaragoza, Department of Applied Economics, Faculty of Social Science and Social Work, Violante de Hungría 23, 5009, Zaragoza, Spain
[b] AgriFood Institute of Aragon–IA2 (CITA—University of Zaragoza), Miguel Servet Street, 177, 50013, Zaragoza, Spain
[c] European Commission, Joint Research Centre, Economics of the Food System, Inca Garcilaso 3, 41092, Sevilla, Spain

ARTICLE INFO

Handling Editor: Erik Ansink

Keywords:
Water footprint
Agriculture
Spatial panel model
Africa

ABSTRACT

Improving water efficiency in the agricultural sector is essential to ensure sustainable withdrawals and supply of freshwater in a context of increasing water scarcity and human water demand. The water footprint (WF) is an established metric of resource intensity while the drivers steering WF over time remain under-researched. To advance this line of research, this paper assesses the sign and magnitude of macroeconomic, climatic, and agronomic drivers on the agricultural crop WF in 43 countries of the African continent for the period 2002–2016, using econometric panel data techniques and considering potential spatial patterns. The results reveal a significant spatial dependence in the WF across neighbouring countries. Socioeconomic factors are the most important determinant of water productivity, indicating that economic development facilitates a falling water requirement per unit of production. A negative impact of the temperature variation on the WF is also found, while the share of total land dedicated to agriculture tends to increase the crop WF in the continent. These results support designing adequate agricultural and water management policies to achieve sustainable and resilient food systems capable of adapting to anticipated population growth, climate change and other future threats to human health, prosperity and environmental sustainability in Africa.

1. Introduction

The growth of population, urbanization, and productive activity, together with the effects of climate change, are increasing the pressure on water resources, both in quantity and quality terms, pushing humankind beyond the planet's biophysical limits [1,2]. In the agricultural sector, which is responsible of the 70 % of water withdrawals worldwide, growing population poses one of the main challenges for food security and associated water demands [3].

The international community is aware of the great challenge the world is facing and has consequently developed strategies to tackle it. At the European level, the Green Deal [4] aims at transforming the EU's economy for a sustainable future. Among its objectives are the design of fair, healthy and environmentally-friendly food systems, the preservation and restoration of ecosystems and biodiversity (including freshwater resources), and the elimination of pollution (including the restoration of the natural functions of ground and

* Corresponding author. University of Zaragoza, Department of Applied Economics, Faculty of Social Science and Social Work, Violante de Hungría 23, 5009, Zaragoza, Spain.
E-mail address: p_gracia@unizar.es (P. Gracia-de-Rentería).

https://doi.org/10.1016/j.wre.2024.100248
Received 9 November 2023; Received in revised form 25 June 2024; Accepted 5 July 2024
Available online 6 July 2024
2212-4284/

surface water). At the global level, the Sustainable Development Goals (SDGs) proposed by the United Nations provide an internationally recognisable series of targets to be achieved by 2030 with a view toward coordinating policy initiatives across economic, social, and environmental domains. Among these targets, Goal 6 aims at ensuring the availability and sustainable management of water and sanitation for all and highlights the need of substantially increase water-use efficiency across all sectors [5]. In the agricultural sector, improved water-use efficiency may be achieved through shifts to less water intensive crops, improved agricultural practices, or the use of virtual water trade displacing the production of more water demanding crops to regions with lower water scarcity problems [3].

These examples illustrate how water efficiency could ensure sustainable withdrawals and supply of freshwater in a context of increasing water scarcity and human water demands. The water footprint (WF) has emerged as a relevant metric to measure efficiency in the use of water. The WF refers to the direct and indirect usage of water within a production process and reflects the cumulative consumption of said resource through the entire supply chain [6]. This concept has contributed to a growing body of empirical academic literature. Some relevant papers focus on the drivers of agricultural virtual water trade [7,8], or on the impact of food consumption patterns (diet changes and food loss reduction) on water usage [9,10]. Another strand of the literature uses an ex-ante approach to establish water use projections under different socio-economic pathways [11–13], climate change scenarios [14,15], or consumption patterns [16].

A common denominator of the previous literature is the assumption that the WF remains constant over time (or varies at an assumed rate). Therefore, relatively scant attention has been paid to the drivers of the WF, as pointed by Gracia-de-Rentería et al. [17], which offer an overview at worldwide level of the economic and environmental drivers of the crop WF. The latter work also highlighted some research lines with scope for improvement such as the analysis of the heterogeneity existing within each continent or the consideration of the spatial relationships and dependences between countries.

