Food, energy, and water nexus: A study on interconnectedness and trade-offs

by Ghosh, B., Gubareva, M., Ghosh, A., Paparas, D. and Vo, X.V.

Ghosh, B., Gubareva, M., Ghosh, A., Paparas, D. and Vo, X.V. (2024) 'Food, energy, and water nexus: A study on interconnectedness and trade-offs'. *Energy Economics*, 133, Article number 107521.

Energy Economics 133 (2024) 107521

Contents lists available at ScienceDirect

Energy Economics

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

Food, energy, and water nexus: A study on interconnectedness and trade-offs

Bikramaditya Ghosh [a,b], Mariya Gubareva [c,d,*], Anandita Ghosh [e], Dimitrios Paparas [b], Xuan Vinh Vo [f]

[a] Symbiosis Institute of Business Management, Symbiosis International (Deemed University), Electronic City, Hosur Road, Bengaluru 560100, Karnataka, India
[b] Harper Adams University, Newport, Shropshire TF10 8NB, United Kingdom
[c] Universidade de Lisboa, Lisbon School of Economics and Management (ISEG), Research Centre in Economic and Organisational Sociology (SOCIUS) / Research in Social Sciences and Management (CSG), Rua Miguel Lupi, 20, 1249-078 Lisbon, Portugal
[d] Institute of Business Research, University of Economics Ho Chi Minh City (UEH), Viet Nam
[e] Symbiosis Centre for Management Studies, Symbiosis International (Deemed University), Electronic City, Hosur Road, Bengaluru 560100, Karnataka, India
[f] Institute of Business Research and CFVG, University of Economics Ho Chi Minh City, Ho Chi Minh City, Viet Nam

A R T I C L E I N F O

Keywords:
Quantile vector auto-regression
Food
Energy
Water
Asymmetric quantile connectedness
Spillovers

A B S T R A C T

This study finds interesting outcomes regarding the interlinkage between the food, energy, and water sectors. The UN's Food and Agriculture Organization data from January 1961 till January 2023 are employed for six variables, namely Total Renewable Water resources per capita (TRW), Total Internal Renewable Water resources per capita (TIRW), Total Water Withdrawal per capita (TWW), Global Food Consumption per capita (GFC), Global Crop Production (GCP), and Global Electricity Consumption (GEC). Employing Quantile Vector Auto-Regression (QVAR) methodology, we observe asymmetry in connectedness across quantiles. Positive shocks produce stronger impacts in the variables than negative ones. Crop production mostly acts as a receiver of shocks. Renewable water is a consistent net emitter in all circumstances, while water withdrawal is crucial during negative shocks regime as well as in neutral time.

1. Introduction

The Water-Energy-Food or WEF nexus is all about appreciating and understanding these closely related sectors. Vying for attention to the interlinked nature of global ecosystems, the Food and Agriculture Organization of the United Nations (FAO) investigates how the WEF nexus can bolster sustainable agriculture and food security across the globe.[1] Its report entitled "The Water-Energy-Food Nexus" accentuates the importance of the nexus approach to understand the complexity of the interdependence of the food, energy, and water sectors (FAO, 2014). The conceptual framework of the WEF nexus emphasizes the four critical connections between the three systems. The first connection is the water for food, as agriculture accounts for 70% of the total global freshwater withdrawals making it the largest user for water (FAO, 2014). The second connection is the water for energy, as water is required for the extraction, mining, processing, refining and residue disposal of fossil fuels as well as for generating electricity (Spang et al., 2014; Chai et al., 2018). The third is the energy for water interface connection, as energy is required for the purpose of moving, distributing, and treating water (Bazilian et al., 2011; Nair et al., 2014). Lastly, the fourth connection is energy for food interface, as energy is required to produce, transport, and distribute food (Klemes et al., 2008; Morawicki and Hager, 2014; Umar et al., 2021; Bossman et al., 2023). The WEF interlinkage on a global scale was accentuated during the food crisis, which accompanied the 2007–08 Global Financial Crisis (Ringler et al., 2016). During those times a high correlation was observed between food and oil price indices (Rosegrant et al., 2008) as well as the increased energy intensity of agriculture and food supply chain (Ringler et al., 2013). We can also

* Corresponding author at: Universidade de Lisboa, Lisbon School of Economics and Management (ISEG), Research Centre in Economic and Organisational Sociology (SOCIUS) / Research in Social Sciences and Management (CSG), Rua Miguel Lupi, 20, 1249-078 Lisbon, Portugal.

E-mail addresses: b.ghosh@sibm.edu.in, bghosh@harper-adams.ac.uk (B. Ghosh), mgubareva@iseg.ulisboa.pt (M. Gubareva), anandita.ghosh@scmsbengaluru.siu.edu.in (A. Ghosh), dpaparas@harper-adams.ac.uk (D. Paparas), vinhvx@ueh.edu.vn (X.V. Vo).

[1] https://www.fao.org/land-water/water/watergovernance/waterfoodenergynexus/en/.

https://doi.org/10.1016/j.eneco.2024.107521
Received 21 December 2023; Received in revised form 21 March 2024; Accepted 25 March 2024
Available online 3 April 2024

observe a discernible overlap between the 2 billion people globally without access to safe drinking water,[2] the 2.3 billion people in the world who are moderately or severely food insecure,[3] and the 775 million without an access to electricity.[4] This indicates a complex and strong interlinkage within the WEF system. The theme of the WEF nexus first came to prominence in the Bonn-2011 conference on the Food-Energy-Water nexus as a solution for a green economy.[5] As defined by Albrecht et al. (2018), the WEF nexus is a systems-based perspective that focuses on the interdependence and the interactions between the food, energy and water system.

As a response to the production and consumption trade-offs among the resources, the WEF nexus has become a pertinent approach that can support the transition towards a green economy while ensuring resource use efficiency and policy coherence (Hoff, 2011). The nexus approach is supposed to help a) in the removal of conflict related to the alternative uses of common resources, b) the countries in the optimum utilization of resources, and c) in the assessment of the inter-sectoral impact. As the report of the United Nations Economic Commission for Europe (UNECE) on the Methodology for assessing the water-food-energy-ecosystems nexus states, the WEF nexus can be useful in safeguarding the human rights to water and food (UNECE, 2018). Moreover, as the risk of unavailability of food, energy, and water looms large around the world, the WEF nexus approach is useful for designing solutions against the risk of non-supply (Leese and Meisch, 2015). It is also expected that the trilemma between the three sectors may get intensified because of the burgeoning global population, income growth, and climate change. The WEF perspective can help in initiating mutually beneficial actions among the three sectors, targeting to meet the growing global needs in the future.

In the scholarly literature and policy frameworks, the WEF nexus concept has been expanding rapidly. The analytical framework of the nexus approach has majorly adopted mixed quantitative and qualitative methods to study the interlinkage between the food, energy, and water systems. However, most of the nexus studies are skewed toward the conceptual domain (Smajgl et al., 2016). As pointed out in a review paper by Albrecht et al. (2018), approaches like the integrated models, economic tools and environmental management approach have dominated most of the nexus related studies. Most quantitative studies range from the scenario analysis and input-output analysis to principal component analysis and to regression analysis. For instance, the quantitative studies of Bonsch et al. (2016), Ringler et al. (2016) have incorporated the scenario analysis to understand the nexus between the food, energy, and water sectors. Some studies such as those of Martin-Gorriz et al. (2014) and Li et al. (2016) have adopted an input-output analysis. Ozturk (2015) has adopted a principal component analysis (PCA) as an analytical framework. A few others (Li et al., 2013; Topi et al., 2016) have concentrated on the regression analysis technique to establish the investigated interlinkage.

It was observed that the existing strand of literature on the nexus approach presents two prominent knowledge gaps. First, there is a lack of a coherent and coordinated policy framework that can acknowledge and abate the adverse implications of the WEF nexus and properly address the food security concerns (Aeschbach-Hertig and Gleeson, 2012), global water stress (Chini et al., 2018), burgeoning greenhouse gas emission (Reffold et al., 2008) and the environmental unsustainability (Cruse et al., 2010). Second, pertaining to the analytical tool, there is a dearth of studies, which employ advanced quantitative financial modelling techniques, including the quantile Vector Auto-Regression (QVAR) analysis, to explore the dynamic spillover effect between the water, energy, and food sectors. In a contribution to narrowing the research gap, this paper investigates the interconnectedness among the food, energy, and water systems. Methodologically, we employ the QVAR methodology to study the spillover/connectedness among the three WEF sectors as this technique allows us accommodating the extreme movements originated by various stress events during 1961–2023. As the relationship among food, energy and water is dynamic that is, actions on one usually have impact on one or two others sectors with profound economic, environmental and social implications.

The novelty in our study is three-fold. First, from an economic, environmental and ethical perspective the topic of our study is relevant, as the complex interlinkage between the sectors along with the policy implications needs a great push to effectively support decision-making. Second, this study is among the first works to undertake the QVAR technique to study the interconnectedness among these three WEF variables. Our study unveils some interesting facets on the dynamic connectedness among the food, energy, and water sectors. With the help of a multivariate framework, we identify significant shock receivers and emitters in the system. Third, this study provides a sound understanding of the origins and drivers of volatility spillovers among the three sectors. It can help the policy makers in adroitly undertaking necessary measures to mitigate conflicts of resources use in the future, trying to prevent undesirable shocks to the economy and the society.

This remaining part of the paper is structured in the following manner. Section 2 reviews the relevant literature. Section 3 discusses the adopted research methodology. Section 4 presents the results of the study and provides their discussion. Section 5 concludes.

2. Literature review

In the domain of the WEF nexus, a growing body of literature has been emerging rapidly, especially around the two following themes. The first is the interlinkage among the three WEF sectors, while the second addresses the evolution of the nexus approach methodology. In this *section, we review the aforementioned strands of literature to identify the research gaps.*

2.1. Interlinkage between the food, energy, and water

In exploring any network study, it is important to characterise network anatomy as structure always impact functions (Strogatz, 2001). Concomitantly, as we explore the Food-Energy-Water network we seek to capture the dynamics of the resources and how each of the them are interlinked (Perrone and Hornberger, 2014). The humanity is approaching the boundaries of resource use especially global freshwater use, land use and energy resources (Rockström et al., 2009). Consequently, the intertwined connection between the food energy and water sectors becomes more complexed and dynamic. The Food-Energy-Water network is composed of four important connections such as: a) water for energy b) water for food c) Energy for water and d) energy for food. We therefore, present an overview of the nexus studies assessing the competing demand for food, energy and water in the nexus as well as their interlinkage with its implications.

2.1.1. Water for food

Agriculture is the most water demanding sector claiming >85% of the water (Falkenmark and Rockstrom, 2004). Water is crucial for crop production, food security and rural livelihood (D'Odorico et al., 2020). A study by Mashnik et al. (2017) evidenced that irrigated water is required to achieve the gains from high-yielding fertilizer responsive crop varieties as it helps fight pests through products diluted in water, improvement in the physical properties of land and the eradication of salinity from the soil. In fact, Döll and Siebert (2002) have shown that irrigated land has the capacity to produce approximately around

[2] https://www.who.int/news-room/fact-sheets/detail/drinking-water.

[3] https://www.fao.org/newsroom/detail/un-report-global-hunger-SOFI-2022-FAO/en.

[4] https://www.iea.org/commentaries/for-the-first-time-in-decades-the-number-of-people-without-access-to-electricity-is-set-to-increase-in-2022.

[5] https://www.water-energy-food.org/events/conference-the-water-energy-and-food-security-nexus-bonn2011-nexus-conference.

40–50% of the global food supply. However, in the context of scarcity of resources, the water for food interface has a serious environmental implication. A growing body of literature have actually shown that the global agricultural production is heavily dependent on unsustainable irrigation practices (Gleeson et al., 2012; Konikow, 2011; Mekonnen and Hoekstra, 2016). As defined by Rosa et al. (2019), the unsustainable irrigation is the water withdrawal more than the availability of renewable water. Reliance of agriculture on unsustainable irrigation practices can have adverse repercussions on the aquatic habitat (Dudgeon et al., 2006; Poff et al., 1997) as well as can lead to the depletion of both the groundwater resources and the fresh water stock (Famiglietti, 2014; Rodell et al., 2018). This can further add to the burgeoning global water and food security concerns (Aeschbach-Hertig and Gleeson, 2012; Turner et al., 2019). Lastly, factors like globalization through trade and investment can make the water and food network more dynamic which can put more constraints on the resource availability (D'Odorico et al., 2018).

2.1.2. *Water for energy*

The synergised use of water and energy resources provides a substratum for the advancement of the human society and the overall modernisation process (Li et al., 2020). However, water as a resource is extensively used in a plethora of energy production processes. A study by Spang et al. (2014) categorised four main energy production processes as fossil fuel extraction and processing, uranium mining, bio-fuel cultivation and processing and electricity production, which requires intensive use of water. In fact, 10 to 15% of the global freshwater withdrawal and the 3% of the global water consumption has been attributed towards the energy sector worldwide (Ferroukhi et al., 2015; IEA, 2017). Within the energy sector, water utilization is mostly prevalent in thermal power plant for the generation of electricity (Terrapon-Pfaff et al., 2020). In most of the geothermal facilities, fresh water supply is used to manage dissolved solids and reduce scaling (Clark et al., 2010). Electricity generating technologies depending on their configuration use water for various processes (Macknick et al., 2012). A study by Turchi et al. (2010) show that in most of the thermal electricity technologies such as CSP, biopower, coal, nuclear and gas technologies, water is used as working liquid in a thermodynamic process. Moreover, hydropower is also considered to be a water-intensive energy carrier (Zhou et al., 2019). Many studies have also shown that the future demand of water for energy production will witness a prominent surge (Mekonnen et al., 2016). Consequently, it will make the power sector vulnerable and dependent on the availability of water resources, which will further get exacerbated due to climate change and growing population (Bates et al., 2008; Ganguli et al., 2017; Webster et al., 2013). The water for energy interface can lead to global water stress (Chini et al., 2018; Chu and Majumdar, 2012). This will further adversely affect the renewable and the non-renewable energy production (Scherer and Pfister, 2016; Chai et al., 2018).

2.1.3. *Energy for water*

The energy for water interface includes the energy consumption for water use. The use of energy has been attributed mainly to the supply of water for the residential, agricultural and industrial purposes. The use of energy is necessary for extracting, treating and transporting water to the end users (Bazilian et al., 2011; Nair et al., 2014). Process such as extraction of freshwater from surface and groundwater sources through desalination as well as treatment of waste water rely on the availability of energy resources (IEA, 2017). In fact, around 7 pr cent- 8% of the global total generated energy is utilised for drinking water production and distribution (Sharif et al., 2019; Yang et al., 2010). Apart from the water distribution, energy is also intensively used in the pumping and pressurizing irrigation technologies (Daccache et al., 2014; Rodríguez Díaz et al., 2011). Around 48% of the energy utilised for crop production is mainly for on-farm pumping purposes (Singh et al., 2002). But, the energy utilization in the process of supplying, conveying, treating, and using water can contribute towards greenhouse emissions (Reffold et al., 2008). Moreover, it can further add to the grave concern of global climate changes (Escriva-Bou et al., 2018; Pathak et al., 2018).

