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Data-driven quantification of the global water-energy-food system

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ABSTRACT

There is increasing interest in the global water-energy-food (WEF) system and potential system trajectories, especially considering growing concerns over resource exploitation and sustainability. Previous studies investigating different aspects of this system have a number of shortcomings, meaning it is difficult to identify system-wide tradeoffs, and makes comparison difficult. A global analysis of the WEF system linked to gross domestic product (GDP) growth is presented, integrating the four sectors into a coherent analysis and modelling framework. GDP was included as previous related work demonstrates a link between GDP and each WEF sector. A system dynamics modelling approach quantifies previously qualitative descriptions of the global WEF-GDP system, while a Monte-Carlo sampling approach is adopted to characterise national-level variability in resource use. Correlative and causal analysis show links of varying strength between sectors. For example, the GDP-electricity consumption sectors are strongly correlated while food production and electricity consumption are weakly correlated. Causal analysis reveals that 'correlation does not imply causation'. There are noticeable asymmetries in causality between certain sectors. Historical WEF-GDP values are well recreated. Future scenarios were assessed using seven GDP growth estimates to 2100. Water withdrawals in 2100 and food production in 2050 are close to other estimations. Results suggest that humanity risks exceeding the 'safe operating space' for water withdrawal. Reducing water withdrawal while maintaining or increasing food production is critical, and should be decoupled from economic growth. This work provides a quantitative modelling framework to previously qualitative descriptions of the WEF-GDP system, offering a platform on which to build.

1. Introduction

It is becoming increasingly clear that we live in a 'hyperconnected' world (World Economic Forum, 2016) in which natural resource exploitation and human development are bound together in an extraordinarily complex system. An important event to make explicit this system and to bring it to the wider consciousness was the Bonn Nexus Conference in 2011 (Hoff, 2011), which focussed particularly on the water-energy-food (WEF) nexus. Since then, the 'classical' WEF nexus has evolved to include land use, the environment, climate change, and/or the economy (e.g. WWF and SABMiller, 2014; Sušnik, 2015; WWAP, 2015; Fasel et al., 2016; Feng et al., 2016; World Bank, 2016; World Economic Forum, 2016). It has been expanded to cover human development and mental health (Biggs et al., 2015; Fabiola and De Rosa, 2016; Hernandez, 2016; Sušnik and van der Zaag, 2017), and in some cases has been 'shrunk' to become more focussed, for example in detailed investigations on (urban) water-energy relationships (e.g. Kenway et al., 2011; Davies et al., 2013; Holland et al., 2015; Hussein et al., 2017; Valek et al., 2017). Steffen et al. (2015) alluded to this complex system when the idea of planetary limits was put forward. It is increasingly clear that which of these planetary limits are exceeded, when, and by how much, are related to each other (e.g. the volume of water required for all uses will change as energy demand changes, as the energy mix changes, and as diets change globally). Others have used different terms to mean a complex system connected at the global scale, and in which actions to one sector can have significant impacts on other sectors, sometimes without prior knowledge of these connections even existing (e.g. the idea of 'teleconnections', especially in the climate system; Najibi et al., 2017). Global think-tanks and multinational corporations are showing increased interest in the nexus and its potential implications to business (e.g. IMechE, 2013; WWF and SABMiller, 2014; EEA, 2015; World Bank, 2016; World Economic Forum, 2016). Some major European Union research projects focussing on the nexus have recently begun, of which two merit particular attention: SIM4NEXUS (Sustainable Integrated Management FOR the NEXUS of water-land-food-energy-climate for a resource-efficient Europe; www.sim4nexus.eu), which assesses policies and pathways in the water, food, energy, land and climate sectors that will help enable a resource efficient Europe and which will develop a policy-maker interfacing serious game based on state-of-the-art science. MAGIC (http://magic-nexus.eu/) is focussed on policy and integration, and is testing how changes to policy can contribute to a more efficient nexus in Europe.