Of special interest is the consideration of the spatial dependence that, in the case of WF, may be due to shared hydrogeological conditions and/or to imitation of neighbouring countries' behaviour [18,19]. On the one hand, hydrogeological dimension refers to the existence of spatial correlation on soil geology and agricultural production capability since neighbouring countries usually share land conditions. Moreover, the existence of share bodies of water (both surface and groundwater) may lead to a similar water availability in neighbouring countries sharing these water resources [20]. On the other hand, mimicry implies that countries tend to observe their neighbouring countries' behaviour related to aspects such as the type of crops produced, the production volume, or the policies aimed at improving water efficiency, and reacts consequently thereby resulting in a 'spillover' effect on the WF indicator. According to Zhi et al. [18], this may be especially due to the influence of neighbouring countries on the economic development level [21] and on agricultural production behaviours [22]. Moreover, interactions between countries are especially relevant when analysing the WF, since international trade also implies a virtual water trade that drives the water usage of countries [23]. This contrasts with the scarcity of studies on these spatial patterns (see Long et al. [24] as an exception that applies a spatial econometric model to analyse the relationship between water scarcity and water use efficiency).

This paper focuses on the African continent as a relevant case study with a two-fold interest. First, the performance of the agricultural sector plays a crucial role for eradicating hunger and improving food security in Africa, and heavily influence economic growth and employment. Second, the availability of water resources strongly conditions agricultural production and crop productivity, especially in the African continent with a higher drought occurrence and a larger dependence on rain-fed agriculture than other regions in the world [25].

Therefore, the assessment of the drivers of crop WF in the African continent could provide valuable information about how a series of macro-level variables affect African crop water use. This information is important for the design of adequate agricultural and water resource management policies with the aim of achieving sustainable and resilient food systems capable of adapting to population growth, climate change (and specially, to its consequences in water resources) and other potential risks and future threats to human health, prosperity, and environmental sustainability.

Moreover, the consideration of geographical patterns may inform the spatial relationships and dependences between African countries. This could provide helpful information to assess the impact that the African Continental Free Trade Agreement (AfCFTA), which is expected to increase intra-Africa trade of agricultural commodities [26], or Africa's Agenda 2063 may have on water resources. Moreover, this global component of the WF also implies that the study of the African continent can also help to guide the agricultural and trade policy of other regions of the world [23]. As an example, according to Eurostat [27], the European Union was the largest trade partner for Africa in 2020, with 28 % of both exports and imports (a higher share than for intra-Africa exports and imports, which account for 23 % and 13 % respectively).

With this motivation, the aim of the paper is to assess the sign and magnitude of a series of drivers related to the agricultural performance, as well as the socioeconomic and environmental conditions, on the agricultural crop water footprint in the African continent. Using econometric panel data techniques and accounting for spatial dependence across countries, the objective is to obtain elasticities that could serve as a guide for water and agricultural policies.

After this Introduction, Section 2 presents the database for the African continent, Section 3 describe the methodological approach, Section 4 present the main results and Section 5 concludes.

2. Data

Data for the water footprint (WF) required to produce crop products comes from the database developed by Mekonnen and Hoekstra [6], which was modified to be time-variant according to the approach by Tuninetti et al. [28]. The original database provides, for several specific products and countries, information about the blue WF, the green WF and the grey WF in m^3 of water per ton of production averaged over the period 1996–2005. In this paper, the WF is considered as the sum of both the green and blue WF and defined as the ratio between evapotranspiration (in m^3 per hectare) and crop yield (in ton per hectare). Note that the blue WF refers to the consumption of surface and groundwater resources through e.g. irrigation, while the green WF refers to the consumptive use by crops of rainwater stored in the soil. The grey WF refers to the volume of freshwater that would be required to assimilate the load of pollutants given natural background and existing ambient water quality standards [29]. As it is not a real water withdrawal but a hypothetical one, the grey WF is excluded from the analysis.

To introduce some time variability to this WF metric, the approach proposed by Tuninetti et al. [28] was used, as in other relevant papers [17,30–32], assuming that evapotranspiration remains stable over time and WF changes are only driven by yield variations:

$$WF_{p,c,t} = WF_{p,c}\frac{Y_{p,c}}{Y_{p,c,t}} \tag{1}$$

where p,c,t are the product, country and year, respectively; $WF_{p,c,t}$ is the annual crop WF; $WF_{p,c}$ is the average WF for the period 1996–2005 from Mekonnen and Hoekstra [6]; $Y_{p,c}$ is the average crop yield for the period 1996–2005 and $Y_{p,c,t}$ is the annual crop yield. Information about the crop yield was extracted from the Food and Agriculture Organization (FAO) [33].

The next step in data management is to aggregate the WF of the different crop products. For this purpose, the average crop WF weighted by the value of production was calculated to obtain the WF of the whole crop production of each country. Information about the value of production in constant dollars was obtained from FAO [33] and represents the importance of each product on total agricultural production. With this, we have information about the crop WF of 43 African countries[1] for the period 2002–2016, that represent around 80 % of the countries of the continent, 85 % of the total agricultural land of the continent and more than 90 % of the total agricultural production value according to FAO data [33]. The period analysed is the same as in Gracia-de-Rentería et al. [17], facilitating the comparability of results, and was mainly conditioned by data availability of the WF drivers.