2.1.4. *Energy for food*

Around 30% of the global energy consumption corresponds to the agriculture and food sector (FAO, 2017). Approximately, 200 EJ per year of the energy consumption has been attributed to the food sector (EIA, 2017). Given these evidences, a growing body of literature encompass the theme of energy for food, which revolves around the energy consumption in the agriculture and food sector (Klemes et al., 2008; Morawicki and Hager, 2014; Pimentel, 2012; Stanhill, 2012). There is a strong linkage between the energy consumption and the crop production wherein an increase in the energy inputs significantly leads to an increase in the crop production (Singh et al., 2002). A plethora of studies have also captured the energy use patterns in the cultivation of different crops. These ranged from cereals (Banaeian and Zangeneh, 2011; Chaudhary et al., 2006; Veiga et al., 2015), to vegetables (Hatirli et al., 2006; Ozkan et al., 2004) and to nuts and oilseed (Keshavarz Afshar et al., 2013). As per the study by Hatirli et al. (2006), factors like farming system, crop seasons and farming conditions are the prominent determinants of the energy use patterns in agriculture. The irrigation practise in the overall farm operations consume the maximum energy (Elsoragaby et al., 2019). Additionally, in the food processing industry, the type of energy consumption during food processing can vary from thermal to electricity given the product type (Morawicki and Hager, 2014). But the energy for food interface is also linked to large levels of greenhouse gas emissions and depletion of resources (FAO, 2017). This is because the crop production activities heavily rely on fossil energy and machinery, which can cause environmental issues such as global warming and climate change (Cruse et al., 2010). The food industry also relies on fossil fuels like natural gas and petroleum for manufacturing process, making the energy for food nexus environmentally unsustainable (EEA, 2015).

2.2. *Water-energy-food nexus assessment*

The existing literature on the WEF nexus have adopted a variety of tools and methodology to demystify the nexus as well as understand the interconnectedness and the trade-offs. This section discusses diverse specific tools, which are frequently used in the WEF nexus studies. These nexus modelling tools range from scenario analysis to input-output analysis, principal component analysis, and regression and trend analysis. Within the scenario analysis, many studies undertook life cycle assessment technique to study the environmental impact of the three systems (Bonsch et al., 2016; De Laurentiis et al., 2016; Ringler et al., 2013). Other techniques in the scenario analysis approach included integrated assessment technique (Daccache et al., 2014). In the input-output analysis domain studies such as (Grindle et al. (2015), Li et al. (2016b), Martin-Gorriz et al. (2014b), have all assessed the nexus and the trade-offs between the food-energy-water sector. Under the quantitative analysis, the main techniques adopted were principal component analysis (Ozturk, 2015), regression analysis (Li et al., 2013; Topi et al., 2016) and the trend analysis (Xiang et al., 2017). Moreover, very few studies in the nexus approach adopted the financial modelling technique such as GARCH to capture the volatility spillover among the three sectors (Peri et al., 2017) or a multifactor market model to study the impact of agriculture and energy prices on the stock performance of the water industry (Vandone et al., 2018).

The two important strands of literature on the WEF nexus have alluded us to some pertinent knowledge gaps (Kholod et al., 2021), which give us clues for further scope of research. Firstly, as we disintegrate the nexus into interfaces (water for food and energy and energy for food and water), we have observed that each of these interactions have determinantal environmental implication, raising the concerns of sustainability. Therefore, there is a need for coordinated, and consistent policy recommendations and suggestions that can support the interlinkage between the three sectors (Ogbolumani and Nwulu, 2024). Secondly, there is a dearth of studies, which have undertaken quantitative financial modelling methodology to understand the Food-Energy-Water nexus. Thirdly, to the best of our knowledge no other studies have adopted a Quantile Vector Autoregression (QVAR) technique to capture the dynamic connectedness between the Food-Energy-Water systems. We thus, through our study attempt to fill-in the knowledge gap by exploring how the relationship between the three sectors varies across different quantiles, to capture the spillover effect under extreme market conditions.

3. Research methodology

3.1. Empirical framework

We use the extended Diebold and Yilmaz (2012, 2014) connectedness /spillover mathematical construct (Diebold and Yilmaz, 2012, 2014). Commencing from Ando et al. (2022), we use the quantile vector autoregression to investigate the spillover/connectedness among food, energy and water-based variables across the extreme lower, lower, median, upper, and extreme upper quantiles, namely, 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, and 0.9 (Ando et al., 2022). This way we could accommodate the extreme market movements between 1961 and 2023.[6] Quantiles such as Q0.01,0.05, 0.95 or 0.99 etc. won't produce outcome with lesser error if the length of the dataset is relatively smaller (Iacopini and Poon, 2022). Moreover, it has been proved that 10th & 90th quantiles depict extreme large negative and positive shocks (Bouri et al., 2021), whereas median quantile is more of a reference point. The degree of asymmetry could be clearly observed due to shocks (from the median quantile). That's why we're calibrating the median quantile.

Furthermore, we estimated the quantile vector autoregression, QVAR(p) as:

$$y_t(\tau) = \mu(\tau) + \sum_{j=1}^{p} \phi_j(\tau)\, y_{t-j} + u_t(\tau) \tag{1}$$

In the eq. (1) t denotes time whereas τ denotes the quantiles. Here, y_t is a vector of n variables, including food, energy, and water related parameters $\mu(\tau)$.Further, $\phi_j(\tau)$ denote coefficient matrices. Again, $u_t(\tau)$ shows the error vector. Following specific existing literature, we kept the maximum lag length (p) as 4 (Blanchard and Perotti, 2002; Linnemann and Winkler, 2016). Then on we used Wold's theorem, and transformed the QVAR(p) in eq. (1) to a moving average representation. According to this premise, a stationary stochastic process can be decomposed into a pair. One being deterministic, and the other being a moving average process. Although the maximum lag length is 4, which is intuitively correct as AQUASTAT, FAO (FAO, 2014) aggregates quarterly data to generate annual data.[7] We however found out the optimum lag length as 1(as per BIC), which is producing the minimum L-step GFEVD following (Chatziantoniou et al., 2021).

Mathematically, it can be expressed as: QVMA(∞): $Q_\tau\ (F_{t-1})\ = \mu(\tau) + \sum_{i=0}^{\infty} A_i(\tau) u_{t-i}(\tau)$, with $A_i(\tau) = \Theta_1(\tau)A_{i-1}(\tau) + \Theta_2(\tau)A_{i-2}(\tau) + \ldots$ for $i = 1, 2, \ldots.; A_0(\tau) = I_n$ and $A_i(\tau) = 0$ for $i < 0$. I_n is an $n \times n$ identity matrix. From the robustness perspective, we calibrated L-step ahead generalized forecast error variance decomposition (GFEVD) as follows:

$$\psi^g_{i,j,\tau}(L) = \frac{\sigma_{jj}^{-1} \sum_{l=0}^{L-1} \left(e_i^T A_l(\tau) \Sigma e_j\right)^2}{\sum_{l=0}^{L-1} \left(e_i^T A_l(\tau) \Sigma A_l(\tau)^T e_i\right)} \tag{2}$$

Here Σ represents the variance matrix of the error term vector. Further, σ_{jj} denotes the standard deviation of the error term of variable j. e_i is a $n \times 1$ vector that would be 1 for element i and 0 otherwise. Finally, we compute the normalized generalized forecast error variance decomposition (GFEVD) following existing literature (Koop et al., 1996; Pesaran and Shin, 1998).

$$\tilde{\psi}^g_{ij,\tau}(\mathrm{L}) = \frac{\psi^g_{ij,\tau}(L)}{\sum_{j=1}^{k} \phi^g_{ij,\tau}} \tag{3}$$

$\tilde{\psi}^g_{ij,\tau}(\mathrm{L})$ depicts the percent of forecast error variance in i which can be explained by j as and when i is in quantile τ. Next, all the spillover indices are calculated to illustrate the complete overall connectedness/ spillovers across the variables:

$$FROM_{i,\tau}(L) = \frac{\sum_{j=1, j\neq i}^{n} \tilde{\psi}^g_{ij,\tau}(L)}{n} \times 100 \tag{4}$$

$$TO_{i,\tau}(L) = \frac{\sum_{j=1, j\neq i}^{n} \tilde{\psi}^g_{ji,\tau}(L)}{n} \times 100 \tag{5}$$

$$NET_{i,\tau}(L) = TO_{i,\tau}(L) - FROM_{i,\tau}(L) \tag{6}$$

$$TCI_{\tau}(L) = \frac{\sum_{i,j=1, j\neq i}^{n} \tilde{\psi}^g_{ji,\tau}(L)}{n} \times 100 \tag{7}$$

It has to be noted that TO indicates the overall impact i has on all other j. Whereas, FROM illustrates the impact of shocks all j on i. NET illustrates the net spillovers from i to all other j, where a positive (negative) value indicates i is a shock transmitter (receiver) inside this network. Lastly, the total connectedness index (*TCI*) captures the overall spillover/connectedness among all the variables in the network and therefore, it is considered as a valid proxy for market risk contagion.

In the empirical analysis (we have received the initial codes from David Gabauer's GitHub[8]), we focus on documenting the quantile connectedness at the 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9 quantiles. These quantiles depict the connectedness among WEF variables (discussed in the data sub-section) across extreme negative, median and extreme positive movements. In addition to the static connectedness, we analyze the time-varying connectedness by calculating the rolling spillover indexes with a rolling window of 40, 50 & 60 observations. In fact, we have a total of 63 yearly observations for each of the chosen variables from AQUASTAT, FAO. Therefore, choosing an optimum becomes rather difficult; further, tiny window increases the volatility and a large window level the same, therefore mid to higher level of windows are recommended (Antonakakis et al., 2020). According another study observations over 46 are optimum (Haslbeck et al., 2021) for these of VAR calibrations. That is why we chose 40, 50, and 60 observations, although our choice suffered from constraints of data availability. If AQUASTAT provides daily/monthly data over a large time period, this study would have been extremely robust.

3.2. Data

We choose six variables, namely, Total Renewable Water resources per capita (TRW), Total Internal Renewable Water resources per capita (TIRW), Total Water Withdrawal per capita (TWW), Global Food Consumption per capita (GFC), Global Crop Production (GCP), and Global Electricity Consumption (GEC). The annual frequency time series cover the period from January 1961 till January 2023. The data is sourced

[6] This research method accounts for spillover and interlinkages between the variables under regular and stressful conditions. Further, this methodology can accommodate more than two variables without increasing computational complexity. This method allows identifying the direct/indirect linkages across all the variables in any complex and intertwined network. Moreover, it illustrates the cardinal sources of shock transmission across the variables. This method has been used to study the extreme spillovers across different markets in the last couple of years (see, Chen et al., 2022; Farid et al., 2022; Yousaf et al., 2022; Ghosh et al., 2023a, 2023b; Patel et al., 2024).

[7] https://unstats.un.org/unsd/envstats/fdes/manual_bses.cshtml.

[8] https://github.com/GabauerDavid.

from AQUASTAT FAO,[9] UN FAOSTAT[10] and World Bank[11] (refer Appendix C). The water variables included in the study are selected based on the criteria that it should encompass the dimensions of sustainability (Pires et al., 2016). The water variables adopted in the study are the indicators for sustainable water resources development which are considered to best represent the overall status of a country's water resources and usage.[12] For representing water resources, total renewable water capita (Kheirinejad et al., 2022) as well as total internal renewable water resources (FAO) has been extensively adopted. Moreover, for representing water usage, the per capita water withdrawal (TWW) indicates absolute or per-person value of yearly water withdrawal gives a measure of the importance of water in the country's economy. When expressed in percentage of water resources, it shows the degree of pressure on water resources. All the data points are converted to log returns. TRW works as a proxy for total renewable water, TIRW for internal renewable water, TWW for total water withdrawal, GFC for food consumption, GCP for crop production, and GEC for electricity consumption. In our study, we have used two types of water sector indicators: a) water resource indicator and b) water use indicator. The relevant sustainable water resource indicators are assessed mainly based on its relative availability and human pressure on the resources.[13] As two additional water indicators, we have selected TIWR and TRW. TIWR accounts for the surface and ground water produced internally representing the average annual flow of rivers and groundwater generated from endogenous precipitation, after ensuring that there is no double counting. The TRW is the total of the country's internal renewable water resources and incoming flow from outside the country. This value, unlike internal resources, can change over time if upstream development diminishes water supply near the border. Furthermore, for representing the water consumption we selected Total water withdrawal per capita (TWW) as the absolute or per-person value of yearly water withdrawal measures the importance of water in the economy. These variables are carefully chosen based on our extensive literature review. The information regarding the data collection/methodology is provided with the help of a Data Summary Table (Appendix C).

All the variables are non-normal, mean-reverting (stationary) time series and exhibit varying degree of fat tails (leptokurtic), see Table 1 and Fig. 1. The presence of fat tails confirms deviation from the Gaussian distribution theory.

