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

Pilar Gracia-de-Rentería[1,2], Victor Nechifor[3] and Emanuele Ferrari[3]

[1] Centro de Investigación y Tecnología Agroalimentaria de Aragón (CITA). Department of Agrifood Economics. Avda Montañana 930, 50059 Zaragoza (Spain)

[2] AgriFood Institute of Aragon–IA2 (CITA—University of Zaragoza), Miguel Servet Street, 177, 50013 Zaragoza, Spain

[3] European Commission, Joint Research Centre, Economics of the Food System, Inca Garcilaso 3, 41092, Sevilla, Spain

Abstract

The water footprint (WF) is an established metric of resource intensity, although the drivers that guide this indicator over time remain under-researched. To advance this line, this paper assesses the impact of macroeconomic, climatic, and agronomic drivers on the agricultural crop WF in Africa using econometric panel data techniques and considering the existence of potential spatial patterns. The results reveal a highly significant spatial dependence in the WF across neighbouring countries. Per capita GDP is the factor with the highest influence on the WF, 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 tend to increase the crop WF in the continent. These results could help guide the design of adequate agricultural and water resource management policies to achieve sustainable and resilient food systems.

Keywords: water footprint, agriculture, spatial panel model, 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 (Gleick and Cooley, 2021; Steffen et al., 2015). 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 (UN Environment, 2019).

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 (European Commission, 2019) 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 surface water). At the global level, the Sustainable Development Goals (SDGs) fronted 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 (UN, 2015). 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 (UN Environment, 2019).

These examples illustrate how water efficiency is viewed as the key to 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 (Mekonnen and Hoekstra, 2011). This concept has contributed to a growing body of empirical academic literature. Some relevant papers focus on the drivers of agricultural virtual water trade (e.g., Fracasso, 2014; Duarte et al., 2019), or on the impact of food consumption patterns (diet changes and food loss reduction) on water usage (e.g., Vanham et al. 2013; Mekonnen and Fulton, 2018).

Another strand of the literature uses an ex-ante approach to establish water use projections under different socio-economic pathways (e.g., Ercin and Hoekstra, 2014) or consumption patterns (Philippidis et al., 2021).

A common denominator of the previous literature is the assumption that the WF remains constant over time (or varies at an assumed rate), whilst relatively scant attention has been paid to the drivers of the WF, as pointed by Gracia-de-Rentería et al. (2020). The latter work offers an overview at worldwide level of the economic and environmental drivers of the crop WF. However, they 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, which may occur if one country strategically mimics the policies of its neighbouring countries aimed at improving water efficiency, thereby resulting in a 'spillover' effect on the WF indicator. On this point, one should note that interactions between countries are especially relevant when analysing the WF, since international trade implies also a virtual water trade that conditions the water usage of countries. This contrasts with the scarcity of studies on these spatial patterns (see Long et al, 2017 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, water resources availability 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 (OECD/FAO, 2020).

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 patters may inform about 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 and improve food security, may also 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 policy of other regions of the world (D'Odorico et al., 2019). As an example, according to Eurostat (2021), the EU was the largest trade partner for Africa in 2020, with 28% of both exports and imports (a higher share that for intra-Africa exports and imports, which accounts 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 (WF) 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 WF required to produce crop products comes from the database developed by Mekonnen and Hoekstra (2011), which was modified to be time-variant. The original database provides, for several specific products and countries, information about the blue, green and grey WF in m^3 of water per ton of production averaged over the period 1996–2005, which is defined as the ratio between evapotranspiration (in m^3 per hectare) and crop yield (in ton per hectare). To introduce some time variability, the approach proposed by Tuninetti et al. (2017) was used, as in other relevant papers (Duarte et al., 2014, 2016; Gracia-de-Rentería et al., 2020; Soligno et al., 2019), assuming that evapotranspiration remains stable over time and WF changes are only driven by yield variations:

$$WF_{p,c,t} = WF_{p,c} \frac{Y_{p,c}}{Y_{p,c,t}} \qquad (1)$$

where p,c,t are the product, country and tear, 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 (2011); $Y_{p,c}$ 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, 2022).