Obtaining data for relevant crop WF drivers for the African continent was one of the main challenges addressed by this study. The spatial econometric approach of the present analysis requires a perfectly balanced panel, so the dataset cannot contain missing data for any country or any year of the sample. After revising the drivers of WF and water productivity used in the previous literature, three main categories of drivers were identified: agronomic factors, such as input yields (production quantity per input unit) or intensities (input quantity per hectare), agricultural area by m^3 of water available [e.g., [17,34–36]; socioeconomic drivers like GDP, population, agricultural population density [e.g., [17,36,37]; and environmental variables like temperature, precipitation, solar radiation or water availability [e.g., [17,24,34–37].

For the African case study, information about input yields or intensities is especially incomplete (for example, FAO [33] does not offer input use data by product while the time coverage for some countries is very limited). Hence, agricultural performance of countries was proxied by the percentage of agricultural land with respect to the total area of the country, giving an idea of the importance of agriculture and the existence of a more intensive or extensive agricultural system. This variable was extracted from FAO [33] and its definition includes three components: arable land, permanent pasture, and under permanent crops. The per capita GDP was used as a socioeconomic variable to measure the level of development of countries, whose information was taken from the World Bank [38]. Regarding the environmental conditions, the temperature variation and the water stress index were considered as the relevant factors. However, these two variables are highly correlated, so the temperature variation variable was finally used to avoid the potential endogeneity problems that the use of a water related variable may cause in the econometric models. Temperature has also been included in previous relevant studies [17,34,35] as a variable that reflects the effects of climate change on water availability conditions and yield performance, which directly condition the crop WF. Specifically, the selected variable measures the annual temperature variation (in $^\circ$ C) of each year with respect to the baseline period 1951–1980 and was extracted from FAO [33].

Table 1 presents a description of the variables used in this study, as well as a descriptive statistic. The data reveal that during the period analysed (2002–2016) the crop WF has been reduced by 12.70 %, while the per capita GDP, the percentage of agricultural land and the temperature variation increased by 26.13 %, 5.11 % and 55.43 %, respectively. However, these trends are not homogeneous and significant differences emerge among the diverse countries. Fig. 1 shows the percentage of variation of WF over the period analysed by country, evidencing this heterogeneous trend, with some countries that have experienced a decrease in WF of by more than 40 % (Cameroon, Lesotho, and Madagascar), while others have increased their WF by over 20 % (Morocco, Democratic Republic of the Congo, and Mozambique).

3. Methodology

3.1. Exploratory Spatial Data Analysis

Exploratory Spatial Data Analysis provides an insight into patterns and geographical associations in data to confirm whether the water footprint (WF) variable exhibits a spatial autocorrelation. Fig. 2 presents the average crop WF of production for the African

[1] Countries included in the study are: Algeria, Angola, Benin, Botswana, Burkina Faso, Cabo Verde, Cameroon, Chad, Comoros, Congo, Côte d'Ivoire, Democratic Republic of the Congo, Egypt, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Sao Tome and Principe, Senegal, Sierra Leone, South Africa, Togo, Tunisia, Uganda, United Republic of Tanzania, Zambia, Zimbabwe.

Table 1
Descriptive statistics of variables.

Variable	Description	Average 2002–2016	2002	2016
WF	Crop water footprint of production (m^3/ton)	2141.77 (1294.81)	2309.84 (1375.49)	2016.44 (1255.06)
GDPpc	Per capita GDP (constant US$)	2171.91 (2479.66)	1861.52 (2223.53)	2348.01 (2520.17)
Agriland	Agricultural land/Total area (%)	43.88 (19.97)	42.63 (20.09)	44.81 (20.25)
TempVar	Temperature variation with respect to 1951–1980 (°C)	0.99 (0.39)	0.92 (0.30)	1.43 (0.35)

Note: The data represents the average value and the standard deviation (in parentheses).

countries considered for the year 2016.[2] A first visual inspection reveals the presence of similar values in neighbouring countries, suggesting the existence of spatial correlations. We observe the existence of clusters of countries with a higher WF in West African countries, as well as in southern Eastern Africa/northern Southern Africa countries.

To confirm whether the general behaviour of the WF variable exhibits global spatial autocorrelation, the Moran's I test [39] was applied to test the null hypothesis that data exhibit no spatial association. Table 2 presents the results of the test for the endogenous variable (WF) for each year of the sample, confirming the rejection of the null hypothesis. This result indicates that the WF shows positive autocorrelation with spatial clusters around similar values, so neighbour countries tend to exhibit similar WF values.

This positive spatial autocorrelation is also presented in Fig. 3, where the Moran's scatterplot [40] for 2016 illustrates a measure of local spatial autocorrelation.[3] In particular, the figure illustrates a positive relationship between the WF of each country (horizontal axis) and the WF of nearby countries (vertical axis). Therefore, countries located in the upper-right quadrant are those with WF values above the mean and that the average of its neighbour countries is also above the mean. On the contrary, countries in the lower-left quadrant have WF values below the mean and the average of its neighbour countries is also below the mean.

