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Unsustainable global freshwater consumption driven by economic growth ☆

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ABSTRACT

Freshwater, a vital resource for ecosystems and societies, faces increasing threats from anthropic uses and climate change, exacerbating water stress for two-thirds of the global population. The paper examines whether economic growth can alleviate or contribute to the impending water crisis. We examine the interplay between per capita GDP and water demand for food production and consumption across 121 countries over 24 years. Using the CWASI database, a unique global longitudinal dataset on water footprint, our analysis reveals a consistently monotonic increase in the water footprint of consumption at the global scale, as economies grow. The rising pressure is mainly driven by the increasing volume of water embedded in food consumed within each country, even as the water footprint of local food production tends to decline slightly once countries reach a sufficiently high level of per capita income. Our findings suggest that the anticipated improvements in water use efficiency associated with technological and institutional development appear insufficient to counter the global rise in freshwater demand. Instead, the slightly virtuous evolution in the water footprint of production observed in wealthier countries is largely sustained through virtual water imports from less developed regions. Notably, the turning point in water footprint of production for richer countries occurs at per capita levels exceeding the renewable freshwater endowment available in many parts of the world. These findings build on and extend previous evidence of spatial displacement of water use, raising critical concerns about the sustainability of future global water supply, development trajectories, and food security.

1. Introduction

Global freshwater resources, crucial for the survival of ecosystems and human societies, are under increasing anthropogenic pressure. Exacerbated by the escalating impacts of climate change, the unsustainability of water consumption looms as one of the significant challenges of this century (He et al., 2021; Mekonnen & Hoekstra, 2020), with about 48% of world countries projected to be water scarce by 2050 (renewable water resources per capita below 1700 m^3/year, according to the Water Stress Index) (Baggio et al., 2021). Scientific literature points to population growth and economic expansion as major drivers of the impending water crisis (Hoekstra & Wiedmann, 2014; Unesco, 2019).

The demographic factor acts mainly through increased global demand for food (FAO, 2017; Raiser et al., 2023). Economic growth drives increased water demand by raising per capita consumption and shifting habits, most notably through dietary changes that favour more water-intensive products (Molden et al., 2007; Vanham et al., 2017). These trends are becoming increasingly problematic as climate change compounds the pressures created by demographic and economic forces. Rising temperatures and changing precipitation patterns are expected to intensify both wet and dry seasons, worsening agricultural and ecological droughts, as well as flooding. Such events often carry sewage, pesticides, and industrial waste, further degrading water quality and threatening the accessibility and reliability of water resources (Lee et al., 2023; Masson-Delmotte et al., 2021; Water, 2018).

Behind global averages, significant disparities exist in terms of the physical distribution of water between and within world regions, of demographic and economic drivers, of the physical impacts of climate change, and of the consequences on human welfare and vulnerability

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[1] Sadly, Prof. Marco Maria Bagliani, passed away in July 2024 while this paper was under revision. We wish to dedicate this paper to a dear colleague and friend.

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of local socioeconomic systems. The annual renewable freshwater resources per capita on a national scale vary widely, from more than 30,000 cubic meters per capita in nations such as Bhutan, Guyana, and Iceland to less than 100 cubic meters per capita in Yemen, Algeria, and Saudi Arabia (Baggio et al., 2021).

The main drivers of change in aggregate water demand also exhibit substantial regional disparities: population trends vary significantly across world regions, reaching annual growth rates of up to 3% in African countries and stabilizing at near-zero or negative growth in most European countries (OECD, 2022). An even more substantial disparity is displayed by economic trends, with real GDP growth rates ranging between 5.3% of countries in Emerging and Developing Asia and the average 0.8% of the Euro Area (International Monetary Fund, 2023).

Finally, significant spatial differences are evident in how freshwater scarcity impacts socioeconomic welfare and human development. Water stress indices worsen for two-thirds of the world's population, with approximately 50% of it at risk of a severe lack of water for at least part of the year (Boretti & Rosa, 2019; Lee et al., 2023). The impacts on human welfare are heavily mediated by socioeconomic, territorial, and institutional factors, with most drought-related deaths occurring in Africa (Naddaf, 2023). And while in 2015 the countries facing water scarcity were predominantly located in the MENA region, the 15 nations expected to experience the most significant declines in freshwater resources per person between 2015 and 2050 all hail from Sub-Saharan Africa (Baggio et al., 2021). This has significant implications for worldwide and regional economic and human development trends.

In such a complex context, a fundamental issue for predicting future outcomes and formulating policies is understanding whether economic growth will alleviate the pressure through technology-driven improvements in water efficiency and enhanced governance capacity or, conversely, whether increased production and consumption will contribute to the impending water crisis. This paper seeks to address this question by providing the first analysis of the relationship between per capita GDP and water demand, using the CWASI original worldwide water footprint (*WF*) panel data covering 121 countries over 24 years (Tamea et al., 2021; Tuninetti et al., 2017). The database contains the water footprint of production, i.e. all the water used for food production (crops and animal-based products) within each country, and the water footprint embedded in the import and export of water alongside the international food trade (FAO, 2017; Pastor et al., 2019; Peters, 2008; Simas et al., 2017) used to calculate the water footprint of consumption, which is the sum of all water abstracted anywhere in the world to satisfy a country's food demand. The joint analysis of these two indicators allows us to consider not only direct local uses but also indirect ones throughout the entire food supply chain, including water flows embodied in international trade (D'Odorico et al., 2014; Tamea et al., 2021; Wiedmann & Lenzen, 2018). After some descriptive statistics of the worldwide *WF*'s evolution over time, we use a panel data econometric analysis to investigate the relationship between *WF* and economic growth.

Results show that, in per capita terms, the relationship between income and water footprint reveals two different behaviours for the *WF* of production and consumption. The former displays a mild inverted U-shape, whereas the latter shows a monotonically increasing pattern. This suggests that the technology- or governance-driven improvements in water efficiency associated with economic growth are insufficient to reverse the increasing global trends in total freshwater demand. The pressures from rising aggregate food consumption and population growth are satisfied by richer countries through net imports of virtual water. This evidence questions the sustainability of current global water uses by extending to water resources previous literature disputing the existence of absolute delinking between economic growth and environmental impacts,[2] and poses serious concerns about future trends in global water stress and potential shocks on world food markets.

The paper is organized as follows. Section 2 defines the *WF* metric and its subdivision into the components of the water footprint of consumption and of production. It also surveys the previous literature on the relationship between economic growth and water use — in general, as well as using *WF* as a unit of measure of countries' pressure on water resources. Section 3 describes the dataset and the methodology, including preliminary tests conducted on the panel data to guide the choice of the model employed for the econometric analysis. The results are presented in Section 4 and discussed in Section 5, which also offers our conclusions and policy implications.

2. Economic growth and water

2.1. Water footprint

The notion of water footprint was introduced by Arjen Y. Hoekstra and first used in Hoekstra and Hung (2002) to integrate the ecological footprint metric into water accounting and thus translate in quantifiable terms Tony Allan's 1993 virtual water concept. The *WF* captures the complete spectrum of water usage, encompassing both direct and indirect consumption, throughout the whole production chain (Hoekstra et al., 2009). The concept gained wider attention since Mekonnen and Hoekstra (2011b), becoming a valuable tool for assessing water usage in the production of commodities across diverse spatial and temporal scales (Calzadilla et al., 2011; Mekonnen & Hoekstra, 2011b).

Food production generates approximately 70% of global water withdrawals, up to 90% in arid countries (Rossi et al., 2019). The WF methodology distinguishes between the portion of water derived mainly from natural precipitation, absorbed by soil and utilized by plants through evapotranspiration (termed "green water"), and the portion extracted for irrigation purposes from rivers, lakes, and aquifers ("blue water") (Hoekstra & Wiedmann, 2014; Mancosu et al., 2015; Mekonnen & Hoekstra, 2011a). Despite accounting for just 20% of global agricultural land, irrigated areas are responsible for around 40% of total agricultural output worldwide (Aldaya et al., 2012; Rost et al., 2008). The relative reliance on green and blue water for agricultural production differs significantly between developing and industrialized countries. A large share of agriculture in developing countries is rainfed, especially in Sub-Saharan Africa, parts of Asia, and Latin America. In industrialized countries, well-developed irrigation systems enable a much more intensive use of blue water. The water footprint of agricultural production is also contingent upon local climate, influencing agricultural water requirements (Deihimfard et al., 2022).