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. 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 agricultural production value according to FAO (2022) data. The period analysed is the same as in Gracia-de-Rentería et al. (2020), facilitating the comparability of results, and was mainly conditioned by data availability of the WF drivers.

In fact, 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 used in 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 (e.g., Gracia de Rentería, 2020; Levers et al., 2016; Li et al., 2016; Tilman et al., 2011); socioeconomic drivers like GDP, population, agricultural population density (e.g., Gracia de Rentería, 2020; Neumann et al., 2010; Tilman et al., 2011); and environmental variables like temperature, precipitation, solar radiation or water availability (e.g., Gracia

---

[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.

de Rentería, 2020; Levers et al., 2016; Li et al., 2016; Long et al., 2017; Neumann et al., 2010; Tilman et al., 2011).

For the African case study, information about input yields or intensities is especially incomplete (for example, FAO (2022) does not offer input use data by product and time coverage for some countries is very limited), so agricultural performance of countries was proxied by the percentage of agricultural land with respect to the total area of the country, so this could give an idea of the importance of agriculture and the existence of a more intensive or extensive agricultural system. The per capita GDP was used as a socioeconomic variable to measure the level of development of countries. Regarding the environmental conditions, the temperature variation and the water stress index were considered as 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. The selected variable measures the temperature variation (in º C) with respect to the baseline period 1951–1980 and was extracted from FAO (2022), as well as the data for the percentage of agricultural land. Information about the per capita GDP was from the World Bank (2022).

Table 1 presents a description of the variables used in this study, as well as a descriptive statistic. Data reveal that during the period analysed 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.

Table 1. Descriptive statistics of variables

Variable	Description	Average 2002-2016	2002	2016
WF	Crop water footprint of production (m3/ton)	2,141.77 (1,294.81)	2,309.84 (1,375.49)	2,016.44 (1,255.06)
GDPpc	Per capita GDP (constant US$)	2,171.91 (2,479.66)	1,861.52 (2,223.53)	2,348.01 (2,520.17)
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 (ºC)	0.99 (0.39)	0.92 (0.30)	1.43 (0.35)

Note: average value is presented, as well as the standard deviation in parenthesis.

6

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 WF variable exhibits a spatial autocorrelation. Figure 1 presents the average crop WF of production for the African countries considered for the year 2016.[2] A first visual inspection reveals the presence of similar values in neighbouring countries, with a cluster of countries with a higher WF in West African countries suggesting the existence of spatial correlations.
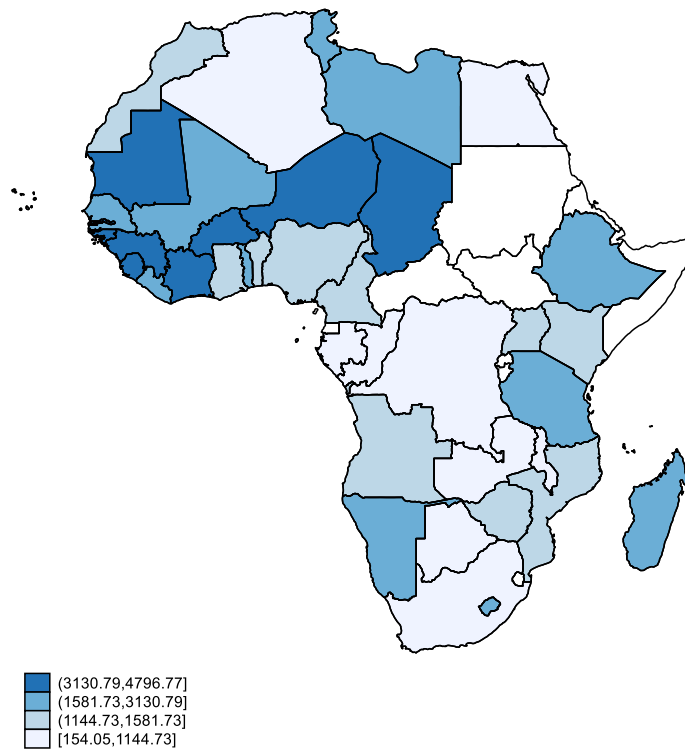