3.2. Econometric model

The exploratory analysis of Section 3.1 confirmed the presence of spatial dependence in WF. Therefore, the econometric model has to take into account this spatial pattern to avoid biased results, as highlighted in Section 4 below. The popularity of spatial econometric models in the recent literature contrast with the scarcity of studies considering the existence of spatial patterns in the WF metric. Note that, as aforementioned, Long et al. [24] is the unique previous study that applies these models to analyse water efficiency.

In this paper, a spatial econometric model is used to consider the dependence among observations across space by means of the so-called spatial weight matrix W that describes the relationship of the spatial units of the sample. Given that the country sample encompasses islands, we opt for the inverse distance criterion as the basis for our W matrix, as it is more suitable than other alternative specifications in such cases. The inverse distance W matrix is defined as:

$$w_{ij} = \begin{cases} \dfrac{1}{d_{ij}} if i \neq j \\ 0 \; if \; i = j \end{cases} \tag{2}$$

where d_{ij} is the geographical distance between the centroids of countries. Note that this matrix is assumed to be constant over time and has been normalised to allow the comparison between spatial parameters of the models.

To select the most adequate spatial model among the existing alternatives, we start from the General Nesting Spatial Model (GNS) that includes all possible types of interaction effects:

$$\begin{aligned} \ln(WF_{it}) = \alpha_0 + \rho W \ln(WF_{it}) + X_{it}\beta + WX_{it}\theta + u_{it} \\ u_{it} = \lambda W u_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

where α_0 is the constant term; ρ is the spatial autoregressive coefficient associated with the nonnegative $N \times N$ weights matrix W, providing information about the intensity of spatial dependence in the dependent variable. X represents the $TN \times K$ matrix of explanatory variables that are described in Table 1; β is the $K \times 1$ vector of coefficients; θ is an array of dimension $K\times 1$ associated with the $N \times N$ weights matrix W that contains the parameters that determine the marginal effect of the explanatory variables from neighbouring observations on the WF; and u_{it} includes the spatial autocorrelation coefficient (λ) associated with the interaction effects among the disturbance term of the different units (Wu), as well as the error term (ε). Country fixed effects are also included to capture additional country heterogeneity.

From this GNS model, a set of derived models can be obtained by imposing restrictions on one or more parameters. Therefore, the next step is to test these restrictions to select the most suitable spatial model to be estimated. First, the LM test is used to test the null that $\theta = 0$ and results indicate that the null cannot be rejected ($\chi^2(3) = 5.38; p - value = 0.15$), so the Spatial Autoregressive Combined Model (SAC) is more adequate. Second, when the SAC model is estimated, the parameters ρ and λ are statistically significant (see Table 3), confirming the suitability of the SAC model in comparison with the spatial lag model (SAR) or the non-spatial OLS model.

[2] Results for other years of the sample exhibit a very similar pattern.
[3] Similar results are obtained for the other years of the sample.