As said before, the *WF* metrics can be based on a production-oriented or consumption-oriented approach, providing insights into the intricate international dynamics of water uses. The water footprint of production (*WFP*) denotes the aggregate volume of water used in the production processes of all commodities and services within a country, irrespective of their ultimate consumption destination (Hoekstra & Hung, 2003). In contrast, the water footprint of consumption (*WFC*) quantifies the total water used to produce all commodities and services that are consumed within a specific country, regardless of where they were produced. Mathematically, *WFC* is expressed as the sum of the water footprint of production plus the water content embedded in imported products (water footprint of imports, *WFI*), subtracting the water content associated with exported goods (water footprint of exports, *WFE*) and considering the variation in stocks[3]:

$$WFC = WFP + WFI - WFE + \Delta S. \quad (1)$$

[2] For a survey on delinking see Parrique et al. (2019).

[3] This variation is overall negligible, except for few specific products.

This distinction acknowledges that virtual water transfers occur through international trade, linking production areas as exporting regions to consumption areas as importing regions, thus creating a dynamic system where water usage transcends local boundaries. The comprehensive *WF* metric adopted in our analysis enables the reconstruction of the network of water embedded in international trade flows. This approach offers insights into the spatial distribution of responsibility for the depletion of global water resources (Wiedmann & Lenzen, 2018). More importantly, it provides a robust foundation for exploring the complex relationship between water consumption and economic development, offering a clearer view of potential future trajectories and underscoring the urgent need for informed policy interventions.

2.2. Economic growth and water use

A wide stream of economic literature has empirically investigated the hypothesis according to which countries, in their development process, tend to go through an initial stage of increasing pressure on natural resources, followed, when they reach a sufficiently high income level, by a phase in which further economic growth is associated with improvements in environmental conditions. Growing out of poverty would thus eventually lead countries to a more sustainable relationship between the socioeconomic and the ecological systems, decoupling their economic growth from that of environmental pressures (Grossman & Krueger, 1991; Panayotou et al., 1993; Shafik, 1994).

This result, known under the label of the *Environmental Kuznets Curve (EKC)*, would imply a trend of initially increasing environmental degradation, which then reaches a turning point, depicting an inverted U-shaped relationship between economic growth and pollution or natural resource use. A composite set of drivers may underlie this effect: richer countries tend to have easier access to more advanced technologies, more developed water governance institutions, and a higher share of the tertiary sector in their GDP composition. They may also potentially have more environmentally aware consumption patterns.

However, the increase in aggregate demand, due to rising individual consumption levels and population growth, and the associated increase in the scale of production imply more resource extraction and greater generation of polluting residuals. This "scale effect" drives towards a monotonically increasing relationship between economic growth and environmental pressure.

The net effect is ultimately an empirical question. In the last thirty years, many studies have tested the existence of an inverted U-shaped relationship between environmental degradation and per capita income using different environmental indicators. Complete literature reviews can be found in Anwar et al. (2022), Destek and Sarkodie (2019), Naveed et al. (2022) and Saqib and Benhmad (2021). Also, the econometric methodology has substantially evolved over time, following the seminal paper by Stern (2004); see, for example, Datta and De (2021) and Stern (2017). Results are, in essence, indicator-specific. Early studies, typically urban and country-level and focusing on local air pollutants (e.g. SO_2, particulate matter) often found confirmation of an EKC relationship (e.g. Balogh and Jámbor (2017), Coggin (2023) and Grossman and Krueger (1995)). Subsequent studies, using different measures – global pollutants such as CO_2 emissions or non-delocalizable impacts such as volumes of municipal waste, but also water pollution and deforestation, to name a few – did not generally find evidence of a turning point followed by a decline in impacts with increasing per capita income (Azomahou et al., 2006; Cole et al., 1997; Farooq et al., 2023 among others).

The most general demarcation line between studies that do or do not find improvements in environmental impact as countries' income increases is, however, the adoption of production- versus consumption-based indicators to quantify environmental impacts. Most empirical evidence of delinking between economic growth and environmental pressure derives from studies using environmental pressure indicators that reflect the local impact on the environment of human activities related to local production, such as air or soil pollution. This led, for example, Caviglia-Harris et al. (2009), Roca (2003) and Rothman (1998) to conclude that local improvements in some dimensions of environmental quality may, in reality, simply reflect a delocalization of impacts away from wealthier nations. To provide an indication of sustainability, one should find evidence of an EKC relationship between economic growth and environmental quality using consumption-based aggregate measures of environmental impact (Bagliani et al., 2008). Through this latter kind of indicators we can observe the relationship between economic growth and the whole impact caused, anywhere in the world, by the associated growth in consumption. In essence, more resource-specific studies, including both production- and consumption-based indicators, are required to deepen the empirical verification of the EKC hypothesis by distinguishing between a real turn towards sustainable development and mere delocalization of impacts (Parrique et al., 2019; Skubał A., 2018; Wiedmann et al., 2020).

The relationship between countries' income and environmental pressure has been explored before also with specific reference to water resources. An up-to-date review can be found in Zhang et al. (2023). In synthesis, the findings from existing literature testing the EKC hypothesis on water use can be categorized into three primary types: monotonic relationships, U-shaped or inverted U-shaped patterns, and N-shaped or inverted N-shaped patterns. Among monotonic relationships, Wang et al. (2017), for example, show that a linear regression model provides the best fit to the data for the Urumqi region in China, with a positive parameter linking water demand and income. This leads to predicting a proportional increase in total water demand as GDP and GDP per capita rise over time. Among studies finding evidence of EKC, Rock (1998) observed an inverted U-shaped relationship between per capita income and water consumption in the USA; Jia et al. (2006) between industrial water consumption and income in most OECD countries; Duarte et al. (2013) between per capita water consumption and per capita income for 65 countries; Najafi Alamdarlo (2016) between per capita income and water consumption on an Iranian inter-provincial panel data; Gu et al. (2017), Sun and Fang (2018) and Zhao et al. (2017) between water consumption and economic growth in various departments in China.

Among studies that find N-shaped or inverted N-shaped relationships, Zhao et al. (2017) analysed panel data from 27 countries and discovered an N-shaped pattern between per capita urban water consumption and per capita GDP; Hao et al. (2019) between per capita water consumption and per capita GDP on panel data from 29 provinces in China.

Whether empirical analyses find an inverted U-shaped relationship between water and income depends on a number of factors. A crucial role is played by differences in water indicators used (water withdrawals, water quality, access to water and sanitation), which respond to income differently (Katz, 2015). Secondly, existing studies refer to different countries and a mix of different territorial scales, varying from cities, provinces, and groups of countries. Some are single-country studies, some are panel studies with heterogeneous temporal scopes. Finally, methodological choices varying from standard least squares to non-parametric models contribute to explaining the high heterogeneity in the empirical results.

While many of these studies focus broadly on water use or consumption, only two, to date, have adopted water footprint as the indicator of environmental pressure in testing the EKC hypothesis (Miglietta et al., 2017; Sebri, 2016). Both studies found an N-shaped relationship. This means that environmental impacts initially increase with income, then decline after a first turning point, but return to increase for higher levels of per capita income, in disagreement with the EKC hypothesis. A key limitation of these two studies is that, due to the lack of sufficiently large *WF* datasets at the time, they were constrained to rely on cross-sectional data. This, as acknowledged in Miglietta et al. (2017), does not allow the time dimension to be considered in the

Table 1
Variable description and descriptive statistics.

Variable name	Abbreviation	Mean	Min	Max	St.Dev.	Unit of measure	Source
Water footprint of production	*WFP*	5.3E+10	1.9E+07	1.1E+12	1.4E+11	m^3 per year	CWASI - https://www.watertofood.org/
Water footprint of consumption	*WFC*	5.4E+10	2.0E+08	1.1E+12	1.3E+11	m^3 per year	CWASI - https://www.watertofood.org/
Population	*P*	5.1E+07	1.0E+06	1.4E+09	1.6E+08	Unit	FAO - https://www.fao.org/faostat/en/#home
Real gross domestic product at constant national prices	*GDP*	6.1E+11	5.3E+08	1.9E+13	1.8E+12	2017 US$	Penn world table https://www.rug.nl/ggdc/productivity/pwt/?lang=en
Harvested area	*HA*	9.6E+06	2.2E+03	2.0E+08	2.5E+07	ha per year	FAO - https://www.fao.org/faostat/en/#home
Vegetal protein supply	*VPS*	2.4E+09	3.6E+07	8.9E+10	8.4E+09	g per day	FAO - https://www.fao.org/faostat/en/#home

analysis. In this paper, thanks to the now available CWASI database, we can re-investigate the relationship between economic growth and water footprint with panel data, taking into account the time evolution of water use at a global level. Furthermore, we investigate whether and how per capita income relates to countries' pressure on water resources from the perspective of both production and consumption-based approaches — which was not done in previous works.