Figure 1. Average crop water footprint (m^3/ton) in 2016

To confirm whether the general behaviour of the WF variable exhibits global spatial autocorrelation, the Moran's I test (Moran, 1950) 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 for each year of the sample, confirming the rejection of the null. This result indicates that 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 Figure 2, where the Moran's scatterplot

---

[2] Results for other years of the sample exhibit a very similar pattern.

(Anselin, 1988) 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.

Table 2. Moran's I test

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 parenthesis.

---

[3] Similar results are obtained for the other years of the sample.

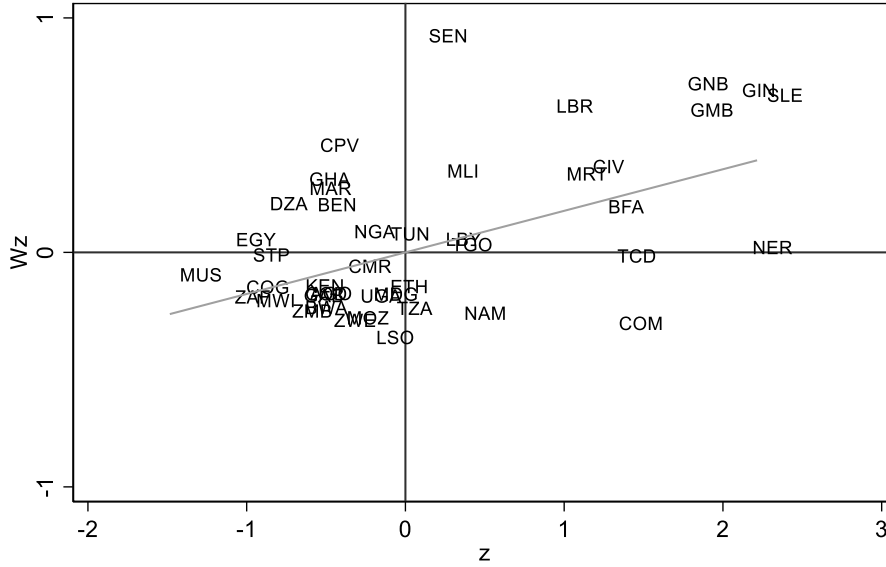Figure 2. Moran's scatterplot for 2016

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. In this sense, 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 (see Long et al, 2017 as an exception that applies a spatial econometric model to analyse the relationship between water scarcity and water use 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. Among the alternative specifications of the W matrix, in this study we based it on the inverse distance:

$$w_{ij} = \begin{cases} \dfrac{1}{d_{ij}} \, if \, i \neq j \\ 0 \, if \, i = j \end{cases} \qquad (2)$$

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:

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

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 Kx1 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.

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

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

4. Results

Table 3 presents the results of estimation of the 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., 2017), implies that 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.

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 parenthesis.

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 (Elhorst, 2014) to obtain the marginal effects presented in Table 4. The direct effect 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 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. 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 Table 4, 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.

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 parenthesis.

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 (Cai et al., 2011; Gracia-de-Rentería et al., 2020; Long and Pijanowski, 2017), 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.

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. However, the indirect effect, although positive, seems to not be statistically significant. The higher WF of more extensive agricultural systems is due to the lower yields associated to these extensive systems that, according to the literature, could lead to a lower efficiency in the use of water resources (e.g., Gracia-de-Rentería et al., 2020; Levers et al., 2016; Li et al., 2016; Neumann et al., 2010; Tilman et al., 2011).

Finally, a reduction in the WF of African countries is observed given an increase of the temperature variation of the given country (-0.029) or the nearby countries (-0.018).