As we analyze the graphs in Fig. 1, some intriguing facets of each variable are revealed that are crucial for our current study. We have provided a detailed discussion of the volatility in each of the series, along with the plausible reasons across the period selected for analysis. These events are also linked to Table 4

a) Global Crop Production: The volatility in global crop production is mainly attributable to enhanced agricultural production for industrial use, robust demand from emerging economies, and the biofuel sector ever since 1960s[14]. Furthermore, during 2010 a drop in the Global Crop Production was also observed as the production of the two major cereal crops namely wheat and maize, was severely hit by the drought in Russian Federation and excess rainfall conditions in the US.[15]
b) Global Electricity consumption: The movements in Global Electricity consumption witnessed two significant spikes in 1970s and 1990s. The 1970s spike is mainly ascribed to the excess demand for electricity generated due to the fuel shortage in the 1970s, rapid population, and industrial growth. As the energy crisis of 1973 began to mount up causing high energy prices, during 1973s and 1974s the global electricity consumption dropped drastically.[16] Another spike in global electricity consumption happened during the 1990s which can also be attributable to the 1990s energy crisis resulting from the gulf war.
c) Global Food consumption- Extreme values in GFC are attributable to the rise in food consumption, especially grain. Grain consumption in the developing countries doubled between 1960 and 1980. This rate of growth was nearly twice the rate of population growth and is unmatched in history. The development and spread of high-yielding wheat and rice varieties (HYVs) during mid 60's dramatically increased the yields.[17]
d) Water resource variables- For the total renewable water resources per capita, we can observe a steep drop during the start of the sample i.e., during 1960s. This observation aligns with the findings of a study by Kummu et al. (2010) which shows that by 1960s the per cent of the global population experiencing chronic water shortage drastically increased to 9% from 2% during 1900s.Furthermore, we can observe that both the total renewable and total internal renewable water resources have exhibited high volatility since 2000. The high degree of volatility in the water resource variable is inextricably linked to the global climate change events, such as episodes of droughts, floods, and rising sea levels, happened since 2000.[18] A United Nations report (2022) highlighted that since 2000, we have witnessed of about a 29% increase in the number and duration of drought and a whopping 134% increase in the flood related disasters globally. The world witnessed some of the worst-hit episodes of droughts in many parts, such as the occurrence of Megadrought in western US in 2000, some specific incidents of droughts in the Mediterranean regions of Spain and Portugal in 2001, 2004 and 2005. The episodes of drought were witnessed globally even after 2015, attributable to the episodes of the California Drought,[19]or the multi-year drought witnessed from 2015 to 2019 in South Africa (Archer et al., 2022) or the prolonged drought between 2015 and 2018 witnessed in South Asia because of the El Niño-Southern Oscillation (ENSO).[20]
e) Total water withdrawal- For total water withdrawal, we can observe extreme movements during the start of the sample as due to green revolution during 1960s and 70s caused water transfer from distinct basins and on seawater desalinization, thus expanding the annual renewable supply of water. Moreover, the decade of 1950–60 witnessed the most significant increase in water withdrawal of about 4.2% per year.[21]

We have further studied the correlation between the variables. The table is presented in Appendix A. A glance at the correlation table in Appendix A gives us an insight into some of the essential correlations among the variables. For instance, the variables such as total renewable water resources per capita and total internal water resources per capita have relatively high correlation values (0.8). Similarly, Global food consumption and total water withdrawal per capita also have high correlation values (0.88). Furthermore, variables such as total water resources per capita, total water withdrawal

[9] https://data.apps.fao.org/aquastat/?lang=en.
[10] https://www.fao.org/faostat/en/#data/QI.
[11] https://databank.worldbank.org/id/b3ab275c?Report_Name=Electricity-production.
[12] https://www.fao.org/3/W4745E/w4745e0d.htm.
[13] https://www.fao.org/3/W4745E/w4745e0d.htm.
[14] https://agriculture.ec.europa.eu/system/files/2023-03/agri-market-brief-08_en.pdf.
[15] https://www.fao.org/3/i2050e/i2050e07.pdf.
[16] https://americanhistory.si.edu/powering/past/history3.htm.
[17] https://www.elibrary.imf.org/view/journals/022/0022/004/article-A003-en.xml.
[18] https://www.unwater.org/water-facts/water-and-climate-change.
[19] https://www.weforum.org/agenda/2015/01/why-world-water-crises-are-a-top-global-risk/.
[20] https://www.unescap.org/op-ed/ready-dry-years-building-resilience-drought-southeast-asia.
[21] https://www.fao.org/aquastat/en/overview/methodology/water-use.

Table 1
Descriptive statistics.

	TRW	TIRW	TWW	GFC	GCP	GEC
Mean	−0.003	0	0.483	0.001	−0.003	−0.001
Variance	0.006	0.005	12.993	0	0.021	0.006
Skewness	1.039***	1.36***	7.47***	4.23***	0.770**	0.369
Kurtosis	4.090***	5.34***	53.8***	25.361***	22.444***	11.989***
JB	52.621***	89.78***	7787.7***	1785.54***	1265.214***	360.725***
ERS	−0.198	−5.27***	0.69	0.243	−2.965***	−2.034**
Q (10)	29.492***	43.49***	0.514	3.156	18.384***	16.030***
Q2(10)	11.492**	14.55***	0.002	0.515	14.461***	14.607***

Notes: This figure presents the returns of the WEF variables under study, where returns are calculated by log-differencing.

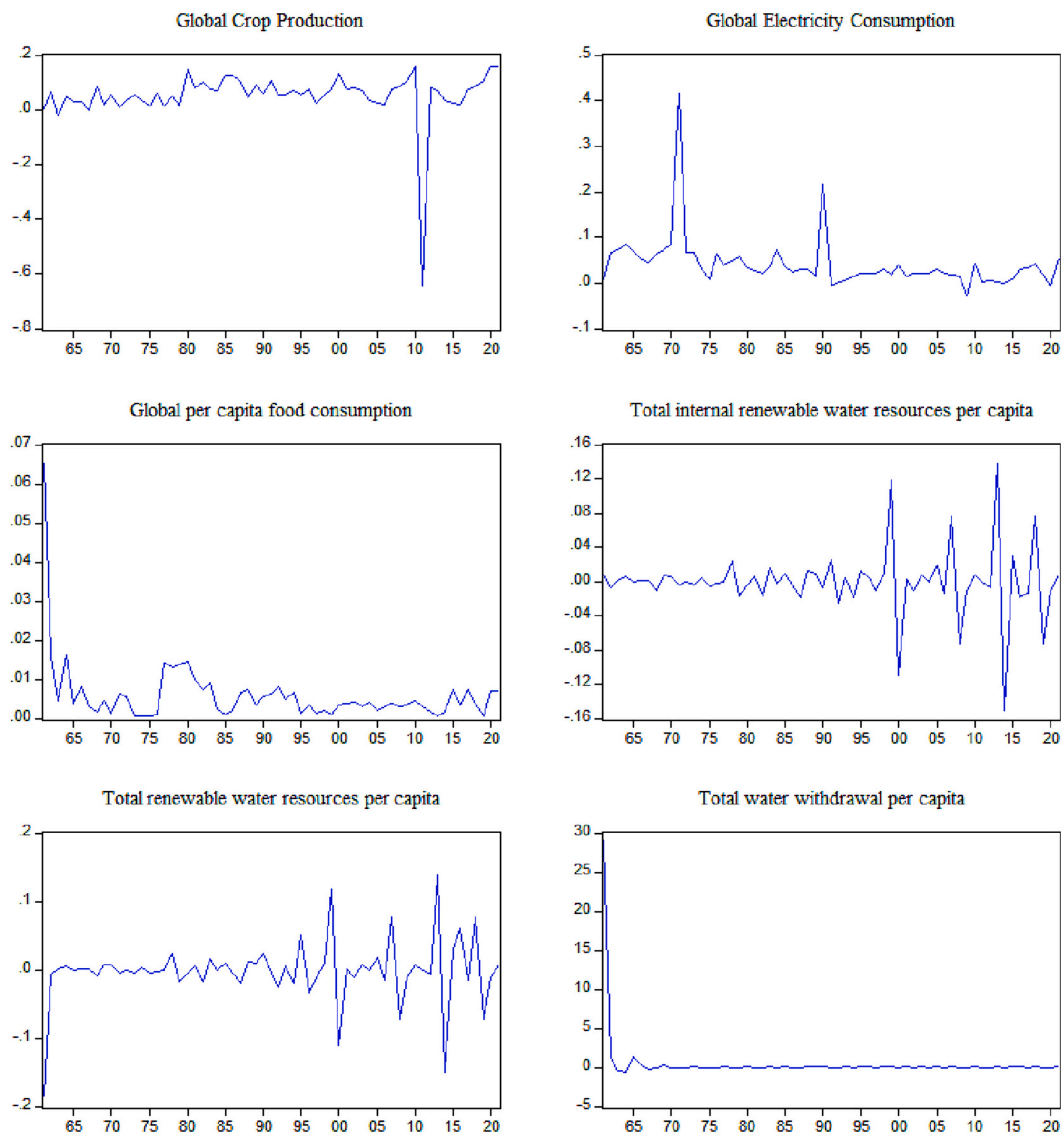


Fig. 1. TRW, TIRW, TWW, GFC, GCP, and GEC; 1961–2023.

per capita, global food consumption, and total renewable water resources per capita had low and negative correlation coefficient values (−0.4).

4. Results and interpretation

Table 2 presents the outcomes for average connectedness for the whole sample per quantile, helping us with analysing the patterns of spillover/connectedness and with identifying the emitter/receiver roles of the variables.

As per Table 2, total connectedness/spillover of shocks are lowest (48%) for median quantile $Q_{0.5}$ since it represents a regular environment without much shocks. On the other hand, TCI increases going towards both the lower and upper extreme quantiles, namely, $Q_{0.1}$ and $Q_{0.9}$, which are representative, respectively, of extraordinary negative and positive events and situations. Both $Q_{0.1}$ & $Q_{0.9}$ witness the extremely elevated levels of spillover/connectedness, respectively, 73% and 86%. These results are perfectly plausible and consistent with studies

Table 2
Average connectedness per quantiles.

	TRW	TIRW	TWW	GFC	GCP	GEC	FROM
Panel A: Extreme Lower $\mathbf{Q_{0.1}}$							
TRW	27.27	22.16	14.63	6.66	10.8	18.48	72.73
TIRW	26.78	26.6	14.58	5.33	9.42	17.28	73.4
TWW	17.33	12.77	33.87	8.01	11.19	16.83	66.13
GFC	9.33	6.48	8.45	42.01	15.12	18.61	57.99
GCP	8.67	7.99	8.06	9.25	57.12	8.91	42.88
GEC	9.86	5.84	8.98	13.02	11.78	50.51	49.49
TO	71.97	55.23	54.7	42.26	58.32	80.12	362.6
Inc.Own	99.25	81.84	88.57	84.27	115.44	130.63	
NET	−0.75	−18.16	−11.43	−15.73	15.44	30.63	**TCI = 73%**
NPT	3	1	2	0	5	4	
Panel B: Lower $\mathbf{Q_{0.2}}$							
TRW	34.75	27.3	21.5	3.32	6.36	6.77	65.25
TIRW	30.19	30.32	21.14	3.24	8.29	6.83	69.68
TWW	23.5	21.2	41.94	2.71	4.82	5.81	58.06
GFC	8.3	4.45	5.99	53.16	13.25	14.85	46.84
GCP	12.46	6.45	8.12	6.91	58.31	7.75	41.69
GEC	12.3	5.32	9.5	7.87	2.35	62.66	37.34
TO	86.75	64.72	66.24	24.05	35.08	42	318.86
Inc.Own	121.5	95.04	108.18	77.22	93.39	104.66	
NET	21.5	−4.96	8.18	−22.78	−6.61	4.66	**TCI = 63%**
NPT	5	2	3	0	2	3	
Panel C: Lower $\mathbf{Q_{0.3}}$							
TRW	37.33	30.22	23.43	2.28	2.22	4.52	62.67
TIRW	29.91	36.98	23.92	2.53	1.93	4.72	63.02
TWW	23.18	22.14	46.83	2.61	1.49	3.74	53.17
GFC	5.87	5.05	5.17	65.14	6.37	12.4	34.86
GCP	9.42	5.3	8.02	4.57	66.53	6.15	33.47
GEC	9.08	2.62	6.16	6.49	1.59	74.06	25.94
TO	77.46	65.35	66.71	18.48	13.59	31.54	273.13
Inc.Own	114.79	102.33	113.54	83.61	80.13	105.6	
NET	14.79	2.33	13.54	−16.39	−19.87	5.6	**TCI = 55%**
NPT	3	3	5	0	1	3	
Panel D: Median $\mathbf{Q_{0.5}}$							
TRW	47.15	29.99	9.32	7.48	1.38	4.67	52.85
TIRW	41.91	36.31	11.46	5.87	1.34	3.11	63.69
TWW	23.93	14.52	52.21	6.08	0.8	2.46	47.79
GFC	17.34	1.72	3.81	68.58	1.86	6.69	31.42
GCP	13.87	1.92	1.76	4.63	75.2	2.63	24.8
GEC	11.91	0.72	1.39	6.05	0.94	78.99	21.01
TO	108.96	48.87	27.74	30.11	6.33	19.56	241.56
Inc.Own	156.12	85.18	79.94	98.69	81.53	98.55	
NET	56.12	−14.82	−20.06	−1.31	−18.47	−1.45	**TCI = 48%**
NPT	5	2	1	3	0	4	
Panel E: Upper $\mathbf{Q_{0.7}}$							
TRW	37.36	29.99	22.29	3.91	1.21	5.24	62.64
TIRW	26.99	40.76	23.45	2.68	0.86	5.27	59.24
TWW	21.57	22.89	46.18	3.86	1.3	4.2	53.82
GFC	7.28	7.39	7.75	68.32	6.12	3.13	31.68
GCP	9.75	5.93	6.99	5.1	60.41	11.82	39.59
GEC	9.85	4.79	6.28	3.65	4.85	70.59	29.41
TO	75.45	70.98	66.76	19.2	14.33	29.67	276.39
Inc.Own	112.81	111.74	112.94	87.52	74.74	100.25	
NET	12.81	11.74	12.94	−12.48	−25.26	0.25	**TCI = 55%**
NPT	3	3	5	1	1	2	
Panel F: Upper $\mathbf{Q_{0.8}}$							
TRW	35.41	23.85	22.88	5.03	6.1	6.73	64.59
TIRW	27.81	32.27	23.68	4.59	5.74	5.91	67.73
TWW	22.08	16.79	43.46	6.92	4.91	5.84	56.54
GFC	12.76	8.02	11.9	51.2	11.31	4.8	48.8
GCP	15.75	7.85	13.1	6.87	45.62	10.81	54.38
GEC	14.57	6.1	12.23	5.68	6.42	55.01	44.99
TO	92.97	62.62	83.78	29.09	34.48	34.09	337.04
Inc.Own	128.37	94.89	127.24	80.29	80.1	89.1	
NET	28.37	−5.11	27.24	−19.71	−19.9	−10.9	**TCI = 67%**
NPT	4	3	5	1	1	1	
Panel G: Extreme Upper $\mathbf{Q_{0.9}}$							
TRW	27.12	26.68	15.44	11.26	6.95	12.56	72.88
TIRW	26.1	26.03	14.6	12.28	7.34	13.64	73.97
TWW	18.75	18.86	28.45	13.8	6.48	13.66	71.55
GFC	17.62	18.07	12.65	30.48	5.82	15.37	69.52
GCP	14.14	15.41	10.8	15.95	30.85	12.85	69.15
GEC	15.61	16.44	13.28	19.05	6.31	29.3	70.7
TO	92.21	95.47	66.78	72.35	32.9	68.07	427.78

(*continued on next page*)

Table 2 (*continued*)

	TRW	TIRW	TWW	GFC	GCP	GEC	FROM
Inc.Own	119.33	121.5	95.23	102.83	63.75	97.37	
NET	19.33	21.5	−4.77	2.83	−36.25	−2.63	**TCI = 86%**
NPT	4	5	1	3	0	2	

Notes: Each cell above shows the number of spillovers within the WEF network. The column 'FROM' captures the spillovers from all other variables whereas 'TO' captures the spillovers to all other variables; 'Inc. own' captures the spillovers from each column variable to all variables, including itself & 'NET' captures the net connectedness with a positive (negative) value indicates a shock transmitter (receiver). NPT counts the times of variable j's pairwise TO values exceeding its pairwise FROM values. Results are obtained by means of the QVAR model, based on 50 observations, with lag length of order 1 (BIC) and a 20(L)-step-ahead generalized forecast error variance decomposition.

employing the same methodology in different markets (Ghosh et al., 2023a). This investigation is consistent and independent of the various rolling windows as shown in Table 3.