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Despite the increased interest, and the considerable increase in 'nexus' literature, there is a distinct lack of quantification as to how this system behaves. This is unsurprising given that 'nexus' means different things to different groups. At present, many studies qualitatively describe various nexus relationships (e.g. Cai et al., 2017), explaining how (in principle) changes to one nexus system sector (e.g. water) may impact on other system sectors (e.g. electricity generation). Where quantitative studies have been carried out, they usually either:

i) focus on a small part of a wider system, for example water and energy interactions only (e.g. Valek et al., 2017);
ii) focus on specific case studies that are detailed quantitatively, but can lack the generality to enable wider application (e.g. Hussein et al., 2017);
iii) some combination of (i) and (ii).

There are a few example of studies that are detailed and that cover a wider area or many sectors. Arguably the earliest global study on a nexus (in this case the relationships between population, human capital, agriculture and pollution) was that of Meadows et al. (1972). While initially this study was denounced and its conclusions dismissed, 40 years of subsequent data have revealed that some of the major global system sector *trajectories* were predicted reasonably well (Turner, 2008; Hall and Day, 2009; Turner, 2009), with hindsight allowing numbers to be placed on the y-axes of the Meadows et al. charts, which originally were without a scale (contributing to some of the early dismissal).

The World3 model of Simonovic (2002) is based on the system dynamics modelling (SDM) paradigm (Ford, 1999; Capra and Luisi, 2014). It analyses the consumption of global water resources. Despite its narrow focus, the model includes interaction with the agricultural and industrial sectors, as well as consideration of pollution and population. While the model is broadly applicable at the global scale, and acknowledges the close relationship between these sectors and the economy, it uses data that are now quite old (> 20 years). World3 makes some useful projections of the global water inventory based on gross-scale global system dynamics.

As more recent examples, Feng et al. (2016) use SDM to explore the water-power-environment nexus in Hehuang Region, China. Although spatially very limited, with restricted ability to scale up the conclusions, the study uses comprehensive data across a number of sectors to project water, power and environmental parameter trajectories into the near and far futures, attempting to quantify the system on a local scale and understand its long-term dynamics and evolution. Chen et al. (2018) use a multi-region input-output (MRIO) analysis to show the connection between agricultural production, freshwater use and international trade. It is shown that in general, resource-rich, less-developed countries transfer resources to resource-poor, well-developed countries, and that land productivity and water productivity generally show an inverse relationship.

While there is increasing interest in describing the 'nexus', and while there are more efforts going to better understand different systems, robust quantification of the WEF system, interaction between these sectors and their relationship to the economy through the proxy of gross domestic product (GDP) is lacking on a global level. Fig. 1 shows a familiar schematic of the WEF system linked to GDP. Boxes show the WEF-GDP sectors, and arrowed lines denote connections between the sectors. What form do these relationships take? How can change in one sector be used to estimate change in another? How can the inherent uncertainty involved when making global-scale observations be accounted for? In which way do causal relationships operate? Are the connections of a reinforcing mechanism (c.f. runaway greenhouse warming), or of a balancing mechanism (c.f. birth-death dynamics in classical population models)? How strong, relatively, are these relationships between sectors? These are questions that, so far, have not been well answered, and Fig. 1 remains largely a qualitative description of this globally critical system rather than a quantitative tool.

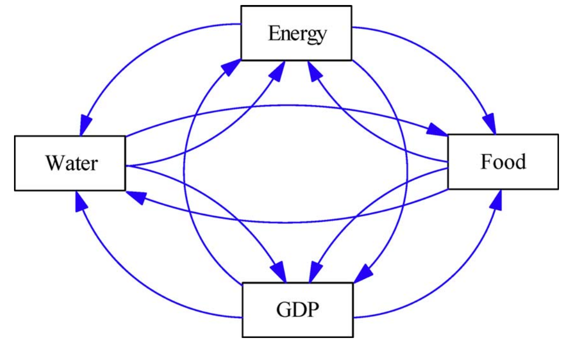

Fig. 1. Schematic representation of the water-energy-food-economy system. Every sector interacts with every other sector in the system.