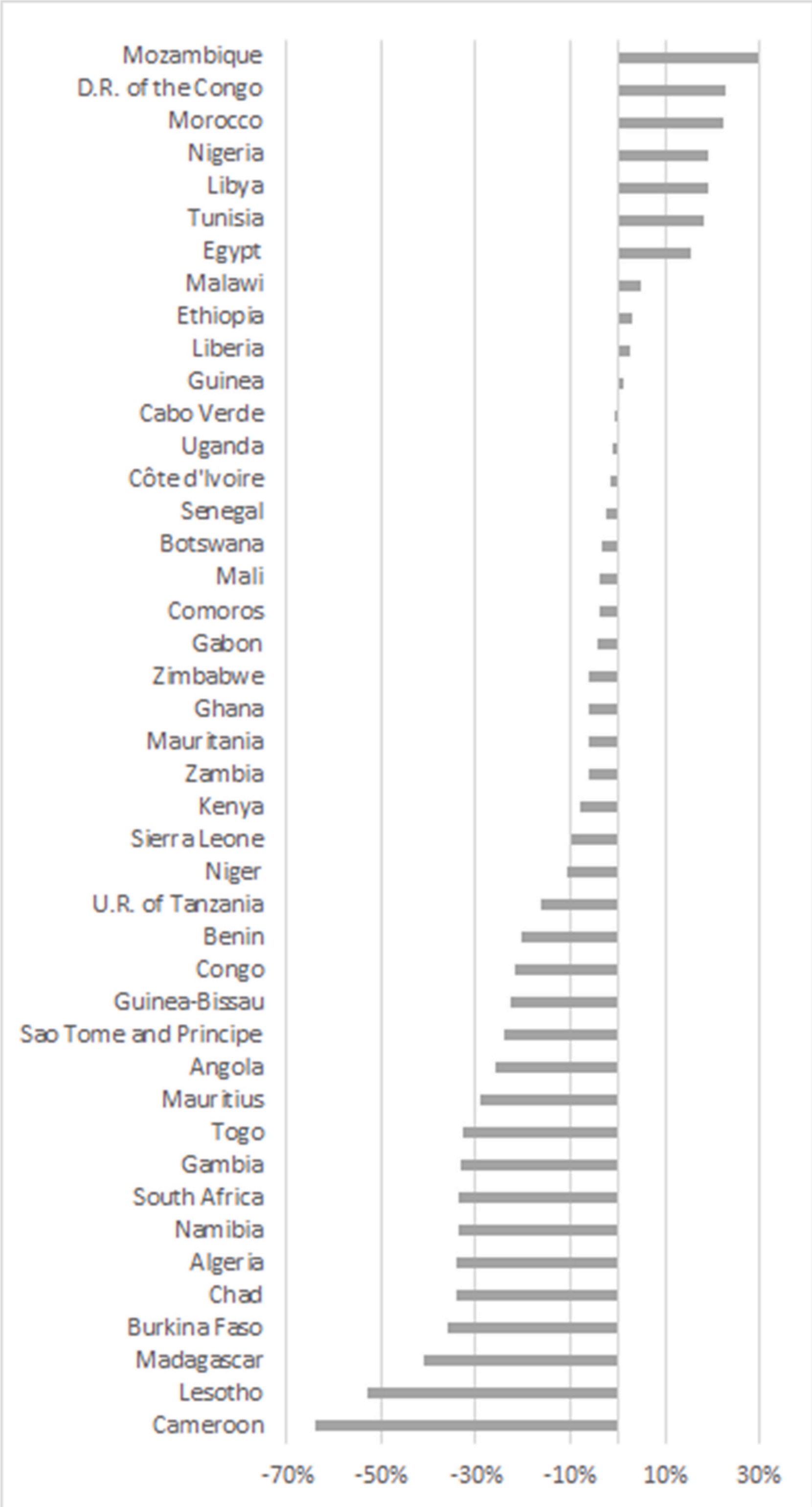

Fig. 1. WF variation over the period 2002–2016 by country.

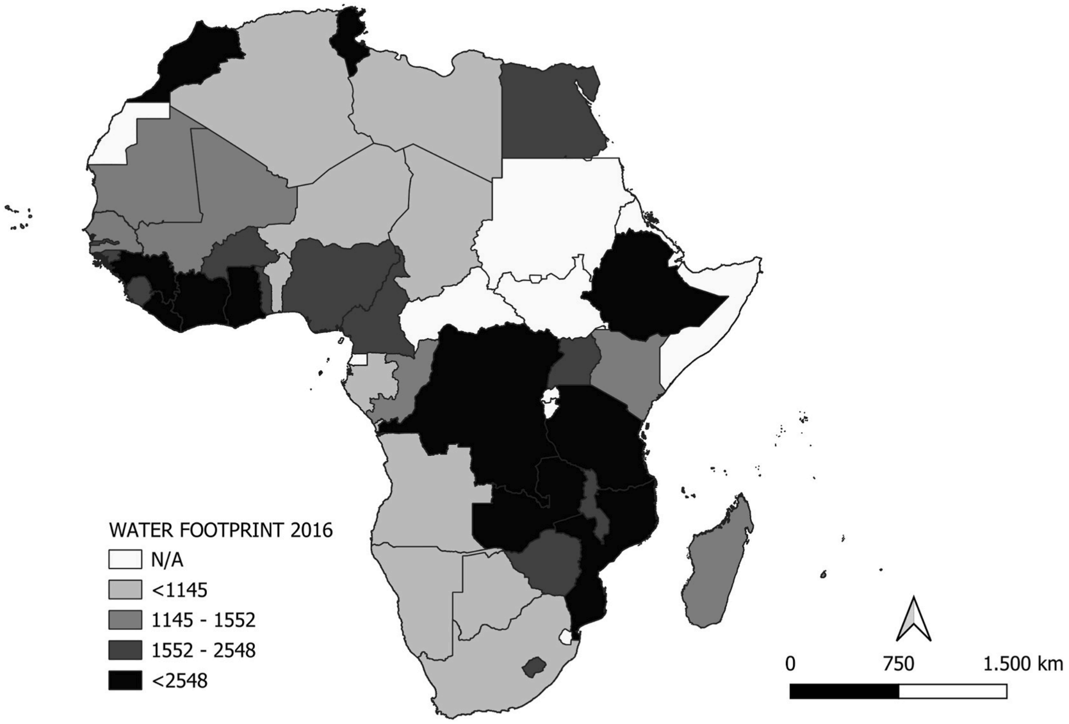

Fig. 2. Average crop water footprint (m^3/ton) in 2016.

Table 2
Moran's I test for the endogenous variable (WF).