At this point we pass to the analysis of emitter/ receiver roles. From Table 2 we infer that TRW is a consistent net emitter across all quantiles except for the extreme lower 0.1 quantile. It means that TRW under normal, positive, and moderately negative conditions remains crucial. TIRW represents the combination of long-term river flow and the continuously replenished groundwater. It acts mainly as a net receiver at normal and negative market conjuncture (except for 0.3 quantile) and turns to be a net emitter in the remaining right-hand side quantiles (except for 0.8 quantile), with the highest innovation transmission intensity observed for the extreme upper quantile (refer Fig. 5). Usually, the negative shock comes from global warming over the crucial 1.5 °C level whereas the positive shock (refer Table 4) comes from Net Zero agreement, as hydroelectricity remains the largest renewable electricity in terms of both capacity and generation over the years.[22] Infrequent droughts play the spoilsport though. Furthermore, TWW, representing water withdrawal, emits shock waves across moderately negative and moderately positive conditions (0.2, 0.3, 0.7, and 0.8 quantiles) but acts as a net receiver at both extremes and in the middle (0.1, 0.5, and 0.9 quantiles). As under the moderate conditions TWW emits shocks, this finding reveals the challenges of "water for agriculture" as global food production bears the brunt of it. These challenges are attributable to many factors such as inadequate policy, under performance of major institutions and the financing constraints which can cause a diversion of water resources to other uses, thereby stressing the global crop production under regular market conditions.[23] Moreover, factors such as increasing water demand, dehydration of freshwater resources due urbanization and climate change can further aggravate the problem of water scarcity for agriculture (Saraiva et al., 2020).

TWW or water withdrawal behave as a receiver of good shocks (UN's COP 28 etc.) or bad shock (Russia-Ukraine military conflict, etc.) and in regular business circumstances ($\tau = 0.5$) (refer Table 4). Recently COP 28 clearly showed that Agriculture is responsible for 70% of freshwater water withdrawal.[24] This could lead to a policy shock, hence TWW becomes a receiver of shock. Similarly Russia-Ukraine military conflict witnessed stress on water resources as a whole, therefore TWW becomes a receiver of shock (Khilchevskyi et al., 2023). In regular times ($\tau = 0.5$) contamination, over-pumping and sinking of land makes water withdrawal as a net receiver (Kumar and Yaashikaa, 2019).

GFC or food consumption is directly linked to nutrition. It acts as a net emitter only at the extreme upper quantile, acting as a net receiver otherwise. GCP or crop production mostly acts as a net receiver of shocks from most other variables, except for the extreme lower quantile (refer Fig. 5). This is rather logical. Crop production depends upon these variables at positive, normal, and moderately negative market conditions, however, during the downside risk events, GCP becomes vitally important, and thus influences other parameters. GEC is among the less connected variables to others variables, except for the extreme lower quantile, when GEC acts as a major net emitter (refer Fig. 5). This is rather a unique finding, which makes GEC a plausible candidate for a possible hedge in the WEF nexus at the extreme bearish market conditions when workable hedging setups are the most needed. Although, it appears logical yet to understand it intuitively we need to delve into the cause. Electricity is required for cultivation and water management. Traditionally electricity is used for irrigation & crop cultivation globally (Maddigan et al., 1982).

According to Table 2 and Fig. 5, the relationship between GFC & GEC changes entirely between two extreme quantiles (namely 0.1 and 0.9). In the lower end (i.e. $\tau = 0.1$) electricity (GEC) exerts pressure on food consumption (GFC) as the requirement of electricity increases owing to negative shocks such as war or border conflicts. Food consumption (GFC) on the other hand exerts pressure to electricity (GEC) as global food consumption always showed a double digit growth recently (Dijk et al., 2021), which typically acts as a positive shock ($\tau = 0.9$). The thickness of the lines connecting the nodes in Fig. 5, typically depict the net shock transmission intensity between the variables.

The variables TRW and TIRW have high connectedness as TIRW is a part of TRW (this is also evident given the 0.8 correlation coefficient values reported in Appendix B). However, this does not undermine the relevance of the water variables for two reasons. First, total Internal water resource per capita is an extremely crucial indicator to represent water security/ scarcity. We can employ Total renewable water resources variable to represent the status of water resources. For instance, if Total water withdrawal is greater than the total internal water flow, then this would represent a decline in the water resources and vice versa. Second, we would reaffirm the results of our study wherein two variables exhibited distinguishable characteristics across the order of the quantiles (refer Table 2).

Low connectedness between global food consumption and production is attributable to the burgeoning disconnect between sustainable food consumption and production due to the emergence of a highly globalised and complexed food system during the last decade (Ng and

Table 3
Time-varying connectedness with 40-, 50-, and 60-observations rolling windows per quantile.

Rolling Window Size (observations)	Total Connectedness Index (TCI)						
	$Q_{0.1}$	$Q_{0.2}$	$Q_{0.3}$	$Q_{0.5}$	$Q_{0.7}$	$Q_{0.8}$	$Q_{0.9}$
40	79%	67%	58%	49%	57%	69%	88%
50	73%	63%	55%	48%	55%	67%	86%
60	71%	61%	52%	46%	53%	66%	83%

Note: This table illustrates the difference between the TCI at all quantiles under consideration, computed based on QVAR with a rolling window of 40, 50, and 60 observations, to prove the consistency of the connectedness/spillover; TCI is largely consistent across these rolling windows, which is the main purpose of choosing these windows. Usually, smaller datasets are used in a single window, however, we used three rolling windows to be surer of the consistency in results.

22 https://www.iea.org/reports/hydroelectricity.
23 https://www.worldbank.org/en/topic/water-in-agriculture.
24 https://www.mckinsey.com/capabilities/sustainability/our-insights/sustainability-blog/cop28-food-and-water.

Table 4
Global events that impacted WEF over the past six decades.[a]

	Food			Energy			Water		
	Years	Events	Geographies	Years	Events	Geographies	Years	Events	Geographies
Common Events to all the WEF	1961–1971, 1975–1985, 1990–1999, 2022	Conflicts & Military hostilities	Asia, Africa, Middle East, Latin America, USSR	1961–1971, 1975–1986, 1990–1999, 2022	Conflicts & Military hostilities	Asia, Africa, Middle East, Latin America, USSR	1961–1971, 1975–1986, 1990–1999, 2022	Conflicts & Military hostilities	Asia, Africa, Middle East, Latin America, USSR
	1973–1979, 1982–1987, 1990–2002, 2008–2012, 2019–2022	Economic shocks	USA, UK, Latin America, Middle East, Asia	1973–1979, 1982–1987, 1990–2002, 2008–2012, 2019–2022	Economic shocks, Energy Crisis	USA, UK, Latin America, Middle East, Asia, Mediterranean	1973–1979, 1982–1987, 1990–2002, 2008–2012, 2019–2022	Economic shocks	USA, UK, Latin America, Middle East, Asia
	1967–1969, 1985–1989, 1994–1996, 2003–2007, 2019–2022	Climate shocks (Major Drought & excess rainfall)	Global	1967–1969, 1985–1989, 1994–1996, 2003–2007, 2019–2022	Climate shocks	Global	1967–1969, 1985–1989, 1994–1996, 2000, 2003–2007, 2015–2019, 2022	Climate shocks (Major Droughts)	Global
Specific Events	1960–1970, 1974,1980,1996, 2006, 2008, 2012, 2021	Green Revolution, Fertilizer price shock	North America, Asia, Russia	1976, 1980, 1985, 1991, 1996, 2007, 2023	Advent & development of lithium battery	UK, USA, Canada, Australia	1978,1988, 1996,2006, 2012, 2016	Water deficit owing to droughts	UK, USA, Canada, Europe, Asia, Australia

[a] https://www.discover.ukri.org/a-brief-history-of-climate-change-discoveries/index.html.

Connor, 2022; Princen, 2002). The consumption decision and production decisions are made in relative isolation. While the production decision is driven by the targets of high yield and production volumes with lesser emphasis on nutritional intake, the consumption decisions on the other hand are made without considering the environmental impact caused by the production activity (Boström et al., 2015). Therefore, the low connectedness value between GFC and GCP can be justifiable across the quantiles.

At this point, we proceed with the analysis of the time dynamics of Total Connectedness Indices (TCI) per each of the considered quantiles. We present the results in Fig. 2.

As per Fig. 2, total connectedness/spillover of shocks is moderate in the middle of the distribution, which is representative of regular environment without extreme shocks; see TCIs for the 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, and 0.8 quantiles. However, it surges in both lower and upper extreme quantiles, indicating the risk of contagion during extreme situations. Both $Q_{0.1}$ and $Q_{0.9}$ witness elevated levels of spillover/connectedness, which corroborates our finding from Table 2 as well as is in line with other studies employing the same methodology (Ghosh et al., 2023a). The overall trend for the seven non-extreme quantiles is an uptrend, visualizing a generalized increase in connectedness along the years. This finding could be explained by the growing integration of financial markets due to the globalization, in general, and by financialization of commodities including food commodities, in particular (Tang and Xiong, 2012; Bossman and Agyei, 2022a, 2022b; Bossman et al., 2023; Kang et al., 2023).

To highlight the importance of asymmetric connectedness, we report the relative tail dependence (RTD) in Fig. 3 computed by taking difference of the TCI for the $Q_{0.9}$ and $Q_{0.1}$.

RTD is predominantly non-zero over here, proving the asymmetry in connectedness across quantiles. Moreover, the positive RTD values indicate higher connectedness during positive shocks, whereas negative values indicate that, on the contrary, connectedness is stronger during negative innovations. A staggering 92% of the RTD values as positives prove that positive shocks have more impact over their negative counterparts in Food-Energy-Water nexus. For instance, Russia-Ukraine

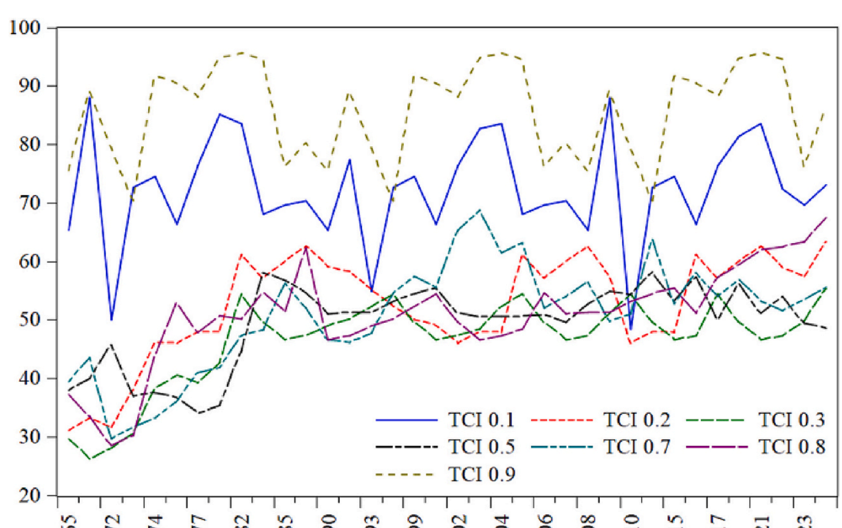


Fig. 2. Total Connectedness Indices (TCI) across quantiles, 1961–2023.
Notes: This figure presents the plots of the Total connectedness indices (TCI) for all the quantiles, considered for this study. The sample period is from January 1961 to January 2023, and the frequency is annual.

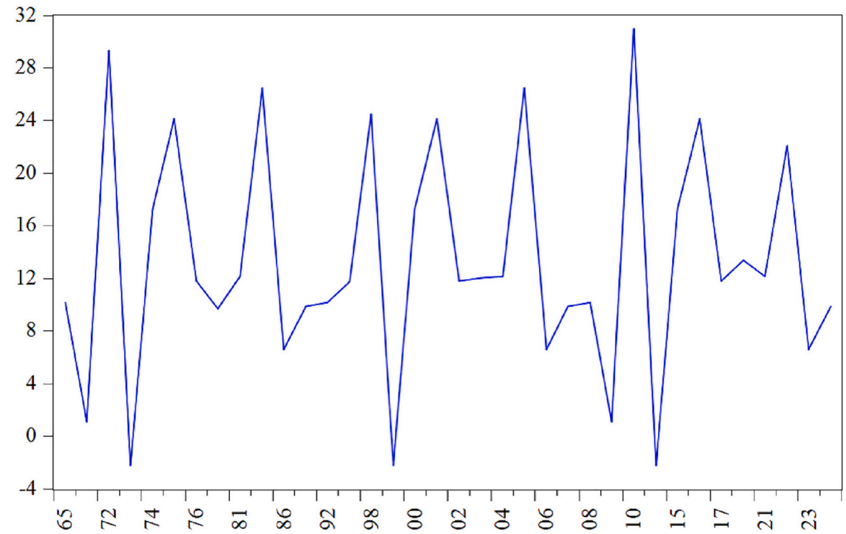


Fig. 3. Relative Tail Dependence (RTD).
Note: This figure illustrates the difference between the TCI at the 90th quantile and 10th quantile, computed based on QVAR with a rolling window of 50 observations.

military conflict did not affect the wheat crisis much longer as, amidst fresh crop availability and supply pressure, the exports from Romania and Poland started to grow and the imports fell, though Poland, Hungary, Slovakia retained the restrictions on the wheat imports from Ukraine (refer Table 4). Moreover, Romania and Poland increased the wheat production in such manner that the wheat exports of EU augmented substantially in late 2023.[25]

At this point, we proceed by illustrating the consistency of our results across different rolling windows, namely 40, 50, and 60.

Fig. 4 depicts the robustness of the construct (non-liner QVAR model with shocks); this shows that everything is in perfect accordance with the standard range of regular GFEVD, i.e., between 0.00 and 1.00; therefore, our calculation is in agreement with the typical pattern of GFEVD curve within the specified range (Lanne and Nyberg, 2016). First, this calibration works well for non-linear models. Second, it showcases the impact of shocks in various time periods. This data starts from 1961, therefore the sharp spike 25 years later indicates 1986. Post that the error decomposition got stabilized. Several impactful events changed the landscape for FEW in and around 1986. Some important events were, the nuclear explosion in Chernobyl, USSR followed by river pollution of the Rhine (along with its tributaries) and controlled usage of pesticides in developing nations to meet their ever-increasing food demand (FAO International Code of Conduct on the Distribution and Use of Pesticides was published in early 1986).[26] Shocks post 1986 were not that virulent it seems (refer Table 4).

Additionally, we calibrated the dynamic pairwise connectedness across all our chosen quantiles (Refer Appendix B). That analysis (Refer Appendix B) examines comprehensive bilateral interconnectedness and asymmetry of return spillovers between TIRW, TRW, TWW, GFC, GCP and GEC for each quantile. The pairwise connectedness analysis helped us identify both synergies and trade-offs between the WEF nexuses.