3. Data

We use a balanced panel dataset, with 121 countries representing about 95% of the world's population for a 24-year time interval from 1993 to 2016.[4] Table 1 shows information about the variables included in the models and the corresponding data source. The final models share as covariates the harvested area per capita (*HA/P*) and the vegetal protein supply per capita (*VPS/P*), aiming to depict a nation's land use and the dietary composition of its population, respectively.

The covariates were selected by paying attention to their correlation with GDP per capita, to avoid multicollinearity, which could lead to unreliable statistical inferences. These variables were included to capture structural and nutritional aspects of agricultural and food systems that could independently influence Water Footprint beyond the effect of income. While they may be partially related to GDP, empirical correlation tests show only modest pairwise correlations with GDP per capita (e.g., $r = -0.3$ and $r = 0.01$ for harvested area per capita and vegetal protein supply per capita, respectively). This indicates that their inclusion does not raise serious multicollinearity concerns. Moreover, likelihood-ratio tests were applied to compare different model specifications and combinations of covariates. These tests support the inclusion of harvested area and vegetal protein supply, as they improve model fit and help control for omitted variable bias.

We also conducted robustness checks by re-estimating the models without these two controls. The main coefficients of interest (particularly those on GDP per capita and its square) are confirmed in sign, magnitude, and significance for WFC. In the case of WFP, as well, the long-run effect is confirmed, with a linear decreasing relationship between WFP and GDP (although without an inverted U-shape). This suggests that the inclusion of these controls does not alter the core results while accounting for structural heterogeneity across countries. Additional covariates considered – including water availability, water stress, surface mean temperature, urbanization rate, and population density – were not retained in the final models, as they were strongly correlated to GDP and/or did not prove to be significantly different from zero.

The CWASI database (Tamea et al., 2021) provides the most up-to-date information on water footprint, adding to previous datasets such as *WaterStat* by Mekonnen and Hoekstra 2011a the significant temporal variability in crop-specific unit water footprints.[5]

We use data on the water used by the primary sector, including 370 crops, crop-based and animal-based commodities, both unprocessed and processed. The water footprint of production (*WFP*) accounts for the above at the national level. In addition to the WFP, the database includes the water flows traded on international markets (the virtual water of international trade), thus allowing us to consider not only locally produced but also imported and exported food.

The relationship between consumption and production in Eq. (1) enables us to evaluate the water footprint of consumption (*WFC*) and analyse both (i) the impact of local production due to local water withdrawals and (ii) the impact of local consumption, due partly to local water withdrawals and partly to foreign withdrawals embedded in imported goods.

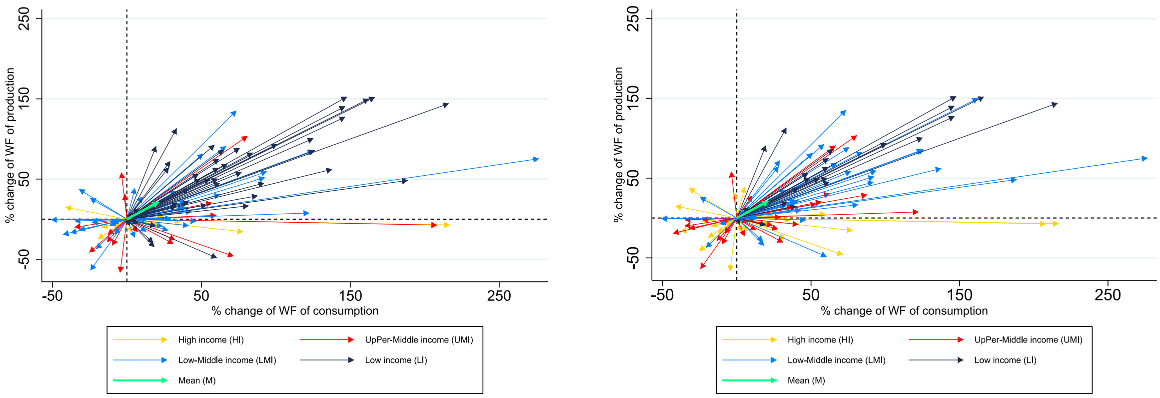
At the global level, at which total imports and exports compensate and hence *WFC* and *WFP* coincide,[6] the world *WF* increased between 1993 and 2016 by about 21%, from about 5725 billion m^3 of *WF* in 1993 to about 6930 billion m^3 of *WF* in 2016. For single countries, instead, food trade and the associated virtual water flows play an important role and give rise to more complex and interesting dynamics.

Some first insights can be obtained by considering the percentage variation from 1993 to 2016 of the total *WFP* and *WFC* of all individual countries, and identifying them according to the World Bank income classification. To account for the dynamic nature of the income status of countries, we consider the 1993 and 2016 classifications as alternative lenses through which to interpret the patterns. Fig. 1 shows the direction in which each country has moved over time in terms of *WFP* and *WFC*, with arrows coloured by income group based on both classifications (panel A and B). The two panels depict the same average relationship (summarized in the green arrow). In both cases for most countries *WFP* and *WFC* increased over time, so that we observe a large concentration in the first quadrant. This pattern is particularly representative of low income (LI) and low-middle-income (LMI) countries (represented in shades of blue). Based on the 2016 classification, 91% of LI countries and 78% of LMI in our dataset are in the first quadrant (against 20% of high income countries (HI) and 35% of upper-middle income countries (UMI)). This means that both *WF*

[4] The list of countries can be found in Table Appendix A.1 in the Supplementary Material.

[5] This variability arises from changes in precipitation, temperature, evapotranspiration, and yields over time. In contrast, the unit water footprint for animal-based commodities (e.g., meat, dairy, eggs, and live animals) remains time-invariant in CWASI, due to the lack of reliable time-series data on country-specific animal diets. These values are based on long-term averages from 1996 to 2005 (Mekonnen & Hoekstra, 2012) and are attributed to the year 2000.

[6] See Eq. (1) and footnote 2.



(a) Income classification based on 1993

(b) Income classification based on 2016

Fig. 1. Scatterplot-like of percentage changes in *WFP* and *WFC* between 1993 and 2016. Arrows' colours represent World Bank income groups, using classifications from 1993 (a) and 2016 (b). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

have increased simultaneously more frequently in developing countries than in industrialized ones.

In the third quadrant, where both *WFP* and *WFC* decrease, high income and low middle income countries are the most frequent (33% and 35% respectively). No low income country falls in this quadrant. Furthermore, we see that 37% of HI and 26% of UMI have increased their reliance on water withdrawals from abroad (quadrant II), compared to just 11% of LMI and 9% of LI. Finally, only five countries (three of them belonging to Eastern Europe) have decreased their *WFC* while increasing *WFP*, meaning that their net food exports have increased (quadrant IV). In the 1993 classification, the distribution of income groups reflects stronger global inequalities: many of the UMI or HI countries in 2016 were still LI or LMI in 1993, resulting in a predominance of blue colours in panel (a).[7]

However, deeper insights emerge if we examine the temporal variation of the water embedded in food production and consumption. By calculating the relative variation in the total water footprint for each income group over the period – where totals are computed by summing the values across all countries within each group – we find that the total *WFP* has increased for LI countries (+68.49%), LMI countries (+30.24%) and UMI countries (+15.25%), while it has decreased (−1.94%) only in HI countries in aggregate. At the same time, the *WFC* has increased in all income groups, by +72,2% in LI countries, +32,71% in LM countries, +13,74% in UM countries, and +2,73% in HI countries. The aggregate global variation is represented by the green arrow in Fig. 1, which shows that both the global *WFP* and the global *WFC* have increased in the 24-year observed period.

We can add further understanding of these dynamics by focusing on the role played by each income group of countries in terms of the total volume of virtual water traded on global food markets. Considering the cumulated value of traded *WF* over the period 1993–2016, HI countries are the only stable net importers of virtual water. Fig. 2 shows that HI countries have increased net water imports by 39% over the 24-year observed period. UMI countries' net exports have increased by 67%, whereas LMI countries, which have been net exporters for most of the observed period, turned into net importers in 2016. LI countries remain on the sidelines of global virtual water trade. This descriptive representation shows that richer states have increased over the observed period their delocalization of food production: they satisfy their rising consumption by increasing net food imports and the associated virtual water.

[7] While our main interest is to observe the dynamics of the total water footprint over time for countries in different income groups, we replicated the analysis using per capita values. The figure in Appendix A2 reveals that the mean global *WF* per capita is decreasing; however, with per capita values many countries shift from the first to the second quadrant. This indicates that they have increased per capita *WFC* while reducing per capita *WFP*, with the per capita perspective more clearly revealing the delocalization of water use associated with food production.