Using global level data at national resolution over the past c. 50 years, the aim of this work is to quantify, at the global level based on national-scale data, the WEF-GDP system in terms of:

a) acorrelation between system sectors;
b) the uncertainty and scatter between these sectors;
c) causal relationships between the sectors, and;
d) system trajectories to 2100 under several economic growth scenarios.

This work aims to add quantification to the currently qualitative Fig. 1, and to start to address some of the main gaps in current understanding described above. In this paper, the focus is the water-energy-food nexus and the link to national economies (GDP). The link to GDP was made explicit by Sušnik (2015) who shows that water, energy and food metrics correlate closely with GDP. In this paper, the word 'system' is used in place of 'nexus' to make explicit the point that this system is in essence observable, quantifiable and able to be modelled robustly in order to i) determine underlying dynamics and; ii) create scenarios of potential system development under global change.

2. Data and methods

2.1. Data

This study uses data from many sources to form relationships between WEF and GDP metrics. All data are at national resolution, and cover over 175 countries representing almost all socio-demographic-economic conditions since the 1960′s. Table 1 summarises the data. Some of the data and results presented in this paper are based on the analysis presented in Sušnik (2015). In such cases, details will not be repeated here, and the reader is referred to Sušnik (2015). The most relevant and important results from the previous work are summarised when required. The three analyses that are used here from Sušnik (2015) are: GDP → total national water withdrawals; GDP → total national food production and; GDP → total national net electricity consumption.

Total water withdrawal is a measure of all the water *withdrawn* in a nation from all sources. Water withdrawn is not the same as water consumed (i.e. water 'lost' from a system, through evaporation for example), which is generally lower. However, data on water withdrawn can be more reliable than for water consumed, and was used here as a measure of the pressure on available water resources. It is likely that substituting water withdrawals for water consumption would affect the results, however predicting how the results might change is difficult. For example, some energy-generating processes withdraw a lot of water, but consume relatively little, and vice-versa. It is probable that increases in energy generation will lead to increases in water consumption generally. It is likely that relationships would remain, but

Table 1
Summary statistics of the data used in this study.

Metric	Total number of countries used in analysis[a]	Temporal coverage [min range; maximum range; completeness]	Data source
Total GDP	203	1960–2013 [1 year; 54 years; variable completeness from totally complete 1960–2013 to patchy or single entry]	World Bank (August 2014; http://data.worldbank.org)
Total national water withdrawal	183	1962–2012. Data are reported in approximately five-year intervals, although the reporting period varies between countries. Data are more complete after the 1980′s. [1 entry; 9 entries; variable from complete records to only one value entered]	UN FAO AQUASTAT database (August 2014)
Total national crop production[b]	176	1961–2013. Data are reported at annual intervals for each country. [8 years; complete coverage; where data are available, coverage is good.]	UN FAOSTAT database (August 2014)
Total national net electricity consumption	184	1980–2011. Data are reported at annual intervals for each country. [6 years; complete coverage; where data are recorded, coverage is good]	US Energy Information Administration (www.eia.gov; August 2014)

[a] This is the total number of countries with at least one data entry in the timeseries. These countries are not all necessarily used in the relationship analyses, which depends on there being corresponding data available in both of the variables. Only when data for a given value and year are available in both parameters is that country used. See text for details.
[b] The total crop production is the sum of many different crop types from the UN FAOSTAT database. See Table 1 in Sušnik (2015) for all the crop types included in this calculation. Production is measured in kg yr^{-1}.

would differ from those found in this study. For food production, the national total is the sum of the following food classifications from the FAOSTAT database: cereal crops, root crops, pulses, treenuts, oil crops, vegetables, fibre crops, fruit, citrus crops and grain crops. National net electricity consumption is used as a measure of energy demand. It is very closely correlated with national net electricity generation (Sušnik, 2015), and in this sense the two can be used interchangeably with little impact on results.