The Dynamic Pairwise Connectedness charts (refer Appendix B) presents the results from 2009 onwards. We have presented the pairwise connectedness values for the recent past only, especially after the Global Financial Crisis in 2008, specifically to capture the impacts of such a Black Swan event (Brinkman et al., 2010; Joo et al., 2020; Leichenko et al., 2010). We can observe relatively higher connectedness in quantile 0.1 in some of the (F-*E*-W) variables in some specific time period as compared to other moderate quantiles (0.2, 0.3, 0.5, 0.7 and 0.8). For instance, the variables TRW and TIRW exhibited slight but relatively higher connectedness from 2010 onwards (relatively higher values during 2010 and 2020). TRW and TIRW exhibited relatively higher connectedness with GCP during 2010. These results can be justified as 2010 witnessed some profound negative economic climate shocks in terms of the aftermath of the global financial crisis (as discussed earlier), occurrence of amazon rain forest drought (Jimenez et al., 2018), flash drought in Russian (Hunt et al., 2021) and the episodes of disastrous hurricanes in the US. Lastly, TWW also exhibited relatively higher connectedness with GEC during 2020. The year 2020 also witnessed some serious climatic setbacks such as episodes of recurrent wildfires, tropical storms, and intense drought.[27] However, the pairwise connectedness was much stronger in the extreme upper quantile (0.9) which also represents the prominence of the positive shocks. These positive shocks after 2015 are attributable to the COP 21 meet (Paris Agreement) in 2015 and a series of positive policy shocks thereafter (refer Table 4). This reflects the synergies between the three sectors which got strengthened because of the positive shocks after 2015.[28] According to a study by (Pham and Sala, 2022), the connectedness during negative shocks acts as an enhancer of trade-offs. Therefore, the connectedness in the extreme lower quantile reflects the trade-offs within the three sectors. The trade-off in our study is about exploring the competing use of water between the food and energy sector (Qin, 2021). The negative shocks act as enhancers of trade off within the three sectors namely Food, Energy & Water. To assess the tradeoffs, we examined the pairwise connectedness index between a) water variables with crop production and, b) water variables with electricity consumption, which showed high connectedness values in some specific time period re-affirming the impact of the negative shocks. Our results are in sync with a recent work which confirms that connectedness acts as a catalyst for tradeoff especially during negative shocks (Pham and Sala, 2022).

[25] https://www.spglobal.com/commodityinsights/en/market-insights/latest-news/agriculture/092723-eu-wheat-tracker-exports-rise-17-on-week-as-prices-soften-imports-fall-18.

[26] https://cdn.un.org/unyearbook/yun/chapter_pdf/1986YUN/1986_P1_SEC2_CH15.pdf.

[27] https://www.cfr.org/blog/ten-most-significant-world-events-2020.

[28] https://farmingfirst.org/2015/05/2015-global-food-security-index-released/.

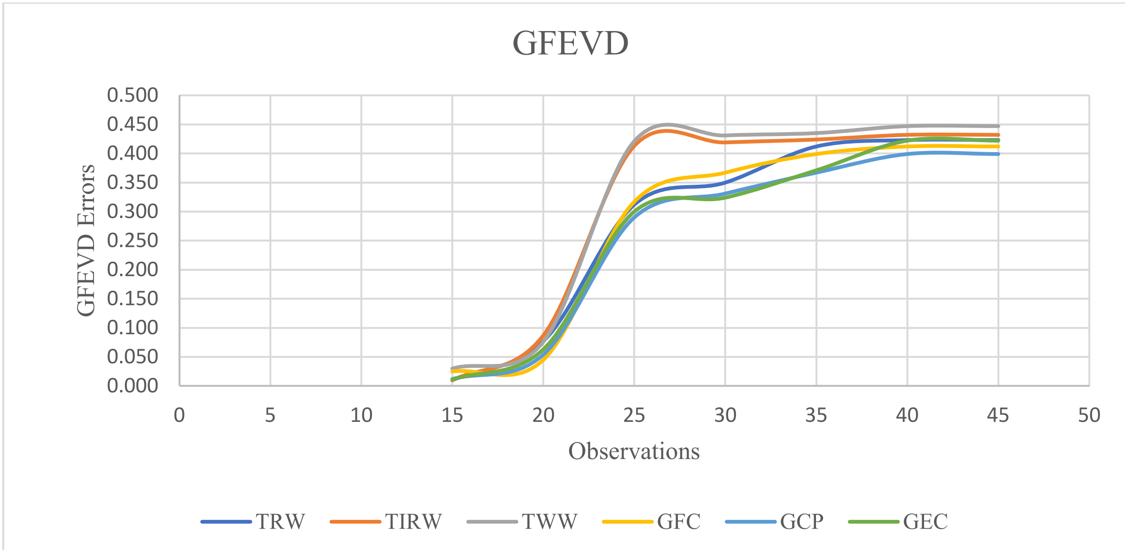


Fig. 4. Generalized Forecast Error Variance Decomposition (GFEVD) for the WEF variables.

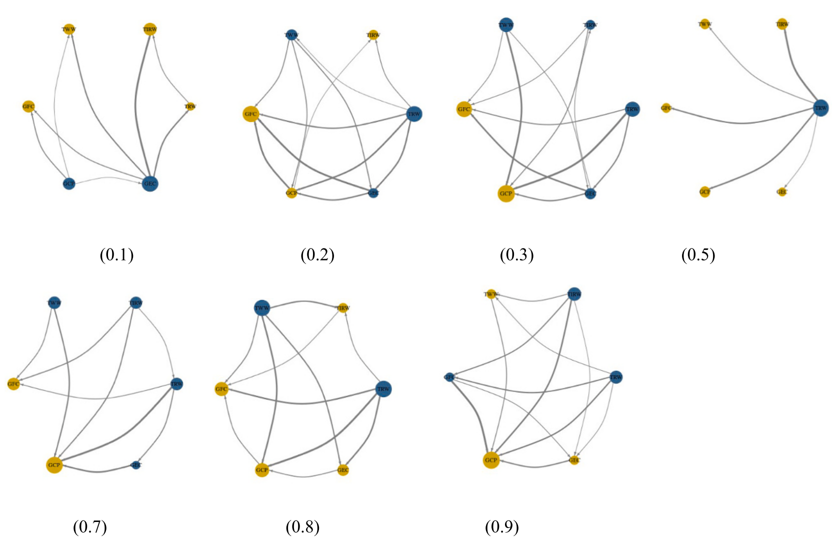


Fig. 5. Network Plot depicting emitter (receiver) as blue (yellow).
Note: This figure illustrates a network plot for the connectedness between the WEF variables across quantiles. Blue (yellow) nodes indicate net shock transmitters (receivers). The size of the nodes corresponds to the absolute values of the net Total Connectedness Index (TCI). Thickness of the lines indicates the intensity of shock (thick lines are more intense compared to thin lines). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5. Conclusion

This study uncovers compelling insights into the interconnectedness of the water, energy, and food (WEF) sectors, offering valuable implications for researchers, policymakers, and investors. Apart from the synergies, the WEF nexus also bring about the trade-offs due to the challenges posed by resource constraint. Reliance of agriculture and electricity on water resources as highlighted in the literature (Dudgeon et al., 2006; Poff et al., 1997; Chini et al., 2018; Chu and Majumdar, 2012) can lead to global water stress. Lack of an integrated planning of water resources can affect equitable distribution of water for different uses causing conflicts in the allocation of water (Pittock et al., 2015). A coherent policy characterized by coordination between different policy making communities can abate the trade-off between the three sectors. For instance, joint efforts by the stakeholders to enhance the soil nutrient levels, seed quality and irrigation system can help in increasing water productivity and food production, thus putting lesser stress on water resources. The conflicting use of water for energy production can be countered through alternative measures such as the use of solar power water pumping for irrigation or promotion of afforestation policies can reduce total water consumption through evapotranspiration and to increase fuelwood availability can create synergies between energy and water sector.[29] Moreover, a model-based decision support that considers multiple plausible futures (Maier et al., 2016) while designing the strategies can a go a long way in solving the trade-offs between the three sectors. For the resource allocation we recommend an optimization model-based policy that seek to find the pareto-optimal (best possible) allocation of benefits between the food-energy-water sectors.

To our knowledge no study has employed quantile connectedness

[29] https://cms.deltares.nl/assets/common/downloads/Operationalizing-the-WEF-nexus_quantifying-the-trade-offs-and-synergies-between-the-water-energy-food.pdf.

analysis to calibrate the impact at various levels of shocks (both positive and negative) in respect to the WEF variables. Therefore, this study bridges the literature gap in many ways. First, time-varying asymmetric connectedness among the variables across various stages of shocks receiving and emitting (connectedness is high at extremes). Second, it is evident that the positive shocks have a stronger impact in these variables over their negative counterparts. Third, food consumption is more relevant during positive shocks (due to nutrition related measures from UN). Fourth, crop production mostly remains as a receiver of shocks. Fifth, electricity consumption remains crucial across most times, irrespective of any positive or negative policy decisions. Sixth, renewable water available is found to be consistent net emitter in all circumstances. Seventh, water withdrawal remains crucial from extreme negative shock up to the neutral time, proving its importance. We propose certain policy recommendations and guidelines for both policymakers and investors. In the first place, our results demonstrate that the magnitude of connectedness in the WEF network increases during extreme periods (denoted by the extreme quantiles). For instance, a COP series would induce positive shock, whereas pandemic or border conflicts would induce negative shocks. Further, there is asymmetry and a bias towards positive incidents. Therefore, limiting the scope of the study to the median quantile would not be fruitful for the investors and policymakers, since they would be ignoring the asymmetric tail dependence. Therefore, we posit that there is a grave need to develop robust and efficient natural resource management strategies, which can incorporate uncertainty into decision-making processes related to planning infrastructure and managing water and energy resources. Second, stabilisation of the WEF variable prices during extreme times (both positive and negative) would certainly assist stabilising the entire connectedness across the WEF variables. Third, energy plays a crucial role especially when we reduce carbon footprint as a policy, predictability of the same remains essential for investors. Fourth, results indicate that crop production and energy consumption are the least connected to other WEF variables across all quantiles under consideration barring 90th quantile. Thus, they are going to be rather perfect hedge for all other WEF variables under a wide range of extreme as well as normal conditions. Fifth, as the negative shocks can put tremendous pressure on water consumption, we recommend techniques such as storing atmospheric water and rain water harvesting to bring balance between water supply and usage. We also suggest greater capacity building and water accounting for institutions as a good water management and governance practice, which is in accordance with another latest work around the same theme (Tye et al., 2022). We recommend possible extensions of our work. Though quantile connectedness model accommodated spillovers across the WEF variables under varied stressed and normal conditions, the use of annually data may not entirely account for the movements. Future research can use data with other frequencies such as daily to test the resilience of our findings. Further, different horizons can be chosen as well to test the consistency of the results.

6. Limitations of the study and scope for future research

Although this study is a novel attempt, yet there are certain limitations. First, the data availability from AQUASTAT, FAO is annual in nature, therefore, it's relatively shorter. Second, TVP-VAR or DCC-GARCH modelling could also be applied. Third, only extreme quantiles such as 0.01 & 0.99 could be calibrated and deciphered.

CRediT authorship contribution statement

Bikramaditya Ghosh: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mariya Gubareva:** Investigation, Funding acquisition, Formal analysis, Conceptualization, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Anandita Ghosh:** Conceptualization, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Dimitrios Paparas:** Conceptualization, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Xuan Vinh Vo:** Formal analysis, Investigation, Validation, Writing – original draft, Writing – review & editing.

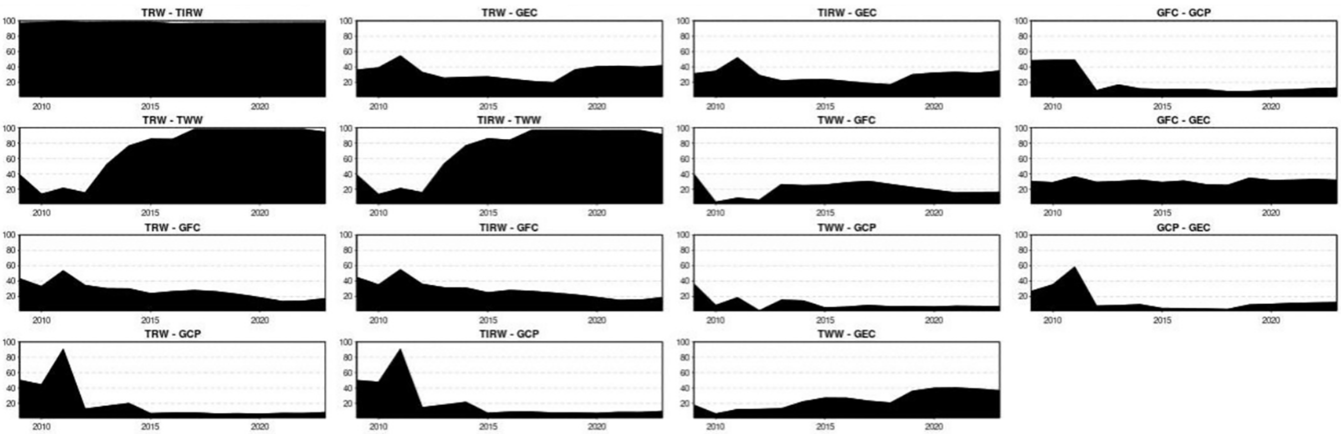
Acknowledgements

This work was supported by FCT, I.P., the Portuguese national funding agency for science, research and technology, under the Project UIDB/04521/2020. This research is partly funded by the University of Economics Ho Chi Minh City, Vietnam (UEH).

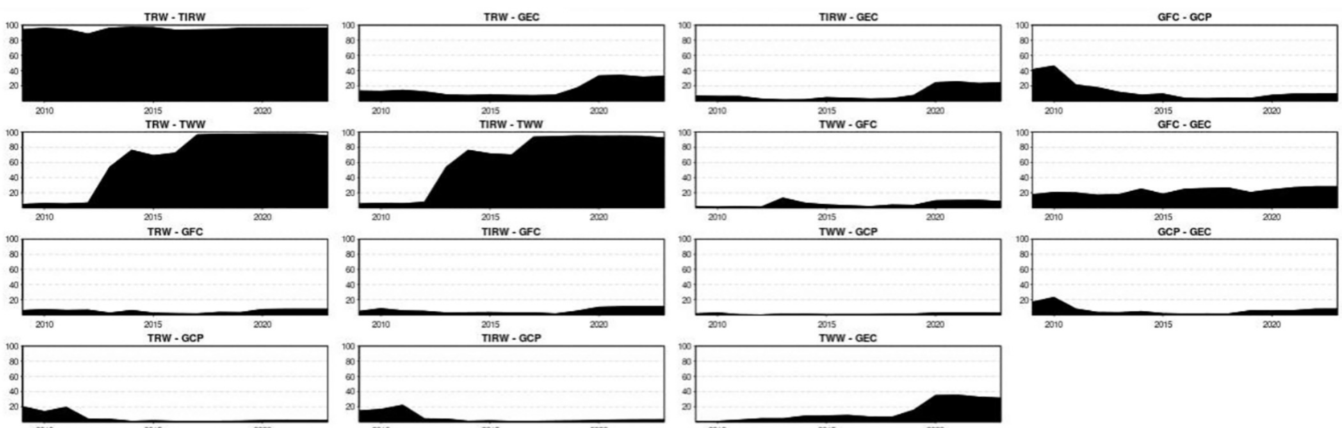
Appendix A. Correlation among the variables.