4. Method

To enhance our comprehension of the relationship between per capita *WF* of consumption and production, GDP per capita, and other covariates, we formalize this relationship by adopting the following model:

$$\ln\left(\frac{WF}{P}\right)_{it} = \beta_0 + \beta_1 \ln\left(\frac{GDP}{P}\right)_{it} + \beta_2 \ln\left(\frac{GDP}{P}\right)^2_{it} + \beta_3 \ln\left(\frac{GDP}{P}\right)^3_{it} + \sum_{j=4}^{J} \beta_j X_{itj} + \epsilon_{it}, \tag{2}$$

with $i = 1, \dots, N$ denoting the cross-sectional units (i.e., countries), $t = 1, \dots, T$ the time periods, X_j represents the j−covariate and β_j the associated coefficients to be estimated. *GDP* is incorporated into the model as a first, second and third-order polynomial to investigate the shape of its relationship with *WF*. Following the seminal methodological paper by Stern (2004), to avoid meaningless negative predicted values and to interpret the estimated coefficients directly as elasticities, we apply a logarithmic transformation to both the dependent and independent variables.

4.1. Preliminary tests on panel data

Building on the contribution of Perman and Stern (2003), various methodologies have been developed to assess the nature of time series and the statistical properties of variables in macro-panels (Eberhardt, 2012). Recent literature has consistently tested a set of assumptions: time series cross-sectional dependence and stationarity, model cointegration, and slope homogeneity of the estimated parameters. A standard regression analysis on time series, or panel data, assumes that all processes are stationary. Regression analyses on non-stationary processes can, in fact, result in spurious relationships. We need, therefore, to test whether the time series of all our variables have mean and variance constant over time and if the covariance between any two variables in the series depends only on the length of the interval between them and not on the moment in time at which the variables are observed.

To select the appropriate test for investigating stationarity, we first assess the cross-sectional dependence of processes using the Pesaran

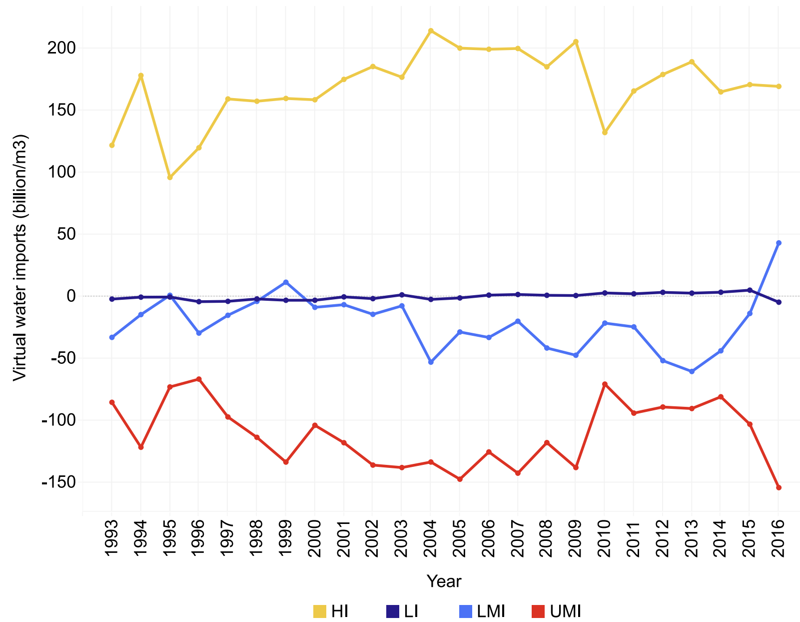


Fig. 2. Time evolution of net virtual water imports (1993–2016) by income per capita categories according to World Bank classifications for 121 countries listed in Appendix A.

Table 2
Pesaran test results.

Variable	Statistics
$\ln(WFP/P)$	6.116 (***)
$\ln(WFC/P)$	5.802 (***)
$\ln(GDP/P)$	13.274 (***)
$\ln(GDP/P)^2$	12.22 (***)
$\ln(HA/P)$	4.419 (***)
$\ln(VPS/P)$	3.293 (***)

*, **, *** significance levels at the 10%, 5% and 1% respectively. The null hypothesis conjectures the absence of cross-sectional dependence.

Table 3
pCADF test (left) and pCADF test on first differences (right).

Variable	Statistics	Variable	Statistics
$\ln(WFP/P)$	2.213 ( )	$\Delta\ln(WFP/P)$	−9.983 (***)
$\ln(WFC/P)$	1.639 ( )	$\Delta\ln(WFC/P)$	−12.235 (***)
$\ln(GDP/P)$	4.027 ( )	$\Delta\ln(GDP/P)$	−3.311 (***)
$\ln(GDP/P)^2$	4.558 ( )	$\Delta\ln(GDP/P)^2$	−3.234 (***)
$\ln(HA/P)$	0.864 ( )	$\Delta\ln(HA/P)$	−11.014 (***)
$\ln(VPS/P)$	0.767 ( )	$\Delta\ln(VPS/P)$	−18.902 (***)

*, **, *** significance levels at the 10%, 5% and 1% respectively. The null hypothesis conjectures non-stationary time series.

test (Pesaran, 2021) under the null hypothesis of cross-sectional independence. This test is suitable for assessing a wide range of models, including stationary dynamic and heterogeneous panels with short T and large N.

The results in Table 2 show the presence of cross-sectional dependence, and therefore, the use of stationarity tests robust to cross-sectional dependence is required. We perform the *pCADF* test (Costantini & Lupi, 2013) and find evidence of non-stationarity for all series (Table 3 left). By considering their first differences, stationarity emerges for all series, which thus turn out to be integrated of order one.[8]

[8] The order of integration indicates the number of times a series must be differentiated to become a stationary process.

Since dealing with series integrated of order 1 raises the risk of providing biased statistical evidence of the relationship among variables, we test whether the models for *WFP/P* and *WFC/P* are cointegrated. Failure to account for cointegration can lead to spurious relationships, wherein variables appear to be correlated but are not. On the contrary, if the series are cointegrated, we ensure that the regression results provide meaningful statistical evidence of the long-run relationships among the variables. To investigate cointegration, we employ the tests proposed by Pedroni (1999, 2004) and Westerlund (2005). These tests consider panel-specific autoregressive (AR) assumptions, and we perform them considering the presence of cross-sectional dependence. The test statistics, when considering *WFP/P* and *WFC/P* as response variables, indicate that the series are cointegrated, as shown in Table 4.

Nevertheless, Wagner (2015) highlights a key limitation in standard cointegration analysis: when non-linear transformations of the series, such as squares or interaction terms, are introduced, the resulting series may not preserve the integration properties of the original ones. This challenges the validity of standard cointegration tests, which assume linear relationships among I(1) series. To address this issue, we follow the approach proposed by Pedroni (2019), which is specifically designed for heterogeneous panel settings and allows testing for non-linear cointegration. The procedure is two-step. After estimating unit-specific slopes for each unit of the panel, in the second stage, these estimated slopes are regressed on polynomial transformations of the independent variable (GDP in our case), using cross-sectional data. This allows us to assess whether and how the relationship between WFP and GDP varies with the order of the GDP polynomial. In essence, the approach uses cross-sectional heterogeneity to uncover richer, possibly nonlinear relationships, without imposing strong prior parametric assumptions. According to Pedroni (2019), this technique is especially valuable in panels with short time dimensions, and it remains valid even when omitted dynamics and common factors are present. The last row in Table 4 includes the non-linear Pedroni test for the Water Footprint of Production. The test rejects the null hypothesis, supporting the presence of non-linear cointegration between *WFP* and per capita GDP. In contrast, for *WFC*, we did not conduct the test because the linear model proved to be the best performing in the analyses. Therefore, traditional cointegration tests were sufficient.

Table 4
Cointegration tests.

Pedroni	*WFP/P* statistic	*WFC/P* statistic
Modified Phillips-Perron t	3.545 (***)	−3.571 (***)
Phillips-Perron t	−7.557 (***)	−21.999 (***)
Augmented Dickey-Fuller t	−11.374 (***)	−25.911 (***)
Westerlund	*WFP/P* statistic	*WFC/P* statistic
Variance ratio	−5.153 (***)	−5.450 (***)
Non-linear Pedroni cointegration Test	*WFP/P* statistic	*WFC/P* statistic
Mean *c*	0.018 (***)[a]	

*, **, *** significance levels at the 10%, 5% and 1% respectively. The null hypothesis conjectures non-cointegrated models.

[a] All the 24 years showed a statistically significant interaction term (c) at 1%. The null hypothesis conjectures the absence of non-linearly cointegrated models.

Table 5
Delta test.