The new relationships in this paper that extend the work of Sušnik (2015) are those between the remaining WEF system sectors: total national water withdrawals – total national food production; total national water withdrawals – total national net electricity consumption; and total national net electricity consumption – total national food production. In addition, the three relations in Sušnik (2015) and the relations above were analysed in reverse. In total therefore, 12 relations are analysed, representing all the couplings in Fig. 1.

2.2. Methods: correlation and causality

First, the data of WEF and GDP were plotted in pairs to analyse potential correlation. Correlated data pairs were then assessed for their best-fit statistical distribution. Finally, correlated data pairs were analysed for causality. These three steps are described below in detail.

1) Correlation between data pairs. The general process is almost the same as that described in Sušnik (2015), but with some important differences. Therefore, the process is described again:

i) Match country names between independent and dependent variables. Variations on country names were accounted for (e.g. United States and United States of America). Exclude non-matches. Exclusion represents a small number of countries (~10-20).
ii) For matched datasets (dependent and independent), data were rationalised to make them directly comparable, country-by-country, year-by-year. Null/empty data were treated as a blank.
iii) Rationalised data were processed to include instances where there was a data entry for a given country *and* a given year in both metrics. If both metrics had no data, or if only one metric had data, these instances were excluded from further analysis.
iv) Final data were plotted (x-y scatter) to identify regression relationships between metrics. Plotting was done for all data combined (i.e. all countries and years together).

For the correlations outlines above, the strength of the correlation was assessed by a best-fit regression line through the data points together with the coefficient of determination (R^2) parameter. There are variable degrees of scatter in the correlations. In order to quantify such scatter, a best-fit distribution analysis was carried out for each correlated pair. This is described next.

2) Analysis of the best-fit distribution. The best-fit regression through data points essentially gives an 'average' prediction of the dependent variable, and the R^2 gives an idea of the scatter. A MATLAB routine (allfitdist.m[1]) was used to assess the best-fit statistical distribution of correlated data pairs, and to derive the statistics of these distributions. The same data series' used in the correlations were used to determine best-fit distributions. Data are entered into the routine which returns the best-fit distribution and descriptors of the distribution. The best-fit distribution is chosen from a set of 17 distributions (see Sušnik, 2015 for a full list). This analysis quantifies the spread around the 'mean' given by the regression analysis. Regional differences in socio-economic growth and the historical development in WEF resource use will lead to locally different national/regional relationships than the global-average assessed here. Some of this variation is captured in the best-fit distributions. Future studies at the regional or national levels could be carried out to investigate in more detail these differences.

3) Analysis of causality between correlated pairs. The causality analysis used the same procedure as Sušnik (2015). For an extensive description of the original development of the convergence cross mapping methodology (CCM), the reader is referred to Sugihara et al. (2012). For full details of the modified multispatial CCM (mCCM) methodology used in this paper, the reader is referred to Clark et al. (2015) and Sušnik (2015). These papers outline the full development, mathematics and application of the (m)CCM methods used here. In this study the 'plots' are the countries and the 'observations' are the metrics reported at various intervals (see Clark et al. (2015) for a full explanation regarding plots and observations). It is assumed here that the gross-scale dynamics between WEF variables and with GDP are everywhere similar. For this analysis, the code of Clark et al. (2015), available as a package in the R programming language (R Core Development Team, 2014), was adapted for this study.

2.3. Methods: quantitative modelling of the WEF system

Quantitative modelling aimed at: i) replicating historical data, accounting for the variability in national observations; and ii) defining trajectories of this global system into the future. A system dynamics modelling (Ford, 1999; Kelly et al., 2013) approach was used to build the WEF-GDP system. SDM was utilised for its ability to account for

[1] Available from https://nl.mathworks.com/matlabcentral/fileexchange/34943-fit-all-valid-parametric-probability-distributions-to-data?requestedDomain = www.mathworks.com

feedback between (sub-)systems in an explicit manner, and for the ability to be able to integrate data from many disparate sectors. The ability to perform Monte-Carlo simulations was also crucial. The latest version of STELLA Professional (www.iseesystems.com/) was used to carry out the simulations in this paper.