Although the previous evidence regarding the influence of climatic conditions on the WF is diverse, with some studies obtaining a positive relationship (Levers et al., 2016) and others a negative one (Gracia-de-Rentería et al., 2020; Li et al., 2016), in general it is argued that higher average temperatures lead to a greater aridity that incentive to make a more efficient use of water resources. In any case, as pointed out by Gracia-de-Rentería et al. (2020), the effect of climatic conditions is usually weaker than the impact of the socioeconomic and agronomic factors.

5. Conclusions

This paper assesses the sign and magnitude of a set of drivers on the agricultural crop WF in the African continent and its spatial pattern. In this sense, the application of spatial econometrics to this field of study is novel and the resulting coefficients of this estimation allow to measure the relation between the WF and the considered drivers over time after controlling for spatial dependence.

The results indicate that economic, environmental and agronomic factors influence the crop WF of African countries. In particular, a positive relationship between the percentage of agricultural land the WF is found, while the WF is negatively influenced by an increase of the temperature variation or the per capita GDP, having the latter the factor a greater effect on the WF. Moreover, the results of this study also reveals a strong spatial dependence on the crop WF in the African continent, highlighting the need for coordinated policies oriented to a more efficient use of water at the same time that an sustainable economic development is promoted.

The study provides valuable information 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 future population growth and climate change. In this regard, the elasticities obtained in this study could be very helpful for the estimation of future WF under diverse scenarios by means of an ex-ante analysis, by introducing some degree of time variability to the WF metric. This 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 an increase in the percentage of agricultural land in the African continent on the other. Even if the undetermined effect would point to a reduction in WF, the question is if that reduction will be enough to feed a growing population in the context of scarce

water resources. Another venue for future research is the consideration of different regions and crop products, or the differentiation between rainfed and irrigated crop production. For this purpose, more data about agronomic factors of specific products is needed, as well as a more complete data availability for the African continent.

References

Anselin, L. (1988). Spatial econometrics: methods and models. Boston: Kluwer.

Cai, X., Molden, D., Mainuddin, M., Sharma, B., Ahmad, M.D. and Karimi, P. (2011). Producing more food with less water in a changing world: Assessment of water productivity in 10 major river basins. *Water International* 36: 42–62.

D'Odorico, P., Carr, J., Dalin, C., Dell'Angelo, J., Konar, M., Laio, F., Ridolfi, L., Rosa, L., Suweis, S. and Tamea, S. (2019). Global virtual water trade and the hydrological cycle: patterns, drivers, and socio-environmental impacts. *Environmental Research Letters* 14, 053001.

Duarte, R., Pinilla, V. and Serrano, A. (2014). The effect of globalisation on water consumption: A case study of the Spanish virtual water trade, 1849–1935. *Ecological Economics* 100: 96–105.

Duarte, R., Pinilla, V. and Serrano, A. (2016). Understanding agricultural virtual water flows in the world from an economic perspective: A long term study. *Ecological Indicators* 61: 980–990.

Duarte, R., Pinilla, V. and Serrano, A. (2019). Long Term Drivers of Global Virtual Water Trade: A Trade Gravity Approach for 1965–2010. *Ecological Economics* 156: 318-326.

Elhorst, J. P. (2010). Applied spatial econometrics: raising the bar. *Spatial Economic Analysis* 5 (1): 9-28.

Elhorst, J.P. (2014). *Spatial econometrics. From cross-sectional data to spatial panels*. New York, Dordrecht, London: Springer Briefs in Regional Science, Springer.

Ercin, A.E. and Hoekstra, A.Y. (2014). Water footprint scenarios for 2050: A global analysis. *Environmental International* 64 : 71-82.

European Commission (2019). Communication from the commission to the European parliament, the European council, the council, the European economic and social

committee and the committee of the regions. The European Green Deal. COM(2019) 640 final. https://eur-lex.europa.eu/resource.html?uri=cellar:b828d165-1c22-11ea-8c1f-01aa75ed71a1.0002.02/DOC_1&format=PDF.

Eurostat (2021). International trade in goods - a statistical picture. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=International_trade_in_goods_-_a_statistical_picture.