Year	Moran's I test
2002	0.09 (0.00)
2003	0.04 (0.03)
2004	0.04 (0.03)
2005	0.07 (0.00)
2006	0.05 (0.01)
2007	0.07 (0.00)
2008	0.04 (0.04)
2009	0.03 (0.09)
2010	0.06 (0.00)
2011	0.08 (0.00)
2012	0.08 (0.00)
2013	0.09 (0.00)
2014	0.08 (0.00)
2015	0.11 (0.00)
2016	0.18 (0.00)

Note: p-value is shown in parentheses.

Therefore, the final specification of the estimated SAC model is the following:

$$\begin{aligned} \ln(WF_{it}) &= \alpha_0 + \rho W \ln(WF_{it}) + X_{it}\beta + u_{it} \\ u_{it} &= \lambda W u_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

4. Results

Table 3 presents the results of estimation of the Spatial Autoregressive Combined (SAC) model specified in equation (4), in comparison with the non-spatial OLS panel model. The result $\rho = 0.38$, which is a highly significant spillover effect (as also found in Long et al. [24]), implies that the water footprint (WF) in a certain country will increase, on average, around 3.8 % in that country if there is an increase of 10 % in the WF of its neighbouring countries. Moreover, the coefficient λ is also statistically significant at 10 %, so the SAC model is preferred in comparison with the SAR or the non-spatial model, which is also supported by the AIC criterion of both models.

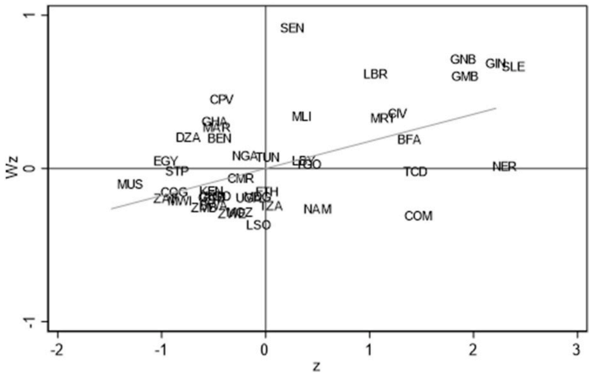

Fig. 3. Moran's scatterplot for 2016.

Table 3
Results of estimation.

Variables	SAC	OLS panel estimation
ln(GDPpc)	−0.349 (0.000)	−0.417 (0.000)
Agriland	0.011 (0.001)	0.003 (0.005)
TempVar	−0.029 (0.045)	−0.043 (0.011)
ρ	0.382 (0.045)	–
λ	−0.481 (0.070)	–
Wald test of spatial terms	9.3 (0.010)	–
AIC	−786.997	−785.0435
Observations	645	645

Note: p-values are shown in parentheses.

Another notable result is that in the case of the non-spatial OLS model the coefficients in Table 3 can be interpreted as marginal effects. On the contrary, in the spatial model, some transformation is required to obtain the marginal effects presented in Table 4 [41]. The direct effect of a kth explanatory variable is obtained as the diagonal elements of $(I-\rho W)^{-1}\beta_k$, and measures the impact of a change in the exogenous variables in a given country on the WF in the country itself; whereas the indirect (or spillover) effect is obtained as the off-diagonal elements of $(I-\rho W)^{-1}\beta_k$, and measures the impact of a change in the exogenous variables in a given country on the WF of the neighbouring countries. Note that the differences between the direct effects and the coefficients of the non-spatial model indicate that lack of consideration of the spatial component may lead to biased results [42]. Moreover, the direct effects obtained in Table 4 are different from the estimated main coefficients in Table 3 due to the so-called feedback effect that is transmitted to neighbouring countries and back to the country itself again. This feedback effect, which is also shown in Tables 4 and is obtained as the difference between the direct effect and the main coefficient estimated, showing very limited feedback effects that represents around 1.43 % of the indirect effect and 0.86 % of the direct effect.

Based on these marginal effects of the SAC model, one can observe that the level of development of a given African country has a negative and significant impact on the WF of this country. Specifically, an increase of a 1 % in the per capita GDP variable leads to a reduction of a 0.35 % in the WF of the same country. This result is in line with the previous literature [17,24,43], suggesting that economic development facilitates a falling water requirement per unit of production due to technological improvements, a better infrastructural capacity, or more stable economic and political conditions. The indirect effect is also negative and statistically significant, indicating that the WF is reduced by 0.213 % given a 1 % increase of the per capita GDP of neighbouring countries, indicating that the aforementioned economic factors that can influence the WF are spread in space from one country to neighbouring ones.

For the percentage of agricultural land, a positive and significant direct effect is obtained, so an increase of a 1 % in the percentage of agricultural land of a given country leads to an increase of a 0.01 % in the WF of this country. This result, although much more limited than that obtained for the per capita GDP, suggest that a greater presence of the agricultural sector or a more extensive agricultural sector increases the water needs per unit of production. The higher WF of more extensive agricultural systems is due to the

Table 4
Direct and indirect marginal effects.