The developed model uses a feedback-driven stock and flow structure (cf. Ford, 1999) in order to estimate the global value of each WEF-GDP sector for the period 1961–2013 (54 years, reflecting the resolution of input data). In the SD model, each sector (WEF and GDP) is linked to all the other sectors (Fig. 1), with the quantitative relationships between each link defined by the correlation, distribution and causality work described above. The WEF-GDP sectors are initialised with global values from 1961. Subsequently, all results are computed by the model and do not depend on historical data. That is, the model is driven by the interacting relationships between the WEF-GDP sectors. For any timestep, the change in a given sector's value from the previous timestep is added to the previous value. This new value then affects the values for the other three WEF-GDP sectors in the next iteration, which in turn influence the original sector's value, and so on. As an example, while certain relationships may be linear (e.g. water → food), a change in the water sector feeds through every other sector. A change in water causes a linear change in food only when considered in isolation. However, a change in water also changes energy and GDP values. These new energy and GDP values contribute to changing the food value (as the value for food is determined by changes in water, energy and GDP in a given timestep. The values for water, energy and GDP also depend partially on the value for food). This means that complex and non-linear changes are brought about from initially simple-looking relationships. In addition, Monte-Carlo sampling means that ultimately the final value for any sector resulting from changes in another is unpredictable.

The value of the WEF-GDP sectors is computed from: i) the regression relationships defining the 'mean' of the dependent variable based on the values of the independent variables; ii) the best-fit statistical distribution accounting for between-country variability; and iii) the causal analysis to determine the fractional contribution of one sector on another. The SDM was run as a Monte-Carlo simulation, with each simulation repeated over 100 iterations. In each iteration, new values from the best-fit distributions for each WEF-GDP sector were pseudo-randomly sampled and added/subtracted from the 'mean' found from the best-fit regressions. Finally, the causal analysis was used to inform the fractional contributions of three sectors to any given sector. Initially, for any given sector an equal contribution of 0.33 was selected from the three affecting sectors. Using the causal analysis as a guide and trial-and-error, these contributions were adjusted until the results closely matched observations. The final fractional contributions to/from each sector are shown in Table 2. The results from the SD simulations were exported to text files and analysed further in R.

Initially, historical values were replicated for validation. After validation, the model was used to project WEF and GDP variables to 2100 under seven GDP growth scenarios. These scenarios are the same as Sušnik (2015):

1) The IMF 2014–2019 global average GDP growth rate of 3.8% yr^{-1} was assumed to remain constant from 2020 to 2100 for all countries.
2) Country-level GDP data for 214 countries from 1960 to 2013 from the World Bank was used (data.worldbank.org). The GDP for each nation was summed for each year during this period, giving an annual global GDP estimate from 1960 and 2013. The percentage change in globally-estimated GDP between two years (e.g. 1960–1961, 1961–1962, etc.) was calculated. Linear regression through the%-change time-series yielded the following: GDP% change = −0.1319*(YEAR) +12.023. This allows GDP to be estimated from one year to the next. This equation was assumed to be valid until 2100, and was used to estimate GDP annually from 2020 to 2100.
3) A constant GDP growth rate from 2020 to 2100 of 2% yr^{-1} was assumed.
4) A constant GDP growth rate of 5% yr^{-1} was assumed.
5) A constant GDP growth rate of −2% yr^{-1} was assumed.
6) A constant GDP growth rate of −4% yr^{-1} was assumed.
7) The IMF dataset was exploited to yield country-level estimates of GDP growth from 2014 to 2019. For each country, the average projected GDP growth from 2014 to 2019 was calculated. This country-level average was assumed constant for that country from 2020 to 2100. The future GDPs for 189 countries were estimated based on the specific growth rates, then aggregated for each year, giving annual global GDP estimates from 2020 to 2100. In the SD model the change in GDP between years for this scenario was evaluated using: GDP%-change = 0.0492*(YEAR) + 3.3269.

Table 2
Final fractional contributions of each WEF-GDP sector used in the system dynamics model.