FAO (2022). Faostat Database. http://www.fao.org/faostat/es/#home.

Fracasso, A. (2014). A gravity model of virtual water trade. *Ecological Economics* 108 : 215-228.

Gleick, P.H. and Cooley, H. (2021). Freshwater Scarcity. *The Annual Review of Environment and Resources* 46 : 319-348.

Gracia-de-Rentería, P., Philippidis, G., Férrer-Pérez, H. and Sanjuán, A.I. (2020). Living at the Water's Edge: A World-Wide Econometric Panel Estimation of Arable Water Footprint Drivers. *Water* 12, 1060.

Levers, C., Butsic, V., Verburg, P.H., Müller, D. and Kuemmerle, T. (2016). Drivers of changes in agricultural intensity in Europe. *Land Use Policy* 58: 380–393.

Li, X., Zhang, X., Niu, J., Tong, L., Kang, S., Du, T., Li, S. and Ding, R. (2016). Irrigation water productivity is more influenced by agronomic practice factors than by climatic factors in Hexi Corridor, Northwest China. *Scientific Reports* 6, 37971.

Long, K. and Pijanowski, B.C. (2017). Is there a relationship between water scarcity and water use efficiency in China? A national decadal assessment across spatial scales. *Land Use Policy* 69: 502–511.

Mekonnen, M.M. and Fulton, J. (2018). The effect of diet changes and food loss reduction in reducing the water footprint of an average American. *Water International* 43(6): 860-870.

Mekonnen, M.M. and Hoekstra, A.Y. (2011). The green, blue and grey water footprint of crops and derived crop products. *Hydrology and the Earth System Sciences* 15: 1577–1600.

Moran, P.A.P. (1950). Notes on continuous stochastic phenomena. *Biometrika* 37: 17–23.

Neumann, K., Verburg, P.H., Stehfest, E. and Müller, C. (2010). The yield gap of global grain production: A spatial analysis. *Agricultural Systems* 103: 316–326.

OECD/FAO (2020). *OECD-FAO Agricultural Outlook 2016-2025*. Paris: OECD Publishing.

Philippidis, G., Ferrer-Pérez, H., Gracia-de-Rentería, P., M'Barek, R. and Sanjuán-López, A.I. (2021). Eating your greens: a global sustainability assessment. *Resources, Conservation & Recycling* 168, 105460.

Riahi, K., et al. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An Overview. *Global Environmental Change* 42: 153-168.

Soligno, I., Malik, A. and Lenzen, M. (2019). Socioeconomic Drivers of Global BlueWater Use. *Water Resources Research* 55: 5650–5664.

Steffen, W., et al. (2015). Planetary boundaries: Guiding human development on a changing planet. *Science* 347, 6223.

Tilman, D., Fargione, J., Wol, B., D'Antonio, C., Dobson, A., Howarth, R., Schindler, D., Schlesinger,W.H., Simberlo, D. and Swackhamer, D. (2001). Forecasting agriculturally driven global environmental change. *Science* 292: 281–284.

Tuninetti, M., Tamea, S., Laio, F. and Ridolfi, L.A. (2017). Fast Track approach to deal with the temporal dimension of crop water footprint. *Environmental Research Letters* 12, 074010.

UN (2015). Resolution adopted by the general assembly on 25 September 2015. A/res/70/1, seventieth session. United Nations 2015, Agenda items 15 and 116. https://www.un.org/en/development/desa/population/migration/generalassembly/docs/globalcompact/A_RES_70_1_E.pdf.

UN Environment (2019). *Global Environment Outlook—GEO-6: Healthy Planet, Healthy People*. Nairobi, Kenya: United Nations Environment Programme (UNEP).

Vanham, D., Hoekstra, A.Y. and Bidoglio, G. (2013). Potential water saving through changes in European diets. *Environmental International* 61: 45-56.

World Bank (2022). World Development Indicators. Available online: https://datacatalog.worldbank.org/dataset/world-development-indicators.