Response variable	Non-adjusted statistics	Adjusted statistics
WFP/P	41.678 (***)	48.125 (***)
WFC/P	34.350 (***)	38.606 (***)

*, **, *** significance levels at the 10%, 5% and 1% level of significance respectively. The null hypothesis conjectures homogeneous coefficients.

Once the assumptions on cross-sectional dependence and stationarity have been verified, testing the intercepts and slopes' homogeneity is essential to select the appropriate estimator. To examine the homogeneity assumption, we employ a Delta test (Blomquist & Westerlund, 2013; Pesaran & Yamagata, 2008) on models for *WFC* and *WFP* per capita. However, given that the Delta test requires N and T to jointly tend towards infinity, we also implemented the mean–variance, or small sample, bias-adjusted Delta test. The results of both tests, as presented in Table 5, strongly indicate the rejection of the null hypothesis of homogeneous coefficients and recommend employing estimators capable of considering variations in intercepts and slopes. This result was expected since the coefficients might demonstrate heterogeneity due to spatial effects, omitted common effects, or spillovers, leading to variations between countries in their relationship between income and water footprints.

4.2. Model estimate

The growing availability of panel environmental data, characterized by large sample sizes (N) and extensive periods (T), has reignited the methodological discussion regarding the robustness of econometric approaches used to assess the validity of empirical tests of EKC, as highlighted, among others, by Perman and Stern (2003). In the econometric literature dedicated to macro-panels, there has been a concerted effort to investigate novel estimation techniques that can effectively tackle methodological challenges associated with the assumption of homogeneous slopes. In fact, despite intercept variations, cross-sectional units may still exhibit shared characteristics of interest, such as spatial effects, omitted common effects, or spillovers. In the presence of cross-sectional error dependence, traditional panel data estimators like fixed or random effects are prone to yielding inconsistent parameter estimates. The investigation of appropriate estimators for heterogeneous panels has followed multiple methodological directions, as outlined in the review by Isik et al. (2021). Among the most prominent approaches are the Fully-Modified Ordinary Least Squares (FMOLS), Autoregressive Distributed Lag (ARDL), Dynamic DOLS Ordinary Least Squares (DOLS), the growth rate approach (Stern, 2017), along with the Mean Group (MG) estimators introduced by Pesaran and Smith (1995). These have been further developed into variants such as the Augmented MG and Common Correlated Effects MG proposed by Teal and Eberhardt (2010). A further promising line of development involves the application of multilevel or mixed effects models to panel data (see e.g. Rabe-Hesketh and Skrondal (2022)).

One key distinction between panel Mean Group estimators and mixed effects models is how they estimate the average effect (constant across individuals) and the individual or random effects. With MG estimators, individual-specific regressions are fitted by ordinary least-squares (OLS), and the individual-specific estimated parameters are then averaged across the panel to derive a quantity representing the overall effect as an average of individual effects. In contrast, mixed effects models estimate directly the parameters representing the common effect, with the random effects derived from the estimated variance–covariance matrix representing the deviation of each individual from the average effect. The meta-analysis conducted by Saqib and Benhmad (2021) on more than 500 papers shows that, regardless of the specific methodology employed, only the quality of the panel data used and the implementation of methods dealing with heterogeneous panels (specifically MG estimators and mixed models) can increase the robustness of EKC hypothesis tests.

In this paper, we employ a mixed effects model to extract insights into the variation in regression coefficients rather than capturing a generalized behaviour as an average of country-specific dynamics. Constrained by limited income ranges, country-specific estimates may, in fact, inadequately discern the curvature within a general function. While the mixed model is not a dynamic error-correction model per se, it is appropriate when the regressors are cointegrated with the dependent variable and the series are stationary. Moreover, fixed-effects models explicitly remove the within-group means (i.e., de-mean the data), mixed-effects models allow for the estimation of both within- and between-group variation by modelling group-specific effects as random. This choice avoids discarding between-country information. In fact, as Stern (2017) notes: “The fact that long-run GDP growth rates filter out non-stationary dynamics, short-run relations, time-varying effects, and variables that might explain variation in the initial level of emissions across countries means that we cannot use our approach to assess these important issues. [...] This omission is shared with the panel data approach with country fixed effects.”. For these reasons, we adopt a mixed-effects modelling strategy that allows us to retain and explicitly model the between-country variation in both intercepts and slopes, while still controlling for unobserved heterogeneity. This structure provides greater flexibility than fixed-effects models, especially when exploring heterogeneous long-run relationships and accounting for country-specific responses to income changes. Furthermore, our model is estimated after testing and confirming the cointegration of the series, ensuring that the estimated coefficients represent long-run equilibrium relationships.

The models presented in Eq. (2) were estimated while testing multiple covariates and up to a cubic polynomial for GDP per capita. Likelihood-ratio tests have been applied to compare different models and to assess the suitability of modelling random intercepts and slopes for GDP/P instead of constant ones. To accommodate heterogeneity in intercept and slope parameters, the parameters to be estimated can be decomposed into a fixed term (constant across countries, also known as a fixed effect) and a random term (different across countries, also referred to as an individual or random effect). Consequently, the β_0, β_1 and β_2 coefficients of the model in (2) can be defined as:

$$\beta_{ij} = \gamma_j + \delta_{ij} \text{ for } j = 0, 1, 2, \tag{3}$$

where δ_{ij} represent the random effects of each country i for the intercept and for the coefficients of $\ln(GDP/P)$ and $\ln(GDP/P)^2$. Thus, Eq. (2) assumes the following form:

$$\begin{aligned}\ln\left(\frac{WF}{P}\right)_{it} &= \beta_{i0} + \beta_{i1}\ln\left(\frac{GDP}{P}\right)_{it} + \beta_{i2}\ln\left(\frac{GDP}{P}\right)^2_{it} \\ &\quad + \beta_{i3}\ln\left(\frac{HA}{P}\right)_{it} + \beta_{i4}\ln\left(\frac{VPS}{P}\right)_{it} + \epsilon_{it}\end{aligned} \tag{4}$$

Additionally, we employed an unstructured random-effects covariance matrix, allowing us to estimate distinct variances and covariances

Table 6
Mixed effect models estimates and summary information for WFP per capita.

	Linear	Quadratic	Cubic
Fixed effects			
$\ln(GDP/P)$	0.009	0.206*	0.836
	(0.009)	(0.108)	(0.889)
$\ln(GDP/P)^2$		−0.0121**	−0.085
		(0.006)	(0.103)
$\ln(GDP/P)^3$			0.002
			(0.004)
$\ln(HA/P)$	0.930***	0.927***	0.927***
	(0.019)	(0.018)	(0.018)
$\ln(VPS/P)$	−0.097***	−0.101***	−0.100***
	(0.036)	(0.038)	(0.037)
Intercept	8.717***	7.932***	6.136***
	(0.180)	(0.378)	(2.511)
Estimated SD for random effects			
sd($\ln(GDP/P)$)	0.112***	0.705***	0.847***
	(0.145)	(0.404)	(0.255)
sd($\ln((GDP/P)^2)$)		0.021***	0.046***
		(0.006)	(0.125)
sd(Intercept)	1.087***	3.576***	3.637***
	(0.101)	(0.591)	(1.268)
sd(Residual)	0.043***	0.042***	0.042***
	(0.004)	(0.000)	(0.004)
N. observations	2904	2904	2904
N. groups	121	121	121
Wald Chisq	2568 (3 d.f.)	2937 (4 d.f.)	2927.14 (5 d.f.)

*, **, *** p-values lower than 10%, 5% and 1% respectively. *Standard Errors robust to heteroskedasticity and serial correlation* in parentheses.

for random effects. The coefficients of the model in (4) with the specification as in (3) have been estimated using restricted maximum likelihood estimators for both *WFC/P* and *WFP/P* (as in Leckie (2014) and Rabe-Hesketh and Skrondal (2022)).

5. Results

Tables 6 and 7 report the coefficient estimates and summary information for the different specifications of the models. We tested linear, quadratic and cubic transformation of *GDP/P* for the *WFP* (the quantity of water per capita that countries extract and use to produce food locally) reported in Table 6 and for the *WFC* (the quantity of water per capita embedded in a country's total demand for food products, regardless of where that food has been produced) in Table 7.

In the case of *WFP/P*, the linear and the cubic models resulted statistically not significant, thus rejecting a linear and a N-shaped relationship between *WFP/P* and *GDP/P*. The quadratic relationship between *WFP/P* and *GDP/P* proved statistically significant, implying that the water footprint of production per capita initially increases with economic growth, but it then reverses the trend and starts to decrease when countries get sufficiently rich, i.e. after a given threshold of per capita income (Fig. 3(a)).