From/To	Water	Food	Energy	GDP
Water		0.05	0.15	0.2
Food	0.33		0.05	0.2
Energy	0.33	0.05		0.6
GDP	0.33	0.9	0.8	

Changes in GDP growth rates were used as the scenarios under the assumption that GDP, on the gross-scale, encapsulates global changes in socio-economic conditions, and therefore goes some way to representing the variations between the Shared Socioeconomic Pathways (SSPs). It is noted that historical GDP is estimated by the model using the relationships developed above. However, after 2020, the GDP estimations are forced with a growth rate corresponding to one of the scenarios above, which in turn will have an impact on the WEF sectors. The range of scenarios tries to express the future uncertainty of global GDP growth, from strong positive growth to strong negative growth. The scenarios also combine data from different sources and at different scales.

3. Results

3.1. Correlation between system sectors

The correlations for GDP with total national water withdrawal, net electricity consumption and food production were carried out by Sušnik (2015). The main points are reiterated. GDP was shown to be well correlated to total national water withdrawals (Table 3; Sušnik, 2015, Fig. 7d). An R^2 of 0.57 suggests that the relationship between these sectors undergoes different underlying dynamics between countries. GDP is shown to be very strongly correlated to total national net electricity consumption (Table 3; Sušnik, 2015, Fig. 8b). GDP and total national food production show a moderate relationship (Table 3).

The study of Sušnik (2015) correlated the above pairs in one direction with GDP as the independent variable. Here, these correlations are reversed to place the WEF metrics as the independent variables (Table 3). It is noted that in all regressions, the *p*-value statistic is < 0.01. With water as the independent variable (Fig. 2a), R^2 is 0.58, and the best fit was found to be a second-order polynomial. For food production plotted with GDP, an exponential fit was found to be best, with R^2 of 0.5. For electricity consumption as the independent variable, the best fit was also an exponential function, with R^2 of 0.9 (Fig. 2b).

Total national water withdrawals are well correlated to total national food production (Table 3, Fig. 3a). A linear regression offered the best fit (R^2 of 0.71). This relationship appears to strengthen at higher volumes of water withdrawal, with less scatter evident towards the right hand side of Fig. 3a. When plotted the other way round, a linear function was found to have the best fit (R^2 = 0.71).

Table 3
Best-fit regressions relationships between the four sectors (WEF and GDP), and best-fit statistical distribution of each sector. All regressions have a p-statistic < 0.01.

Sectoral pairing	Best-fit regression[b]	Adjusted R[b]	Number of correlated points (n)
GDP → total national water withdrawal[a]	y = −0.0446 × [b] + 1.7509 x − 12.932	0.57	243
GDP → total national food production[a]	y = −0.0316 × [b] + 1.3624 x − 0.9717	0.51	3704
GDP → total national net electricity consumption[a]	y = 10.573ln(x) − 23.771	0.9	2555
Total national water withdrawal → GDP	y = 0.0651 × [b] + 0.6669x + 9.9875	0.58	243
Total national food production → GDP	$y = 5.1018e^{0.0701x}$	0.51	3704
Total national net electricity consumption → GDP	$y = 9.5226e^{0.0856x}$	0.9	2555
Total national water withdrawal → total national food production	y = 0.8223x + 9.3133	0.71	472
Total national water withdrawal → total national net electricity consumption	y = 0.8312x + 0.583	0.65	453
Total national net electricity consumption → total national food production	y = 0.6536x + 9.0592	0.5	4964
Total national food production → total national water withdrawal	y = 0.8628 x − 7.9165	0.71	472
Total national net electricity consumption → total national water withdrawal	y = 0.7889 x − 0.3335	0.65	453
Total national food production → total national net electricity consumption	y = 0.1659 × [b] − 2.2934x + 7.2638	0.55	4964
Sector	**Best fit statistical distribution**		
GDP	Gamma. Shape: 93.2779; scale: 0.1080		
Water withdrawals[a]	Normal. Mean: from regression equation; SD: 1.0885		
Food production[a]	Weibull. Scale: 9.9291; shape: 10.1852		
Electricity consumption	Normal. Mean: from regression equation; SD: 1.1577		

[a] Results originally from Sušnik (2015).
[b] x is always the independent variable (the first of the variables in the left-hand column), y is the metric of interest on the right of the metric pairs. SD = standard deviation.