	TRW	TIRW	TWW	GFC	GCP	GEC
TRW	1					
TIRW	0.809496	1				
TWW	−0.48841	0.031519	1			
GFC	−0.45753	0.011263	0.887964	1		
GCP	0.004373	−0.01348	−0.06227	−0.02751	1	
GEC	0.060194	−0.01215	−0.06137	0.007895	−0.01735	1

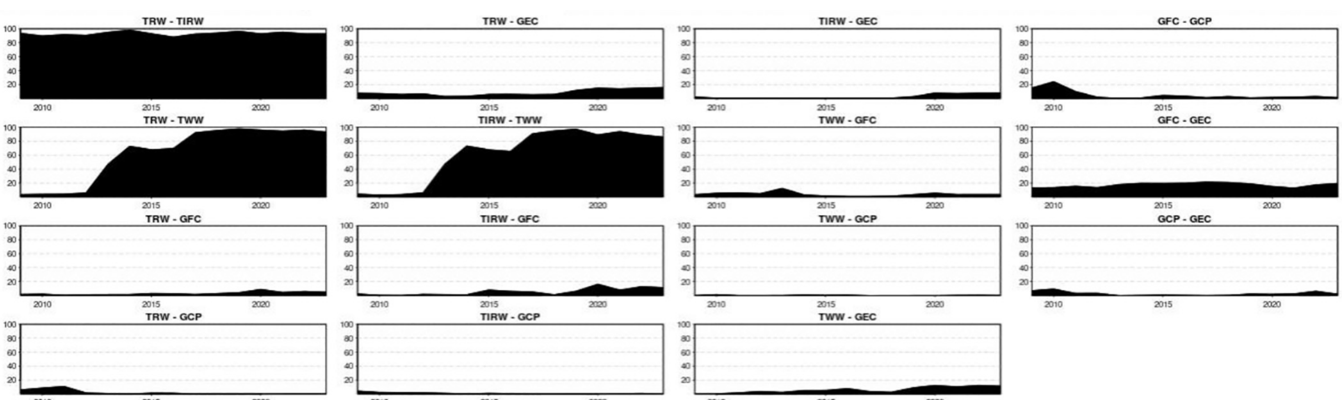
Appendix B. Dynamic pairwise connectedness


TRW - TIRW
TRW - GEC
TIRW - GEC
GFC - GCP
TRW - TWW
TIRW - TWW
TWW - GFC
GFC - GEC
TRW - GFC
TIRW - GFC
TWW - GCP
GCP - GEC
TRW - GCP
TIRW - GCP
TWW - GEC

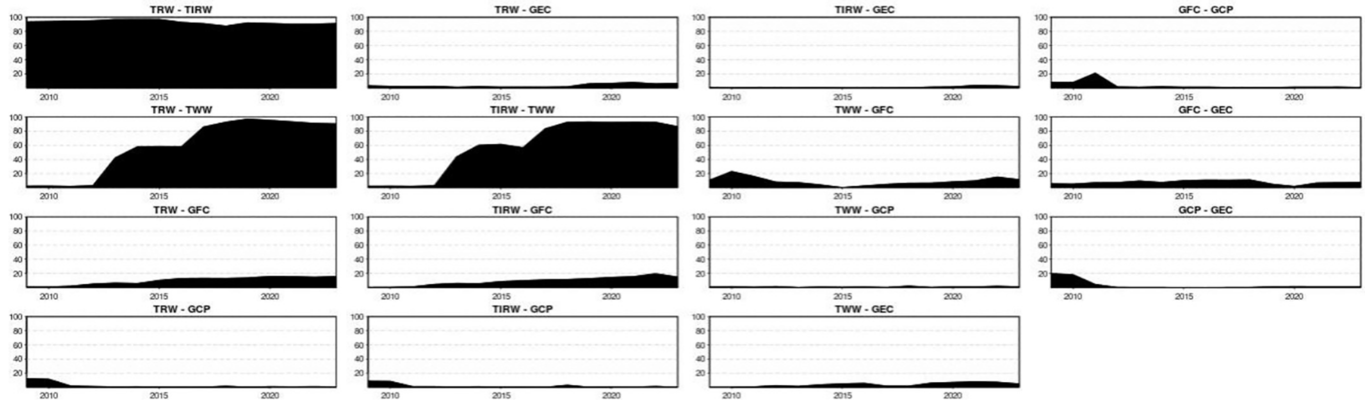
(Q0.1)


TRW - TIRW
TRW - GEC
TIRW - GEC
GFC - GCP
TRW - TWW
TIRW - TWW
TWW - GFC
GFC - GEC
TRW - GFC
TIRW - GFC
TWW - GCP
GCP - GEC
TRW - GCP
TIRW - GCP
TWW - GEC

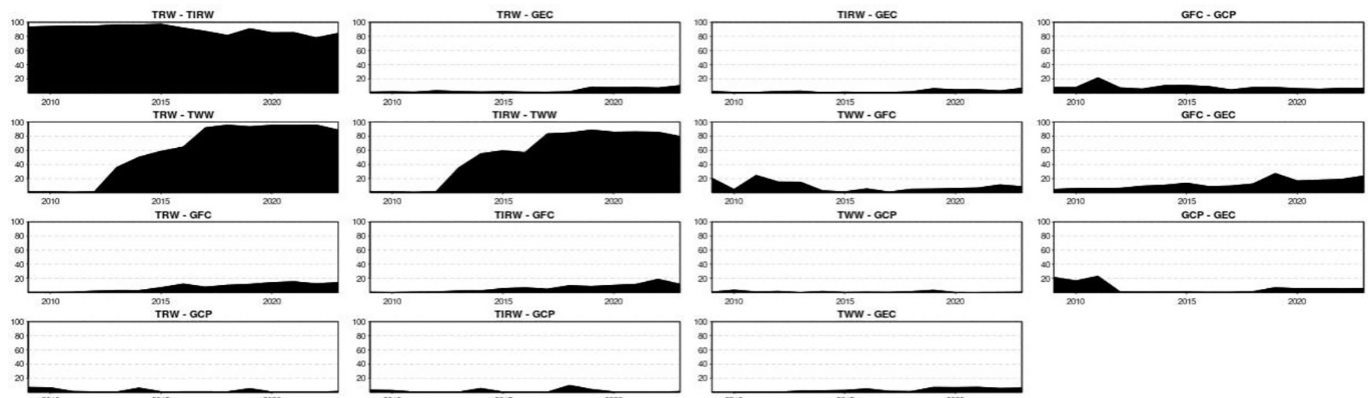
(Q0.2)


TRW - TIRW
TRW - GEC
TIRW - GEC
GFC - GCP
TRW - TWW
TIRW - TWW
TWW - GFC
GFC - GEC
TRW - GFC
TIRW - GFC
TWW - GCP
GCP - GEC
TRW - GCP
TIRW - GCP
TWW - GEC

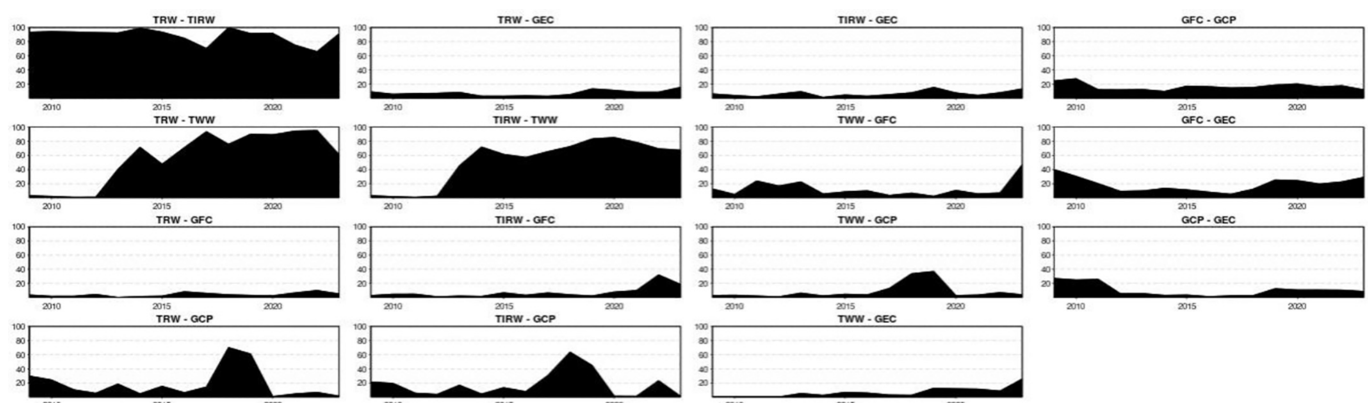
(Q0.3)


TRW - TIRW
TRW - GEC
TIRW - GEC
GFC - GCP
TRW - TWW
TIRW - TWW
TWW - GFC
GFC - GEC
TRW - GFC
TIRW - GFC
TWW - GCP
GCP - GEC
TRW - GCP
TIRW - GCP
TWW - GEC

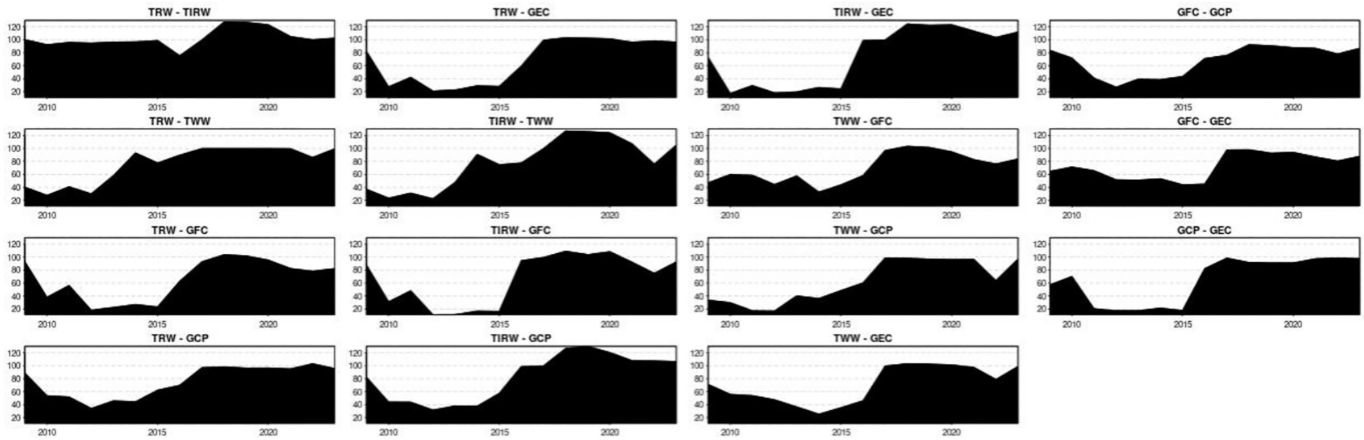
(Q0.5)


TRW - TIRW
TRW - GEC
TIRW - GEC
GFC - GCP
TRW - TWW
TIRW - TWW
TWW - GFC
GFC - GEC
TRW - GFC
TIRW - GFC
TWW - GCP
GCP - GEC
TRW - GCP
TIRW - GCP
TWW - GEC

(Q0.7)


TRW - TIRW
TRW - GEC
TIRW - GEC
GFC - GCP
TRW - TWW
TIRW - TWW
TWW - GFC
GFC - GEC
TRW - GFC
TIRW - GFC
TWW - GCP
GCP - GEC
TRW - GCP
TIRW - GCP
TWW - GEC

(Q0.8)



(Q0.9)

Appendix C. Data summary table

Metric	Number of countries	Methodology/Limitations	Data Source
Total renewable water resource per capita and total internal renewable water resources	183	The data is collected through country surveys and modelled through GIS[a] (geographical information system) and RS (remote sensing). The computation of water resources is based on water resources accounting approach. However, due to lack of information at country level and resources at all levels leads to the problem of data gaps.	FAO Aquastat[b]
Total Water withdrawal	180	AQUASTAT obtains water withdrawal values from national ministries or other governmental agencies. Information on water use by resources consists of surface water, ground water and non-conventional source of water. But data gaps are still persistent.	FAO Aquastat[c]
Global Electricity Consumption	216	World bank provides estimates of global electricity consumption, drawn from international sources (world bank and IEA) and have been standardized as much as possible to facilitate cross-country comparisons.	World Bank[d]
Global Food Production	199	UN FAO provides data on crop yield statistics for 278 products. The source data are collected from surveys, administrative data and estimates based on expert observations.	UN FAOSTAT[e]
Global Food consumption	53	FAO collects data on food intake through quantitative dietary surveys worldwide.	UN FAOSTAT[f]

[a] https://www.fao.org/publications/card/en/c/I9241EN/.
[b] https://data.apps.fao.org/aquastat/?lang=en).
[c] https://data.apps.fao.org/aquastat/?lang=en).
[d] https://databank.worldbank.org/id/b3ab275c?Report_Name=Electricity-production.
[e] https://www.fao.org/faostat/en/#data/QCL.
[f] https://www.fao.org/gift-individual-food-consumption/data/en.

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107521.

References

Aeschbach-Hertig, W., Gleeson, T., 2012. Regional strategies for the accelerating global problem of groundwater depletion. Nat. Geosci. 5 (12), 853–861. https://doi.org/10.1038/ngeo1617.

Albrecht, T.R., Crootof, A., Scott, C.A., 2018. The water-energy-food Nexus: a systematic review of methods for nexus assessment. Environ. Res. Lett. 13 (4), 043002 https://doi.org/10.1088/1748-9326/aaa9c6.

Ando, T., Greenwood-Nimmo, M., Shin, Y., 2022. Quantile connectedness: modeling tail behavior in the topology of financial networks. Manag. Sci. 68 (4), 2401–2431. https://doi.org/10.1287/mnsc.2021.3984.

Antonakakis, N., Chatziantoniou, I., Gabauer, D., 2020. Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. J. Risk Financ. Manage. 13 (4), 84. https://doi.org/10.3390/jrfm13040084.

Archer, E., Du Toit, J., Engelbrecht, C., Hoffman, M.T., Landman, W., Malherbe, J., Stern, M., 2022. The 2015-19 multi year drought in the eastern cape, South Africa: it's evolution and impacts on agriculture. J. Arid Environ. 196, 104630.