Table 6 also reports the estimated standard deviations for the β_0, β_1, and β_2 coefficients. All of these standard deviations are statistically significant, indicating the intercept and slope heterogeneity and thus supporting the use of the mixed effects model.

In order to take into account random effects and to illustrate the extent of variability in the estimated parameters, we rely on the semi-parametric residual bootstrap algorithm proposed by Carpenter et al. 2003. The algorithm obtains parameter estimates

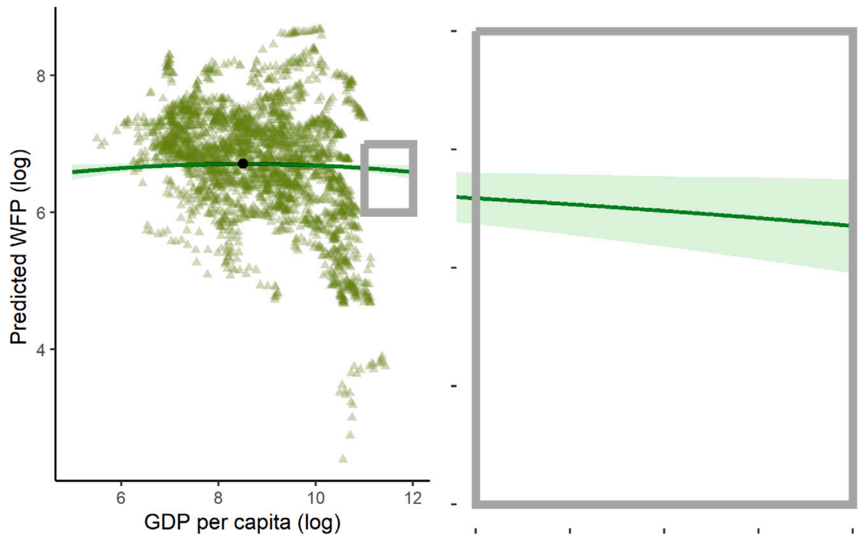
from the fitted model, along with the estimated residuals and Empirical Best Linear Unbiased Predictors (EBLUPs). It then rescales the residuals and EBLUPs so that their empirical variances match the variance components estimated by the model. From these rescaled quantities, the algorithm independently samples with replacement to generate bootstrap replicates. Using these bootstrap samples, new response variables are constructed according to the model equation, producing bootstrap datasets. The model is then refitted to each bootstrap dataset, and the statistics of interest are extracted. This process of sampling, data reconstruction, and model refitting is repeated B times to obtain an empirical distribution of the statistics, which can be used to assess variability and construct confidence intervals. Notably, bootstrapping proves particularly valuable for assessing the uncertainty around random effects, such as country-level intercepts or slopes, where traditional standard errors are (unavailable or) unreliable. In sum, the bootstrapping strategy allows for the distinction of genuine heterogeneity from mere statistical noise. It enhances the inferential power of mixed models, offering a rigorous and interpretable path to inference, particularly in our settings where structural heterogeneity complicates traditional assumptions.

Panel (a) of Fig. 3 presents the fitted relationships obtained from applying residual bootstrap linear mixed-effects models fitted to 1000 bootstrap resamples of the dataset represented by the thin green lines. Fitted values are represented by green triangles (T). The thick black line represents the predicted EKC from the model fitted to the original (non-resampled) data, with the estimated turning point indicated by a black dot. The right-hand panel provides a detailed view of the region highlighted by the grey rectangle in the left panel, allowing for a deeper examination of the variability in the bootstrap-based estimates.

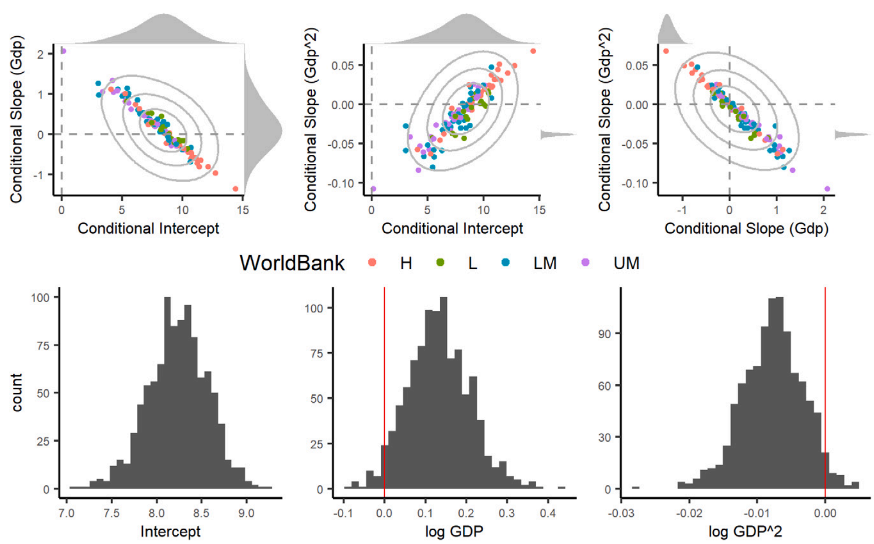
Fig. 3(b) reports the pairwise correlations among the Best Linear Unbiased Predictors (BLUPs) of the random intercept and random slopes parameters across experimental units. Data points are colour-coded according to the World Bank income classification. Ellipses represent bivariate normal confidence intervals, while the marginal density plots along the axes depict the distribution of the corresponding estimated random effects (in grey). The negative correlation between intercept and linear slopes (left panel), and between linear and quadratic slopes (right panel), suggests a systematic trade-off in how country-specific deviations from the fixed effects manifest across different components of the GDP-WFP relationship. These patterns support the presence of heterogeneous responses across countries and reinforce the relevance of allowing for random slopes in modelling the EKC hypothesis.

The histograms (Fig. 3(b)) display the empirical distribution of the marginal (i.e., fixed-effect) estimates for the intercept and slope parameters obtained by residual bootstrap with $B = 1000$. Crucially, for the purpose of testing the EKC hypothesis, it should be noted that the sign of the linear GDP coefficient becomes negative in only 3.6% of the bootstrap replications and the quadratic term becomes positive in only 3.8% of the cases. This indicates that the overall inverted U-shape relationship between *WFP* and GDP per capita is highly robust across the sampled parameter distributions.

After analysing the regression outcomes and the associated variability across bootstrap replications, we assess whether the turning point is reached within the observed level of income – a necessary condition for the positive signal to be such – we compute the latter as $-\left(\frac{\hat{\gamma}_1}{2\cdot\hat{\gamma}_2}\right)$, where $\hat{\gamma}_1$ represents the estimated parameter for the common effect of per capita income, and $\hat{\gamma}_2$ denotes the estimated parameter for its square. This is equivalent to fixing all random effects in the model to their theoretical mean value of 0, representing the overall long-run pattern across countries. This yields a relatively low turning point of 4976.08 US$, falling between the 25th and the 50th per capita income percentiles. One could argue that estimating the turning point should consider the variation in the estimated parameters. Unfortunately, the turning point is approximately distributed as the ratio of two normal random variables, yielding a Cauchy distribution with undefined expected value and variance (Johnson et al., 1995). However, its mode and median are well-defined. To address this issue, we conducted a Monte Carlo simulation to estimate the median turning point. We randomly drew 1000 pairs of $\hat{\gamma}_1$ and $\hat{\gamma}_2$ values from a bivariate normal distribution with mean vector equal to 0.206 and −0.0121 and using their estimated covariance matrix and calculated the corresponding turning point and identified



(a) Fitted relationships obtained from applying residual bootstrap linear mixed-effects models fitted to 1,000 bootstrap resamples of the dataset. The right panel is a detailed view of the quadrant indicated with a grey rectangle in the left panel.



(b) Scatterplot and estimated marginal densities of random intercept and random slopes, differentiated by World Bank classification with marginal density distributions (Top). Histograms of the empirical distribution of the marginal (i.e. fixed effect) intercept and slopes parameters estimated from 1000 bootstraps (Down).