Total national water withdrawals are reasonably correlated with total national net electricity consumption (Table 3, Fig. 3b). The R^2 (0.65) indicates some scatter from the regression line. Unlike with the water-food correlation described above, the amount of scatter about the best-fit regression appears consistent across the data set. When the plotting was reversed, the R^2 of the best-fit regression is 0.65. Water and energy have been shown to be closely related (Olsson, 2012; Davies et al., 2013; Liu et al., 2016), so finding a correlation is not surprising.

Total national net electricity consumption and total national food production shows a weaker correlation with more variability (Fig. 3c). The R^2 values are 0.5 and 0.55 when energy and food are the independent variables respectively.

3.2. Best fit distributions of global sectoral data

The best-fit distributions of each sector to quantify the scatter around the best-fit regressions are summarised in Table 3. It is pointed out that to arrive at the distributions, data for every country and every year were used, accounting for spatial and temporal differences in each WEF-GDP sector.

3.3. Causality between sectors

The slope of correlative relationships suggests the polarity of causal influence. For example, a (linear) increase in y as x increases implies a positive polarity and vice-versa. In this work, all sector pairs are shown to have positive polarity. The mCCM method allows for assessment of the relative strength of causality between metric pairs, however it is not possible to assess the strength of causality of one pair relative to other pairs. GDP is shown to have a stronger causal influence on water withdrawals than the other way round (Fig. 4a). However, the rho value (y-axis) is not high in either direction, indicating moderate causal influence. The rho value represents a correlation coefficient (calculated as such) indicating the extent to which one variable cross maps to another. The rho indicates the skill of the cross-mapping. It signifies the relative strength of causality between two parameters (A → B and B → A). Lower rho values indicate lower relative causal influence, and vice-versa. Fig. 4 show how quickly convergence occurs during the CCM process, and to what extent (higher or lower rho). Quicker convergence (time to stability) and higher rho values indicate stronger causal effects. A full explanation of CCM and the rho value, along with mathematical background is given in Sugihara et al. (2012).

Likewise, GDP appears to influence food production more than the other way round (Fig. 4b), but here the rho value is higher (c. 0.8)

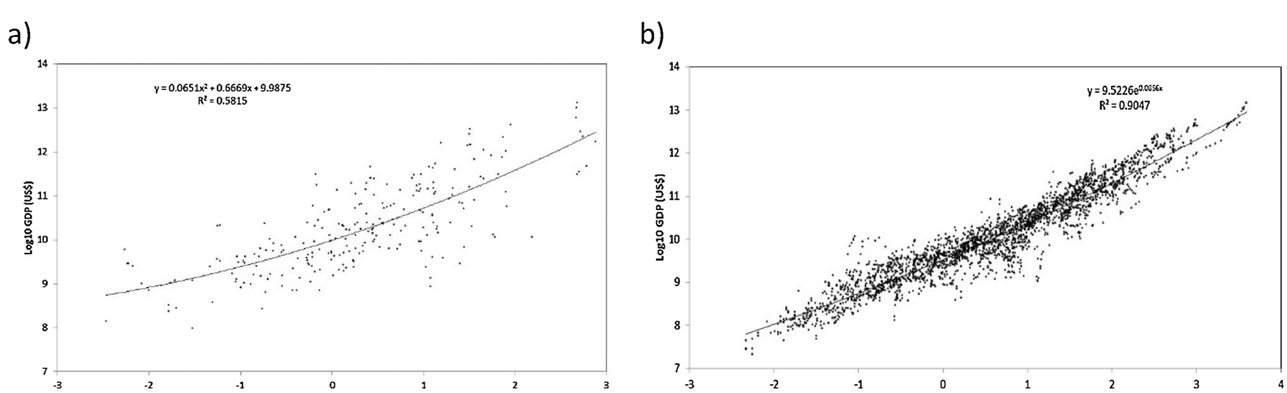

Fig. 2. a) correlation with water withdrawals as the independent variable against GDP; and b) correlation with electricity consumption as the independent variable against GDP.