	Direct effect	Indirect effect	Feedback effect
lGDPpc	−0.352 (0.000)	−0.213 (0.028)	−0.0030
Agriland	0.011 (0.001)	0.007 (0.132)	0.001
TempVar	−0.029 (0.044)	−0.018 (0.092)	−0.003

Note: p-values are shown in parentheses.

lower yields associated to these extensive systems that, according to the literature, could lead to a lower efficiency in the use of water resources [17,34–37]. However, the indirect effect, although positive, seems not to be statistically significant.

Finally, a reduction in the WF of African countries is observed given an increase of the temperature variation of the given country (direct effect of −0.029) or the nearby countries (indirect effect of −0.018). The previous evidence regarding the influence of climatic conditions on the WF is diverse, with some studies obtaining a positive relationship [34] and others a negative one [17,35]. In general, the latter studies argue that higher average temperatures lead to a greater aridity that incentivise a more efficient use of water resources. Since temperature change is a consequence of climate change, this result highlights how climate change adaptation policies have been implemented to compensate for the lack of effective mitigation policies capable to minimize the water related impacts of climate change. In any case, as pointed out by Gracia-de-Rentería et al. [17], the effect of climatic conditions is usually weaker than the impact of the socioeconomic and agronomic factors.

At this point, it should be mentioned that some additional estimations of equation (4) have been run as a robustness check. These results are not presented for simplicity, although authors would make them available upon request. First, the model has been re-estimated including the percentage of arable land instead of the percentage of agricultural land, leading to very similar results than those presented in Table 4. Second, the model has been also estimated including only continental countries to explore whether spatial spillovers transcend geographical boundaries reaching also island territories. Again, results are very similar that those of Table 4, reinforcing the idea of spillover effects that can cross seas.

In order to illustrate the effect that the marginal effects presented in Table 4 would have on future African WF, we carried out a simple foresight analysis combining the obtained marginal effects with projected increases in drivers for the period 2016–2030. We focus on the effect of per capita GDP (ceteris paribus the other drivers) because it is the driver with the greatest effect on the WF and due to the greater availability of projected data. To do so, projections of per capita GDP of each county of our sample were used based on data from the SSP database [44,45], according to the SSP2 scenario (middle-on-the-road scenario) for the OECD model. The growth rate of per capita GDP from 2016 to 2030 was combined with the obtained marginal effect (direct and indirect) from Table 4 to obtain the growth rate of WF for this period.

Results reveal that the WF in Africa would be reduced by 34 % during the period 2016–2030 due to an expected increase of a 60 % in per capita GDP in this period. Consequently, the WF in the continent would decrease from 2016.44 m^3/ton in 2016 to 1338.15 m^3/ton in 2030. All the countries would reduce their WF but with heterogeneous intensities. In this sense, some countries like Angola or Gabon would experience a reduction close to a 10 % while other countries would reduce their WF by a half (Guinea, Sao Tome and Principe, Democratic Republic of the Congo, Côte d'Ivoire) (See Fig. 4, panel a). In panel b of Fig. 4, the projected WF for 2030 is represented showing a very similar spatial pattern compared with that of 2016.

5. Conclusions

Considering the changes in the agricultural crop water footprint (WF) in 43 countries between 2002 and 2016, this paper assessed the sign and magnitude of a set of drivers of water use efficiency in the African continent and its spatial pattern. The application of spatial econometrics to this field of study is novel and the resulting coefficients of this estimation allow measuring the relation between the WF and the considered drivers over time after controlling for spatial dependence.

Africa is characterised by the extremes of having the highest number of least developed countries (32) of which 16 are land-locked