Fig. 3. Results about the relationship between *WFP/P* and *GDP/P*. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the median turning point from these simulated values. By repeating the procedure 10,000 times, we generated an empirical distribution of the median of the turning point. We computed this distribution's mean and standard deviation, resulting in an average median turning point of 5194.75 US$ per capita — remarkably similar to the calculation based on the estimated parameters. We find a modest standard deviation of 115,76 US$/pc, so that the value of the turning point ranges from 4783 US$/pc (around the 40th percentile of the per capita income distribution) to 5662 US$/pc.[9]

From the results presented in Table 6, it is feasible to predict the *WFP* per capita corresponding to the turning point. This prediction involves using the estimated parameters alongside the per capita income at the turning point while setting the remaining variables at their mean values. In this case, the *WFP* per capita calculated at the income turning point is 820 m^3/pc/year, marginally lower than the median of the observed *WFP* per capita. This value corresponds to the level of *WFP* at which further increases in income per capita start yielding a declining *WFP* in a country with an average value of harvested area and an average vegetable protein supply. To gauge the variability in the prediction, we also computed the forecasted consumption by adjusting the other variables to their mean plus/minus their standard deviation. When the other variables are set at their mean minus one standard deviation, the result (391 m^3/pc/year) falls between the 10th and 25th percentiles of the observed *WFP*. In contrast, setting the variables at their mean plus one standard deviation places the result (1723 m^3/pc/year) between the 75th and 90th percentiles.

[9] In Fig. 3, outliers are visible in the bottom right. The points are related to Kuwait, a country with a very low *WFP* per capita but one of the highest *GDP* per capita. We re-estimate the models by excluding Kuwait as a robustness check. We do not report the results because they are almost unchanged with respect to the ones on the full sample (particularly those on GDP per capita and its square).

Table 7
Mixed effect models estimates and summary information for WFC per capita.

	Linear	Quadratic	Cubic
Fixed effects			
$\ln(GDP/P)$	0.055**	0.236	−0.530
	(0.025)	(0.264)	(1.289)
$\ln(GDP/P)^2$		−0.009	0.063
		(0.014)	(0.158)
$\ln(GDP/P)^3$			−0.002
			(0.006)
$\ln(HA/P)$	0.423***	0.423***	0.459***
	(0.060)	(0.043)	(0.057)
$\ln(VPS/P)$	0.124	0.102	−0.122
	(0.091)	(0.086)	(0.101)
Intercept	6.800***	6.011***	8.677***
	(0.378)	(1.156)	(3.518)
Estimated SD for random effects			
$sd(\ln(GDP/P))$	0.253***	2.085***	0.000
	(0.044)	(0.258)	(0.000)
$sd(\ln((GDP/P)^2))$		0.116***	0.102***
		(0.015)	(0.003)
sd(Intercept)	2.302***	9.128***	0.855***
	(0.456)	(1.110)	(0.242)
sd(Residual)	0.136***	0.134***	0.139***
	(0.013)	(0.012)	(0.014)
N. observations	2904	2904	2904
N. groups	121	121	121
Wald Chisq	61.12 (3 d.f.)	100.49 (4 d.f.)	84.28 (5 d.f.)

*, **, *** p-values lower than 10%, 5% and 1% respectively. *Standard Errors robust to heteroskedasticity and serial correlation* in parentheses.

The results for *WFC/P* presented in Table 7 and in Fig. 4 deviate from those of *WFP/P* in that they show a linear relationship between *WFC/P* and per capita income.

The per capita water footprint of consumption increases with income at a rate of 0.05% for every additional percentage point increase in per capita income. The coefficients of the quadratic and cubic terms of income per capita were not statistically different from zero, suggesting a lack of support for an inverted U- or N-shaped relation between *GDP/P* per capita and *WFC/P* (4).

We further examined the relationship between *WFC/P* and *GDP/P* by applying the same bootstrapping procedure used for *WFP/P*. The observed values (light blue circles) follow a predominantly positive slope, suggesting an increasing trend of *WFC/P* as *GDP/P* rises. The thick black line represents the estimate based on the original data, further confirming this positive direction.

In Fig. 4(b) the correlations between the estimated random effects for the intercept and the linear term of *GDP/P* reveal a systematic pattern. Specifically, lower-income countries tend to exhibit lower intercepts coupled with steeper slopes, indicating a more pronounced increase in water footprint as income rises. In contrast, higher-income countries are characterized by higher intercepts and flatter slopes, suggesting that water footprint levels are already high and tend to increase more slowly, or potentially plateau, as income continues to grow. The marginal distributions of the fixed-effect estimates (shown as histograms) indicate limited variability, with the slope associated with GDP/P remaining consistently positive across bootstrap resamples. This provides robust support for a stable and monotonically increasing relationship between per capita income and water footprint.

Regarding the other estimated coefficients, vegetal protein supply per capita and harvested area per capita both show a significant impact on *WFP/P* and *WFC/P*. In our results, an increase in vegetal protein supply decreases *WFP/P* by 0.10%. In contrast, for *WFC* the coefficient is positive. A 1% increase in vegetable protein consumption results in a 0.12% increase in *WFC/P* (even if not statistically significant).

At the global level, on average, during our 24-year observation period the per capita vegetal protein supply has increased by 10%, while per capita meat protein supply (which is highly correlated to income) has increased by 27.7%. The impact of vegetal protein supply on *WFP/P* and *WFC/P* cannot therefore be ascribed to dietary changes. Rather, it could be determined by dominance in the average global effect of an increase over time in per capita vegetal protein supply in low- and middle-income countries, associated with a simultaneous improvement in water efficiency of agricultural production (decreasing *WFP/P*) and with an increase in per capita food consumption (increasing *WFC/P*). The opposite direction of change between the two *WF* could also be interpreted as a result of changes in the balance between virtual water imports and exports (see Eq. (1)). The increase in vegetal protein supply could also be associated with a country's transition towards a reduction of the virtual water content of exports and a simultaneous increase in the virtual water content of imports. An increase of 1% in harvested area per capita generates a statistically significant increase of 0.92% in *WFP/P* and of 0.42% in *WFC/P*. Expanding cultivated areas exerts a more than double influence on *WFP/P* than on *WFC/P*. The relationships expressed in Eq. (1) indicate that an increase in cultivated areas within a country, which translates into an increase in that country's water footprint of production, implies an equal increase in the water footprint of consumption if the trade *WF* balance ($WFI - WFE$) remains unchanged. The fact that our results show a slower increase in *WFC/P* than in *WFP/P* appears to indicate that an increasing per capita harvested areas correlates with a higher propensity to be net virtual water exporters.

6. Discussion and conclusions

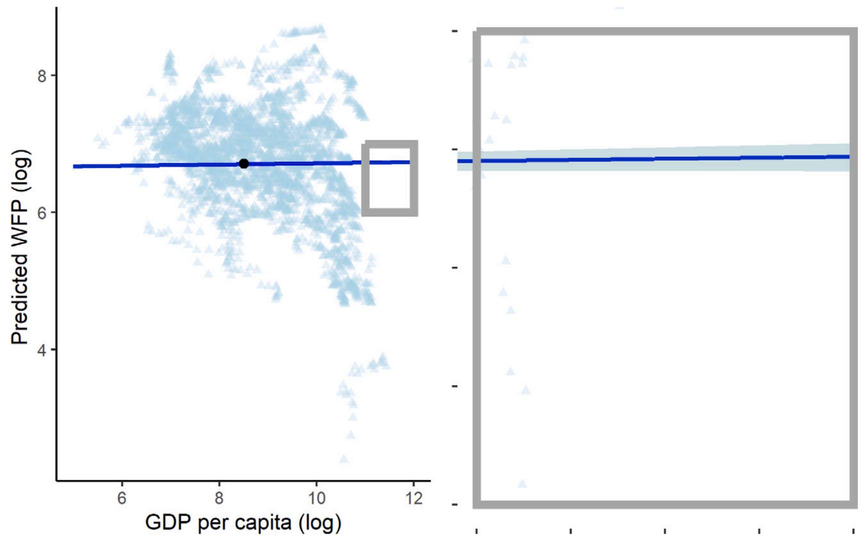
In this paper, we conducted a comprehensive analysis of the relationship between per capita income and the water footprint of both consumption and production across 121 countries over a 24-year period. Our aim was to introduce a potentially innovative perspective on the complex interplay between economic development and the use of freshwater resources.

Methodologically, the paper proposes initial tests aligned with established econometric techniques guiding the specification of a mixed effects model. The latter, thanks to its capacity to deal with heterogeneous panels, allows this study to increase the robustness of the analysis compared to much of the previous literature on the Environmental Kuznets Curve hypothesis. A large and novel dataset on the water footprint of nations enables us to use that analytical strength to shed light on what we can expect from future trends in the national and international allocation of increasingly scarce water resources, 70% of which are globally employed in the production of food.