Banaeian, N., Zangeneh, M., 2011. Study on energy efficiency in corn production of Iran. Energy 36 (8), 5394–5402. https://doi.org/10.1016/j.energy.2011.06.052.

Bates, B., Kundzewicz, Z., Wu, S., 2008. Climate change and water. http://www.taccire.sua.ac.tz/handle/123456789/552.

Bazilian, M., Rogner, H., Howells, M., Hermann, S., Arent, D., Gielen, D., Steduto, P., Mueller, A., Komor, P., Tol, R.S.J., Yumkella, K.K., 2011. Considering the energy, water and food nexus: towards an integrated modelling approach. Energy Policy 39 (12), 7896–7906. https://doi.org/10.1016/j.enpol.2011.09.039.

Blanchard, O., Perotti, R., 2002. An empirical characterization of the dynamic effects of changes in government spending and taxes on output. Q. J. Econ. 117 (4), 1329–1368. https://doi.org/10.1162/003355302320935043.

Bonsch, M., Humpenöder, F., Popp, A., Bodirsky, B., Dietrich, J.P., Rolinski, S., Biewald, A., Lotze-Campen, H., Weindl, I., Gerten, D., Stevanovic, M., 2016. Trade-offs between land and water requirements for large-scale bioenergy production. GCB Bioenergy 8 (1), 11–24. https://doi.org/10.1111/gcbb.12226.

Bossman, A., Agyei, S.K., 2022a. ICEEMDAN-based transfer entropy between global commodity classes and African equities. Math. Probl. Eng. 1–28. https://doi.org/10.1155/2022/8964989.

Bossman, A., Agyei, S.K., 2022b. Interdependence structure of global commodity classes and African equity markets: a vector wavelet coherence analysis. Res. Policy 79, 103039. https://doi.org/10.1016/j.resourpol.2022.103039.

Bossman, A., Gubareva, M., Teplova, T., 2023. Asymmetric effects of market uncertainties on agricultural commodities. Energy Econ. 107080 https://doi.org/10.1016/j.eneco.2023.107080.

Boström, M., Jönsson, A.M., Lockie, S., Mol, A.P., Oosterveer, P., 2015. Sustainable and responsible supply chain governance: challenges and opportunities. J. Clean. Prod. 107, 1–7. https://doi.org/10.1016/j.jclepro.2014.11.050.

Bouri, E., Saeed, T., Vo, X.V., Roubaud, D., 2021. Quantile connectedness in the cryptocurrency market. J. Int. Financ. Mark. Inst. Money 71, 101302. https://doi.org/10.1016/j.intfin.2021.101302.

Brinkman, H., De Pee, S., Sanogo, I., Subran, L., Bloem, M.W., 2010. High food prices and the global financial crisis have reduced access to nutritious food and worsened nutritional status and health 1, 2. J. Nutr. 140 (1), 153S–161S. https://doi.org/10.3945/jn.109.110767.

Chai, L., Liao, X., Yang, L., Yan, X., 2018. Assessing life cycle water use and pollution of coal-fired power generation in China using input-output analysis. Appl. Energy 231, 951–958. https://doi.org/10.1016/j.apenergy.2018.09.178.

Chatziantoniou, I., Gabauer, D., Stenfors, A., 2021. Interest rate swaps and the transmission mechanism of monetary policy: a quantile connectedness approach. Econ. Lett. 204, 109891 https://doi.org/10.1016/j.econlet.2021.109891.

Chaudhary, V., Gangwa, B., Pandey, D., 2006. Auditing of energy use and output of different cropping Systems in India. Agric. Eng. Int. 8. https://cigrjournal.org/index.php/Ejounral/article/view/658/652.

Chen, J., Liang, Z., Diang, Q., Liu, Z., 2022. Quantile connectedness between energy, metal, and carbon markets. Int. Rev. Financ. Anal. 83, 102282 https://doi.org/10.1016/j.irfa.2022.102282.

Chini, C.M., Djehdian, L.A., Lubega, W.N., Stillwell, A.S., 2018. Virtual water transfers of the US electric grid. Nat. Energy 3 (12), 1115–1123. https://doi.org/10.1038/s41560-018-0266-1.

Chu, S., Majumdar, A., 2012. Opportunities and challenges for a sustainable energy future. Nature 488 (7411), 294–303. https://doi.org/10.1038/nature11475.

Clark, C.E., Harto, C.B., Sullivan, J.L., Wang, M.Q., 2010. Water use in the development and operation of geothermal power plants. Argonne National Laboratory, Environmental Science Division, ANV/EVS/R-10/5. https://publications.anl.gov/anlpubs/2010/09/67934.pdf.

Cruse, M.J., Liebman, M., Raman, D.R., Wiedenhoeft, M.H., 2010. Fossil energy use in conventional and low-external-input cropping systems. Agron. J. 102 (3), 934–941. https://doi.org/10.2134/agronj2009.0457.

Daccache, A., Ciurana, J.S., Rodriguez Diaz, J.A., Knox, J.W., 2014. Water and energy footprint of irrigated agriculture in the Mediterranean region. Environ. Res. Lett. 9 (12), 124014 https://doi.org/10.1088/1748-9326/9/12/124014.

De Laurentiis, V., Hunt, D., Rogers, C., 2016. Overcoming food security challenges within an energy/water/food Nexus (EWFN) approach. Sustainability 8 (1), 95. https://doi.org/10.3390/su8010095.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006.

Diebold, F.X., Yilmaz, K., 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. J. Econ. 182 (1), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012.

Dijk, M., Morley, T., Rau, M.L., Saghai, Y., 2021. A meta-analysis of projected global food demand and population at risk of hunger for the period 2010–2050. Nat. Food 2 (July). https://doi.org/10.1038/s43016-021-00322-9.

D'Odorico, P., Davis, K.F., Rosa, L., Carr, J.A., Chiarelli, D., Dell'Angelo, J., Gephart, J., MacDonald, G.K., Seekell, D.A., Suweis, S., Rulli, M.C., 2018. The global food-energy-water Nexus. Rev. Geophys. 56 (3), 456–531. https://doi.org/10.1029/2017RG000591.

D'Odorico, P., Chiarelli, D.D., Rosa, L., Bini, A., Zilberman, D., Rulli, M.C., 2020. The global value of water in agriculture. Proc. Natl. Acad. Sci. 117 (36), 21985–21993. https://doi.org/10.1073/pnas.2005835117.

Döll, P., Siebert, S., 2002. Global modeling of irrigation water requirements. Water Resour. Res. 38 (4) https://doi.org/10.1029/2001WR000355, 8-1-8-10.

Dudgeon, D., Arthington, A.H., Gessner, M.O., Kawabata, Z.-I., Knowler, D.J., Lévêque, C., Naiman, R.J., Prieur-Richard, A.-H., Soto, D., Stiassny, M.L.J., Sullivan, C.A., 2006. Freshwater biodiversity: importance, threats, status and conservation challenges. Biol. Rev. 81 (02), 163. https://doi.org/10.1017/S1464793105006950.

EEA, 2015. The European Environment — State and Outlook 2015: Synthesis Report. European Environment Agency – EEA. https://www.eea.europa.eu/soer/2015.

EIA, 2017. International Energy Outlook 2017. U.S. Energy Information Administration – EIA. https://www.eia.gov/outlooks/ieo/pdf/0484(2017).pdf.

Elsoragaby, S., Yahya, A., Mahadi, M.R., Nawi, N.M., Mairghany, M., 2019. Energy utilization in major crop cultivation. Energy 173, 1285–1303. https://doi.org/10.1016/j.energy.2019.01.142.

Escriva-Bou, A., Lund, J.R., Pulido-Velazquez, M., Hui, R., Medellín-Azuara, J., 2018. Developing a water-energy-GHG emissions modeling framework: insights from an application to California's water system. Environ. Model Softw. 109, 54–65. https://doi.org/10.1016/j.envsoft.2018.07.011.

Falkenmark, M., Rockstrom, J., 2004. Balancing Water for Humans and Nature - the New Approach in Ecohydrology. Routledge.

Famiglietti, J.S., 2014. The global groundwater crisis. Nat. Clim. Chang. 4 (11), 945–948. https://doi.org/10.1038/nclimate2425.

FAO, 2014. The Water-Energy-Food Nexus a New Approach in Support of Food Security and Sustainable Agriculture. Food and Agriculture Organization of the United Nations – FAO. https://www.fao.org/3/bl496e/bl496e.pdf.

FAO, 2017. The Future of Food and Agriculture – Trends and Challenges. Food and Agriculture Organization of the United Nations – FAO. www.fao.org/3/a-i6583e.pdf.

Farid, S., Naeem, M.A., Paltrinieri, A., Nepal, R., 2022. Impact of COVID-19 on the quantile connectedness between energy, metals and agriculture commodities. Energy Econ. 109, 105962 https://doi.org/10.1016/j.eneco.2022.105962.

Ferroukhi, R.A., Nagpal, D., Lopez-Peña, A., Hodges, T., Mohtar, R.H., Daher, B., Mohtar, S., Keulertz, M., 2015. Renewable Energy in the Water, Energy & Food Nexus. International Renewable Energy Agency – IRENA. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2015/IRENA_Water_Energy_Food_Nexus_2015.pdf.

Ganguli, P., Kumar, D., Ganguly, A.R., 2017. US power production at risk from water stress in a changing climate. Sci. Rep. 7 (1), 11983. https://doi.org/10.1038/s41598-017-12133-9.

Ghosh, B., Pham, L., Gubareva, M., Teplova, T., 2023a. Energy transition metals and global sentiment: evidence from extreme quantiles. Res. Policy 86-A, 104170. https://doi.org/10.1016/j.resourpol.2023.104170.

Ghosh, B., Pham, L., Teplova, T., Umar, Z., 2023b. COVID-19 and the quantile connectedness between energy and metal markets. Energy Econ. 117 (1), 106420 https://doi.org/10.1016/j.eneco.2022.106420.

Gleeson, T., Wada, Y., Bierkens, M.F.P., van Beek, L.P.H., 2012. Water balance of global aquifers revealed by groundwater footprint. Nature 488 (7410), 197–200. https://doi.org/10.1038/nature11295.

Grindle, A.K., Siddiqi, A., Anadon, L.D., 2015. Food security amidst water scarcity: insights on sustainable food production from Saudi Arabia. Sustain. Product. Consumpt. 2, 67–78. https://doi.org/10.1016/j.spc.2015.06.002.

Haslbeck, J.M.B., Bringmann, L.F., Waldorp, L.J., 2021. A tutorial on estimating time-varying vector autoregressive models a tutorial on estimating time-varying vector autoregressive models. Multivar. Behav. Res. 56 (1), 120–149. https://doi.org/10.1080/00273171.2020.1743630.

Hatirli, S.A., Ozkan, B., Fert, C., 2006. Energy inputs and crop yield relationship in greenhouse tomato production. Renew. Energy 31 (4), 427–438. https://doi.org/10.1016/j.renene.2005.04.007.

Hoff, H., 2011. Background Paper for THE Bonn 2011 Nexus Conference: THE WATER, ENERGY AND FOOD SECURITY NEXUS.

Hunt, E., Femia, F., Werrell, C., Christian, J.I., Otkin, J.A., Basara, J., McGaughey, K., 2021. Agricultural and food security impacts from the 2010 Russia flash drought. Weather Clim. Extremes 34, 100383.

Iacopini, M., Poon, A., 2022. Bayesian Mixed-Frequency Quantile Vector Autoregression: Eliciting Tail Risks of Monthly US GDP.

IEA, 2017. Water Energy Nexus. International Energy Agency – IEA. World Energy Outlook Special Report. https://www.iea.org/reports/water-energy-nexus.

Jimenez, J.C., Libonati, R., Peres, L.F., 2018. Droughts over Amazonia in 2005, 2010, and 2015: a cloud cover perspective. Front. Earth Sci. 6, 227.

Joo, K., Hwan, J., Lee, D., Ahn, K., 2020. Impact of the global financial crisis on the crude oil market. Energ. Strat. Rev. 30, 100516 https://doi.org/10.1016/j.esr.2020.100516.

Kang, W., Tang, K., Wang, N., 2023. Financialization of commodity markets ten years later. J. Commod. Mark. 30, 100313 https://doi.org/10.1016/j.jcomm.2023.100313.

Keshavarz Afshar, R., Alipour, A., Hashemi, M., Ansari Jovini, M., Pimentel, D., 2013. Energy inputs-yield relationship and sensitivity analysis of pistachio (Pistacia vera L.) production in Markazi region of Iran. Span. J. Agric. Res. 11 (3), 661. https://doi.org/10.5424/sjar/2013113-3877.

Kheirinejad, S., Haddad, O.B., Singh, V.P., Loáiciga, H.A., 2022. The effect of reducing per capita water and energy uses on renewable water resources in the water, food and energy nexus. Scientific Reports. Nature Publishing Group UK. https://doi.org/10.1038/s41598-022-11595-w.

Khilchevskyi, V., De Meester, L., Stepanenko, S., Trokhymenko, G., Hernández-agüero, J. A., Gleick, P., 2023. Impact of the Russia – Ukraine Armed Conflict on Water Resources and Water Infrastructure. https://doi.org/10.1038/s41893-023-01068-x.

Kholod, N., Evans, M., Khan, Z., Hejazi, M., Chaturvedi, V., 2021. Water-energy-food nexus in India: a critical review. Energy Clim. Change 100060. https://doi.org/10.1016/j.egycc.2021.100060.

Klemes, J., Smith, R., Kim, J.K., 2008. Handbook of Water and Energy Management in Food Processing. Elsevier.

Konikow, L.F., 2011. Contribution of global groundwater depletion since 1900 to sea-level rise. Geophys. Res. Lett. 38 (17) https://doi.org/10.1029/2011GL048604.

Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. J. Econ. 74 (1), 119–147. https://doi.org/10.1016/0304-4076(95)01753-4.

Kumar, P.S., Yaashikaa, P.R., 2019. Introduction-water. In: Water in Textiles and Apparel. Elsevier Ltd., pp. 1–20. https://doi.org/10.1016/B978-0-08-102633-5.00001-4

Kummu, M., Ward, P.J., De Moel, H., Varis, O., 2010. Is physical water scarcity a new phenomenon? Global assessment of water shortage over the last two millennia. Environ. Res. Lett. 5 (3), 034006.

Lanne, M., Nyberg, H., 2016. Generalized forecast error variance decomposition for linear and nonlinear multivariate models. Oxf. Bull. Econ. Stat. 78 (4), 595–603. https://doi.org/10.1111/obes.12125.

Leese, M., Meisch, S., 2015. Securitising Sustainability? Questioning the "water, energy and food-security nexus". Water Altern. 8 (1), 695709. www.water-alternatives.org.