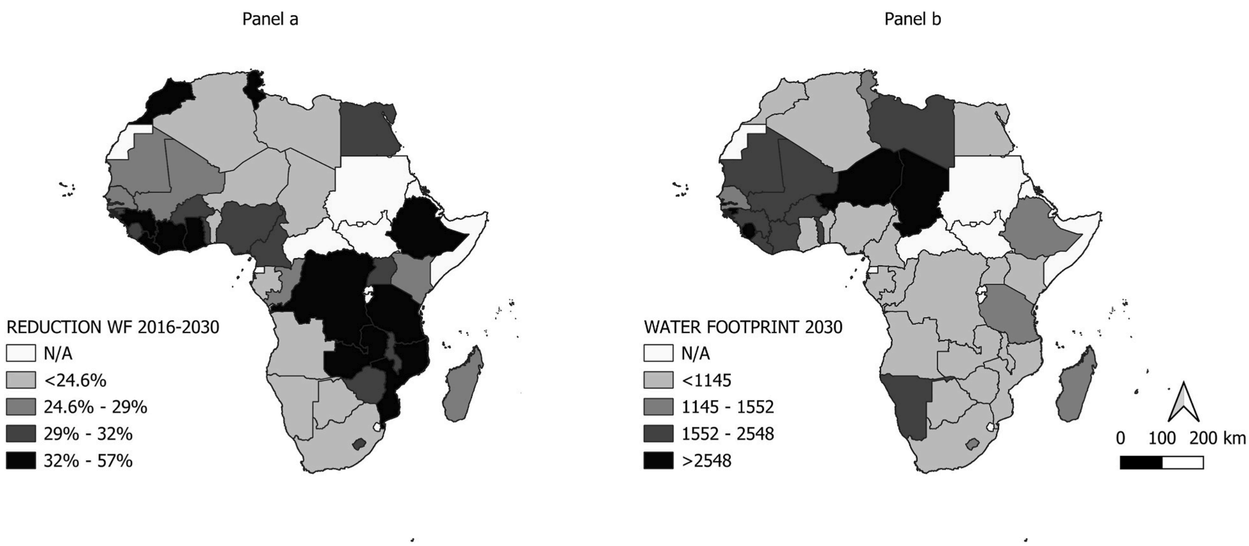

Fig. 4. Reduction of the WF (%) in the period 2016–2030 driven by changes in per capita GDP (panel a) and projected average crop WF (m^3/ton) in 2030 (panel b).

[46]. The results highlight a set of economic, environmental, and agronomic drivers influencing the crop WF common to all African countries. Among these factors, per capita GDP has the greatest effect on the WF indicating that economic development facilitates a reduction of water requirement per unit of production. The importance of the per capita GDP for water use efficiency is particularly policy relevant as, among all continents, Africa and, notably, the Sub-Saharan region is expected to have the highest increase in both population [46] and GDP per capita in the coming century [45]. The results also indicate a negative relationship between the WF and the temperature variation, while the WF is positively influenced by the percentage of agricultural land with respect to the area of a country.

The results also reveal a strong spatial dependence on the crop WF in the African continent. This finding highlights the need for coordinated cross-border policies oriented towards a more efficient use of water at the same time that a sustainable economic development is promoted. These results thus complement the literature highlighting the benefits of increased international cooperation on the management and use of water resources [45,47–50]. The importance of the spillover effects could further justify a focus on water user performance under the Agenda 2063, the main platform through which the fifty-five African countries share a Panafrican vision on economic development and sustainability.

The study provides valuable information for the design of adequate agricultural and water management policies to achieve sustainable and resilient food systems capable of adapting to future population growth and climate change. The elasticities obtained in this study are very helpful for the estimation of future WF under diverse scenarios by means of an ex-ante analyses, by introducing some degree of time variability to the WF metric. These type of studies could help elucidate the undetermined future direction of the crop WF and crop water demand given the opposing effects on WF of per capita GDP and the temperature variation on one hand, and the expected increase in the percentage of agricultural land on the other. Climate change adds further uncertainty regarding the direction of water demand in crop production. The occurrence of extreme weather events already manifested through prolonged droughts and changes in rainfall patterns could render a drastic decrease in productivity of agricultural land [51,52]. The positive effect of higher CO_2 concentrations on yields and crop water productivity could partially offset these negative impacts under low climate change scenarios but could also be cancelled under severe climate change [53]. Furthermore, even if the undetermined effect would point to a reduction in WF, it remains to be investigated whether that reduction will be enough to feed a growing population in the context of scarce water resources. These complex interlinkages between socioeconomic and biophysical systems necessitate the integration of modelling capabilities from different fields.

Another avenue for future research is the consideration of different regions and crop products, or the differentiation between rainfed and irrigated crop production, enabling such differentiation would allow for more targeted interventions. For this purpose, more data about agronomic factors of specific products is needed, as well as the availability of more complete databases for the African continent. In fact, data constraints are the main limitation of this study, preventing the inclusion of relevant variables that may have an impact on crop WF. Data availability also restricted the consideration of the WF only as an aggregate, therefore, the more detailed drivers of change (switching crops or irrigation practices) were not covered. Future studies going into specific irrigation practices within each country could also reveal some spatial patterns and specific spillovers [54], as well as exploring whether these spillovers may be influenced by hydrogeological aspects, like the existence of shared water resources or common soil characteristics.

Funding

Pilar Gracia-de-Rentería acknowledges the receipt of a fellowship from the OECD Co-operative Research Programme: Sustainable Agricultural and Food Systems in 2022 (Contract PO 500113749).

CRediT authorship contribution statement

Pilar Gracia-de-Rentería: Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Victor Nechifor:** Writing – review & editing, Formal analysis, Conceptualization. **Emanuele Ferrari:** Writing – review & editing, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Pilar Gracia reports financial support was provided by OECD Trade and Agriculture Directorate, Co-operative Research Programme: Sustainable Agricultural and Food Systems in 2022 (Contract PO 500113749). If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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