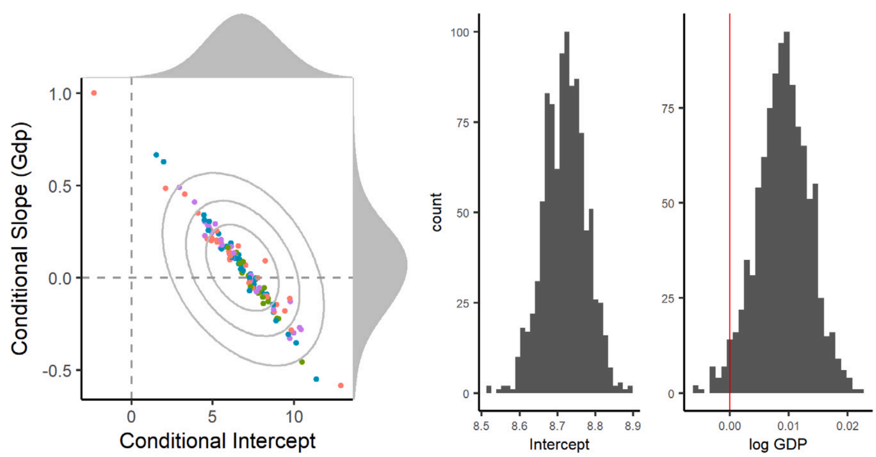
Our findings reveal a quadratic relationship between the per capita water footprint of production and per capita income, with a mildly negative coefficient on $(GDP/P)^2$, consistent with the Environmental Kuznets Curve hypothesis. In contrast, we observe a positive linear relationship between the per capita water footprint of consumption and income.

The EKC pattern in the global water footprint of production suggests that, between 1993 and 2016, countries – on average – intensified their domestic pressure on freshwater resources as their per capita income rose, but only up to a certain threshold. Beyond that level of per capita income, the rate of increase began to slow and eventually exhibited signs of modest decline, indicating a partial decoupling of economic growth from food production-related water use. The turning point is reached when countries' income ranges from 4783 US$/pc to 5662 US$/pc, and the water footprint of production per capita reaches on average 820 $m^3/pc/year$ before starting to decline.

These results require some contextualization. Even the highest estimated turning point of water footprint of production (*WFP*) – 1723 $m^3/pc/year$, calculated between the 75th and 95th percentiles of the observed *WFP* distribution – remains well below the global per capita availability of renewable water resources, which stands at 5479 $m^3/pc/year$ when accounting for minimum viable environmental flows



(a) Fitted relationships obtained by applying residual bootstrap linear mixed-effects models fitted to 1,000 bootstrap resamples of the dataset. The right panel is a detailed view of the quadrant indicated with a grey rectangle in the left panel.



(b) Scatterplot and estimated marginal densities of random intercept and random slopes, differentiated by World Bank classification with marginal density distributions (Top). Histograms of the empirical distribution of the marginal (i.e. fixed effect) intercept and slope parameters estimated from 1000 bootstraps (Down).

Fig. 4. Results about the relationship between *WFC/P* and *GDP/P*. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(FAO AQUASTAT).[10] However, water is a highly localized resource. Entire regions – such as Northern Africa (606 m^3/pc/year), Southern Asia (1278 m^3/pc/year), and Western Asia (1332 m^3/pc/year) – have per capita renewable water availability well below that value. In these areas, reaching the turning point would imply unsustainable levels of water use.

The inversion in trend could be due to the capacity of governance and technology to foster sustainability in managing countries' freshwater resources employed in food production. It could also be due to an increase in the water footprint embedded in net food imports, and thus to a delocalization of environmental pressure between world areas at different levels of development — or a combination of these two channels. In order to discern their relative contribution, we need to consider the results pertaining to the water footprint of consumption. The relationship between *WFC/P* and per capita income does not exhibit signs of delinking. The coexistence of a decreasing *WFP/P* and an increasing *WFC/P* requires an increase in the net water footprint of imports (as clear in Eq. (1)), which is due to a spatial displacement of food consumption's impact on water resources. Becoming richer has not helped countries, so far, to reduce their pressure on freshwater if we also consider the virtual water travelling via the international food trade. For example, every increase of 100 US$ in income per capita at the mean point of the income distribution (12,956 US$/pc) has corresponded to a rise in *WFC/P* of 46.5 m^3/pc/year).

These findings demonstrate that the observed quadratic relationship between the per capita water footprint of production and economic growth should not be misinterpreted as an indicator of sustainability in global freshwater resource management. Disaggregating the water footprint into production and consumption components reveals a critical asymmetry: while higher income levels may lead to marginal reductions in local water abstraction, they do not necessarily correspond to more sustainable or equitable consumption patterns. The escalating demand for food – particularly water-intensive commodities such as meat – appears to outweigh the gains from technological innovation and improvements in governance capacity.

This pattern reflects a broader structural reality: many high-income countries increasingly meet their dietary needs through food imports,

[10] https://data.apps.fao.org/aquastat.

thereby externalizing their water use and environmental pressure via virtual water trade. This strategy effectively displaces the water burden onto lower-income countries, many of which lack the capacity to sustainably meet both domestic and export-oriented food production. Such delocalization of freshwater demand replicates dynamics observed in other domains of environmental degradation, underscoring deep and persistent global inequalities in resource use.

Critically, this strategy is not universally replicable. Countries in water-stressed regions – such as Northern Africa, Southern Asia, and Western Asia – may never have the option to implement the mechanism that has allowed today's rich countries to lower their local water withdrawals. In these areas, rising incomes do not necessarily trigger a sustainable transition. Instead, the turning point in the water footprint of production, where water use begins to decline, tends to occur only after surpassing levels of water abstraction that exceed national per capita renewable water availability. For much of the global South, therefore, economic growth alone may be insufficient – or even counterproductive – in delivering water sustainability without major shifts in global trade and governance frameworks.

These findings call for a re-evaluation of dominant assumptions regarding the relationship between development and environmental sustainability. In an era of intensifying water scarcity – driven by population growth, climate change, and changing dietary preferences – it is essential to prioritize not only technological efficiency and local governance, but also the equity and transparency of global resource flows. By distinguishing between the water footprints of production and consumption, this study highlights the central role played by international food trade networks and the large volumes of virtual water they embed. These networks are not neutral: they redistribute environmental pressures in ways that often reinforce existing geopolitical and economic asymmetries.

A water footprint perspective on food trade thus carries significant implications for development policy. The findings presented here deliver a clear and urgent message for countries that rely heavily on virtual water imports to sustain their food systems — most notably, many European Union member states. At the same time, they offer new quantitative evidence of the self-reinforcing structural imbalances that define North-South relations in the global agri-food system. The consequences are profound, not only for local environmental sustainability in exporting countries but also for their development prospects, food sovereignty, and long-term resilience.

Ultimately, the allocation, governance, and embedded trade of freshwater emerge as some of the most severe and under-addressed challenges of the 21st century. As water scarcity becomes more acute and its geopolitical significance grows, it is imperative to embed water footprint considerations into the design of both national development strategies and international trade and cooperation frameworks. Failure to do so may deepen global inequalities and increase the risk of instability — both in water-stressed regions and across interconnected global food markets. These dynamics warrant greater scholarly attention and more integrated policy responses if the international community is to advance towards equitable and sustainable development outcomes.

Some aspects of this study could benefit from further investigation in future research. First, although the mixed-effects approach accounts for unobserved heterogeneity across countries, the global averages may mask significant differences across regions and income levels. For instance, the turning point in water footprint of production might reflect the trajectory of middle-income countries but may not apply to regions already experiencing severe water scarcity. Second, our analysis does not include projections or dynamic simulations, which would help estimate the implications of future economic and demographic growth on water use. Third, while we distinguish between the water footprint of production and consumption, we do not explicitly model trade flows. Future contributions explicitly focusing on virtual water trade could provide more insights into global dependencies and the geopolitical implications of water use. Fourth, our framework does not directly compare different conceptual approaches, such as the IPAT and Kaya identities, and the Environmental Kuznets Curve. Exploring these models within a unified framework could enhance understanding of the structural drivers and tipping points in global water systems. Advancing research in this direction is essential for developing a more robust and policy-relevant evidence base — one that can better equip decision-makers to address the converging challenges of climate change, demographic shifts, and the increasing strain on limited freshwater resources.

CRediT authorship contribution statement

Vito Frontuto: Writing – review & editing, Writing – original draft, Methodology, Formal analysis. **Tommaso Felici:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Silvana Dalmazzone:** Writing – review & editing, Writing – original draft, Supervision, Investigation. **Benedetta Falsetti:** Writing – original draft, Investigation, Data curation. **Rosaria Ignaccolo:** Writing – review & editing, Supervision, Methodology, Formal analysis. **Francesco Laio:** Writing – review & editing, Supervision, Investigation, Conceptualization. **Marco Maria Bagliani:** Writing – review & editing, Supervision, Investigation, Conceptualization.

Ethical statement

The authors declare that there are no ethical issues arising from this work.

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Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.worlddev.2025.107185.

Data availability

All data that support the findings of this study are included within the article.

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