Leichenko, R.M., Brien, K.L.O., Solecki, W.D., 2010. Climate Change and the Global Financial Crisis: A Case of Double Exposure, 100(4), pp. 963–972.

Li, W., Li, L., Qiu, G., 2013. General Nexus between water and electricity use and its implication for urban agricultural sustainability: a case study of Shenzhen, South China. J. Integr. Agric. 12 (8), 1341–1349. https://doi.org/10.1016/S2095-3119(13)60547-X.

Li, G., Huang, D., Li, Y., 2016. China's input-output efficiency of water-energy-food Nexus based on the data envelopment analysis (DEA) model. Sustainability 8 (9), 927. https://doi.org/10.3390/su8090927.

Li, X., Dong, D., Lin, G., Yan, R., Li, S., 2020. Water use for energy production and conversion in Hebei Province, China. Front. Energy Res. 8 https://doi.org/10.3389/fenrg.2020.558536.

Linnemann, L., Winkler, R., 2016. Estimating nonlinear effects of fiscal policy using quantile regression methods. Oxf. Econ. Pap. 68 (4), 1120–1145. https://doi.org/10.1093/oep/gpw020.

Macknick, J., Newmark, R., Heath, G., Hallett, K.C., 2012. Operational water consumption and withdrawal factors for electricity generating technologies: a review of existing literature. Environ. Res. Lett. 7 (4), 045802 https://doi.org/10.1088/1748-9326/7/4/045802.

Maddigan, R.J., Chern, W.S., Rizy, C.G., 1982. The irrigation demand for electricity. Am. J. Agric. Econ. 64 (4), 673–680.

Maier, H.R., Guillaume, J.H.A., Van Delden, H., Riddell, G.A., Haasnoot, M., Kwakkel, J. H., 2016. Environmental Modelling & Software an uncertain future, deep uncertainty, scenarios, robustness and adaptation: how do they fit together? Environ. Model. Softw. 81, 154–164. https://doi.org/10.1016/j.envsoft.2016.03.014.

Martin-Gorriz, B., Soto-García, M., Martínez-Alvarez, V., 2014. Energy and greenhouse-gas emissions in irrigated agriculture of SE (southeast) Spain. Effects of alternative water supply scenarios. Energy 77, 478–488. https://doi.org/10.1016/j.energy.2014.09.031.

Mashnik, D., Jacobus, H., Barghouth, A., Jiayu Wang, E., Blanchard, J., Shelby, R., 2017. Increasing productivity through irrigation: problems and solutions implemented in Africa and Asia. Sustain. Energy Technol. Assess. 22, 220–227. https://doi.org/10.1016/j.seta.2017.02.005.

Mekonnen, M.M., Hoekstra, A.Y., 2016. Four billion people facing severe water scarcity. Sci. Adv. 2 (2) https://doi.org/10.1126/sciadv.1500323.

Mekonnen, M.M., Gerbens-Leenes, P.W., Hoekstra, A.Y., 2016. Future electricity: the challenge of reducing both carbon and water footprint. Sci. Total Environ. 569–570, 1282–1288. https://doi.org/10.1016/j.scitotenv.2016.06.204.

Morawicki, R.O., Hager, T., 2014. Energy and greenhouse gases footprint of food processing. In: Encyclopaedia of Agriculture and Food Systems. Elsevier, pp. 82–99. https://doi.org/10.1016/B978-0-444-52512-3.00057-7.

Nair, S., George, B., Malano, H.M., Arora, M., Nawarathna, B., 2014. Water–energy–greenhouse gas nexus of urban water systems: review of concepts, state-of-art and methods. Resour. Conserv. Recycl. 89, 1–10. https://doi.org/10.1016/j.resconrec.2014.05.007.

Ng, M., Connor, M., 2022. One size does not fit all — addressing the complexity of food system sustainability. Front. Sustain. Food Syst. 6 (March), 1–5. https://doi.org/10.3389/fsufs.2022.816936.

Ogbolumani, O.A., Nwulu, N.I., 2024. Environmental impact assessment for a meta-model-based food-energy-water-nexus system. Energy Rep. 11 (June 2023), 218–232. https://doi.org/10.1016/j.egyr.2023.11.033.

Ozkan, B., Akcaoz, H., Fert, C., 2004. Energy input–output analysis in Turkish agriculture. Renew. Energy 29 (1), 39–51. https://doi.org/10.1016/S0960-1481(03)00135-6.

Ozturk, I., 2015. Sustainability in the food-energy-water nexus: evidence from BRICS (Brazil, the Russian Federation, India, China, and South Africa) countries. Energy 93, 999–1010. https://doi.org/10.1016/j.energy.2015.09.104.

Patel, R., Gubareva, M., Chishti, M., Teplova, T., 2024. Connectedness between healthcare cryptocurrencies and major asset classes: implications for hedging and investments strategies. Int. Rev. Financ. Anal. 103181 https://doi.org/10.1016/j.irfa.2024.103181.

Pathak, T., Maskey, M., Dahlberg, J., Kearns, F., Bali, K., Zaccaria, D., 2018. Climate change trends and impacts on California agriculture: a detailed review. Agronomy 8 (3), 25. https://doi.org/10.3390/agronomy8030025.

Peri, M., Vandone, D., Baldi, L., 2017. Volatility spillover between water, energy and food. Sustainability 9 (6), 1071. https://doi.org/10.3390/su9061071.

Perrone, D., Hornberger, G.M., 2014. Water, food, and energy security: scrambling for resources or solutions? WIREs Water 1 (1), 49–68. https://doi.org/10.1002/wat2.1004.

Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Econ. Lett. 58 (1), 17–29.

Pham, B.T., Sala, H., 2022. Cross-country connectedness in inflation and unemployment: measurement and macroeconomic consequences. Empir. Econ. 62 (3), 1123–1146. https://doi.org/10.1007/s00181-021-02052-0.

Pimentel, D., 2012. In: Pimental, D. (Ed.), Food and Energy Resources. Elsevier.

Pires, A., Morato, J., Peixoto, H., Botero, V., Zuluaga, L., Figueroa, A., 2016. Science of the Total environment sustainability assessment of indicators for integrated water resource management. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2016.10.217.

Pittock, J., Orr, S., Stevens, L., Aheeyar, M., Smith, M., 2015. Tackling trade-offs in the nexus of water, energy and food. Aquat. Proc. 5, 58–68. https://doi.org/10.1016/j.aqpro.2015.10.008.

Poff, N.L., Allan, J.D., Bain, M.B., Karr, J.R., Prestegaard, K.L., Richter, B.D., Sparks, R.E., Stromberg, J.C., 1997. The natural flow regime. BioScience 47 (11), 769–784. https://doi.org/10.2307/1313099.

Princen, T., 2002. Distancing: Consumption and the severing of feedback. In: Confronting Consumption, 1st ed. The MIT Press. https://doi.org/10.7551/mitpress/2097.001.0001.

Qin, Y., 2021. Global competing water uses for food and energy. Environ. Res. Lett. 16 (6), 064091 https://doi.org/10.1088/1748-9326/ac06fa.

Reffold, E., Leighton, F., Choudhury, F., Rayne, P.S., 2008. Greenhouse Gas Emissions of Water Supply and Demand Management Options. UK Environment Agency. Science report SC070010. https://assets.publishing.service.gov.uk/media/5a7cbfd4e5274a38e5756843/scho0708bofv-e-e.pdf.

Ringler, C., Bhaduri, A., Lawford, R., 2013. The nexus across water, energy, land and food (WELF): potential for improved resource use efficiency? Curr. Opin. Environ. Sustain. 5 (6), 617–624. https://doi.org/10.1016/j.cosust.2013.11.002.

Ringler, C., Willenbockel, D., Perez, N., Rosegrant, M., Zhu, T., Matthews, N., 2016. Global linkages among energy, food and water: an economic assessment. J. Environ. Stud. Sci. 6 (1), 161–171. https://doi.org/10.1007/s13412-016-0386-5.

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F.S., Lambin, E.F., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H.J., Nykvist, B., de Wit, C.A., Hughes, T., van der Leeuw, S., Rodhe, H., Sörlin, S., Snyder, P.K., Costanza, R., Svedin, U., Foley, J.A., 2009. A safe operating space for humanity. Nature 461 (7263), 472–475. https://doi.org/10.1038/461472a.

Rodell, M., Famiglietti, J.S., Wiese, D.N., Reager, J.T., Beaudoing, H.K., Landerer, F.W., Lo, M.-H., 2018. Emerging trends in global freshwater availability. Nature 557 (7707), 651–659. https://doi.org/10.1038/s41586-018-0123-1.

Rodríguez Díaz, J.A., Camacho Poyato, E., Blanco Pérez, M., 2011. Evaluation of water and energy use in pressurized irrigation networks in southern Spain. J. Irrig. Drain. Eng. 137 (10), 644–650. https://doi.org/10.1061/(ASCE)IR.1943-4774.0000338.

Rosa, L., Chiarelli, D.D., Tu, C., Rulli, M.C., D'Odorico, P., 2019. Global unsustainable virtual water flows in agricultural trade. Environ. Res. Lett. 14 (11), 114001 https://doi.org/10.1088/1748-9326/ab4bfc.

Rosegrant, M.W., Zhu, T., Msangi, S., Sulser, T., 2008. Global scenarios for biofuels: impacts and implications. Rev. Agric. Econ. 30 (3), 495–505. https://doi.org/10.1111/j.1467-9353.2008.00424.x.

Saraiva, A., Presumido, P., Silvestre, J., Feliciano, M., Rodrigues, G., Silva, P.O.E., Oliveira, M., 2020. Water footprint sustainability as a tool to address climate change in the wine sector: a methodological approach applied to a Portuguese case study. Atmosphere 11 (9), 934.

Scherer, L., Pfister, S., 2016. Global water footprint assessment of hydropower. Renew. Energy 99, 711–720. https://doi.org/10.1016/j.renene.2016.07.021.

Sharif, M.N., Haider, H., Farahat, A., Hewage, K., Sadiq, R., 2019. Water–energy nexus for water distribution systems: a literature review. Environ. Rev. 27 (4), 519–544. https://doi.org/10.1139/er-2018-0106.

Singh, H., Mishra, D., Nahar, N.M., 2002. Energy use pattern in production agriculture of a typical village in arid zone, India—part I. Energy Convers. Manag. 43 (16), 2275–2286. https://doi.org/10.1016/S0196-8904(01)00161-3.

Smajgl, A., Ward, J., Pluschke, L., 2016. The water–food–energy Nexus – Realising a new paradigm. J. Hydrol. 533, 533–540. https://doi.org/10.1016/j.jhydrol.2015.12.033.

Spang, E.S., Moomaw, W.R., Gallagher, K.S., Kirshen, P.H., Marks, D.H., 2014. Multiple metrics for quantifying the intensity of water consumption of energy production. Environ. Res. Lett. 9 (10), 105003 https://doi.org/10.1088/1748-9326/9/10/105003.

Stanhill, G., 2012. Energy and Agriculture, vol. 14. Springer Science and Business Media.

Strogatz, S.H., 2001. Exploring complex networks. Nature 410 (6825), 268–276. https://doi.org/10.1038/35065725.

Tang, K., Xiong, W., 2012. Index investment and the financialization of commodities. Financ. Anal. J. 68 (6), 54–74. https://doi.org/10.2469/faj.v68.n6.5.

Terrapon-Pfaff, J., Ortiz, W., Viebahn, P., Kynast, E., Flörke, M., 2020. Water demand scenarios for electricity generation at the global and regional levels. Water 12 (9), 2482. https://doi.org/10.3390/w12092482.

Topi, C., Esposto, E., Marini Govigli, V., 2016. The economics of green transition strategies for cities: can low carbon, energy efficient development approaches be adapted to demand side urban water efficiency? Environ. Sci. Pol. 58, 74–82. https://doi.org/10.1016/j.envsci.2016.01.001.

Turchi, C.S., Wagner, M.J., Kutscher, C.F., 2010. Water Use in Parabolic Trough Power Plants: Summary Results from WorleyParsons' Analyses.

Turner, S.W.D., Hejazi, M., Calvin, K., Kyle, P., Kim, S., 2019. A pathway of global food supply adaptation in a world with increasingly constrained groundwater. Sci. Total Environ. 673, 165–176. https://doi.org/10.1016/j.scitotenv.2019.04.070.

Tye, M.R., Wilhelmi, O.V., Pierce, A.L., Sharma, S., Nichersu, I., 2022. The food water energy nexus in an urban context: connecting theory and practice for nexus governance, 12. https://doi.org/10.1016/j.esg.2022.100143 (April).

Umar, Z., Gubareva, M., Naeem, M., Akhter, A., 2021. Return and volatility transmission between oil price shocks and agricultural commodities. PLoS One 16 (2), e0246886. https://doi.org/10.1371/journal.pone.0246886.

UNECE, 2018. Methodology for Assessing the Water-Food-Energy-Ecosystem nexus in Transboundary Basins and Experiences from its Application: Synthesis. United Nations Economic Commission for Europe – UNECE. https://unece.org/sites/default/files/2021-10/ECE-MP-WAT-55_NexusSynthesis_Final-for-Web.pdf.

Vandone, D., Peri, M., Baldi, L., Tanda, A., 2018. The impact of energy and agriculture prices on the stock performance of the water industry. Water Resour. Econ. 23, 14–27. https://doi.org/10.1016/j.wre.2018.02.002.

Veiga, J.P.S., Romanelli, T.L., Gimenez, L.M., Busato, P., Milan, M., 2015. Energy embodiment in Brazilian agriculture: an overview of 23 crops. Sci. Agric. 72 (6), 471–477. https://doi.org/10.1590/0103-9016-2015-0188.

Webster, M., Donohoo, P., Palmintier, B., 2013. Water–CO2 trade-offs in electricity generation planning. Nat. Clim. Chang. 3 (12), 1029–1032. https://doi.org/10.1038/nclimate2032.

Xiang, X., Svensson, J., Jia, S., 2017. Will the energy industry drain the water used for agricultural irrigation in the Yellow River basin? Int. J. Water Resour. Dev. 33 (1), 69–80. https://doi.org/10.1080/07900627.2016.1159543.

Yang, L., Zeng, S., Chen, J., He, M., Yang, W., 2010. Operational energy performance assessment system of municipal wastewater treatment plants. Water Sci. Technol. 62 (6), 1361–1370. https://doi.org/10.2166/wst.2010.394.

Yousaf, I., Youssef, M., Goodell, J.W., 2022. Quantile connectedness between sentiment and financial markets: evidence from the S&P 500 twitter sentiment index. Int. Rev. Financ. Anal. 83 (July), 102322 https://doi.org/10.1016/j.irfa.2022.102322.

Zhou, Y., Ma, M., Gao, P., Xu, Q., Bi, J., Naren, T., 2019. Managing water resources from the energy - water nexus perspective under a changing climate: a case study of Jiangsu province, China. Energy Policy 126, 380–390. https://doi.org/10.1016/j.enpol.2018.11.035.