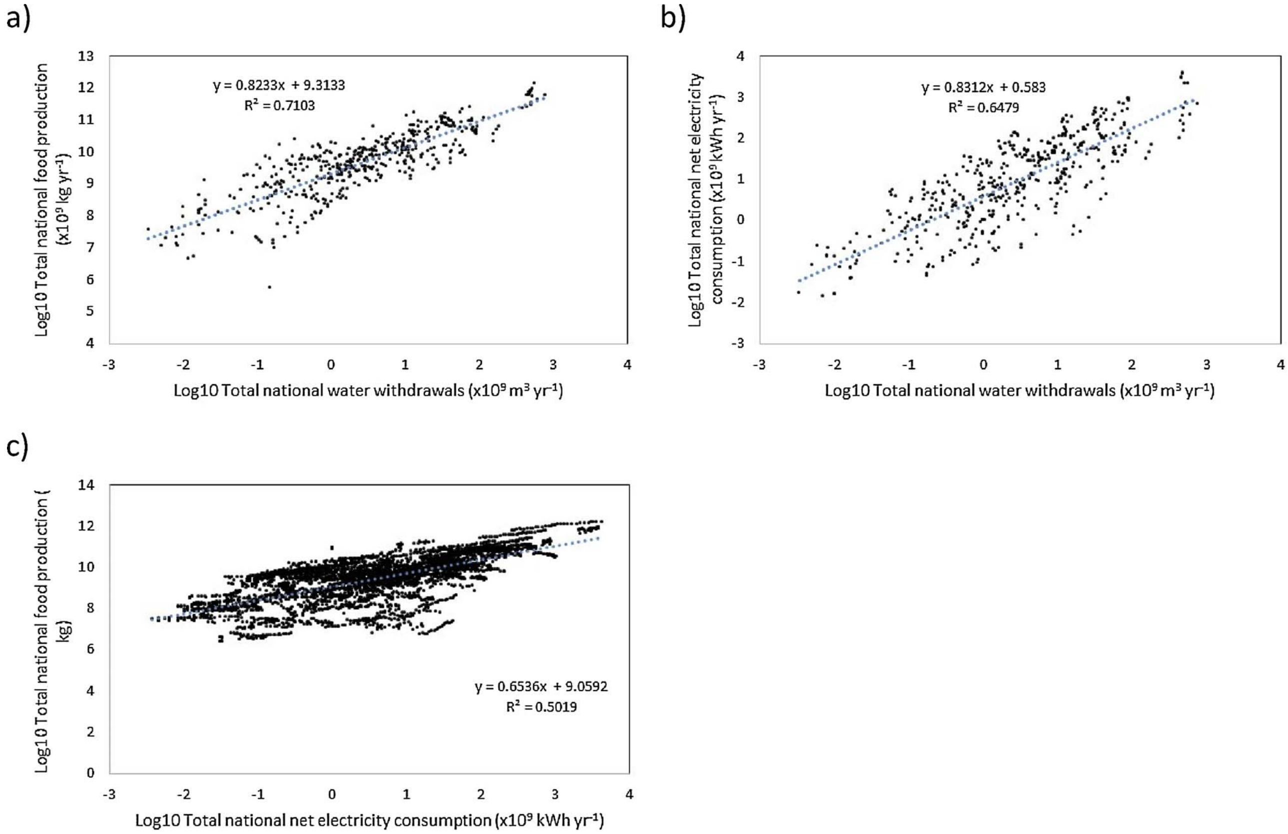

Fig. 3. a) correlation with water withdrawals the independent variable against food production; b) correlation with water withdrawals as the independent variable against electricity consumption; and c) correlation with electricity consumption as the independent variable against food production.

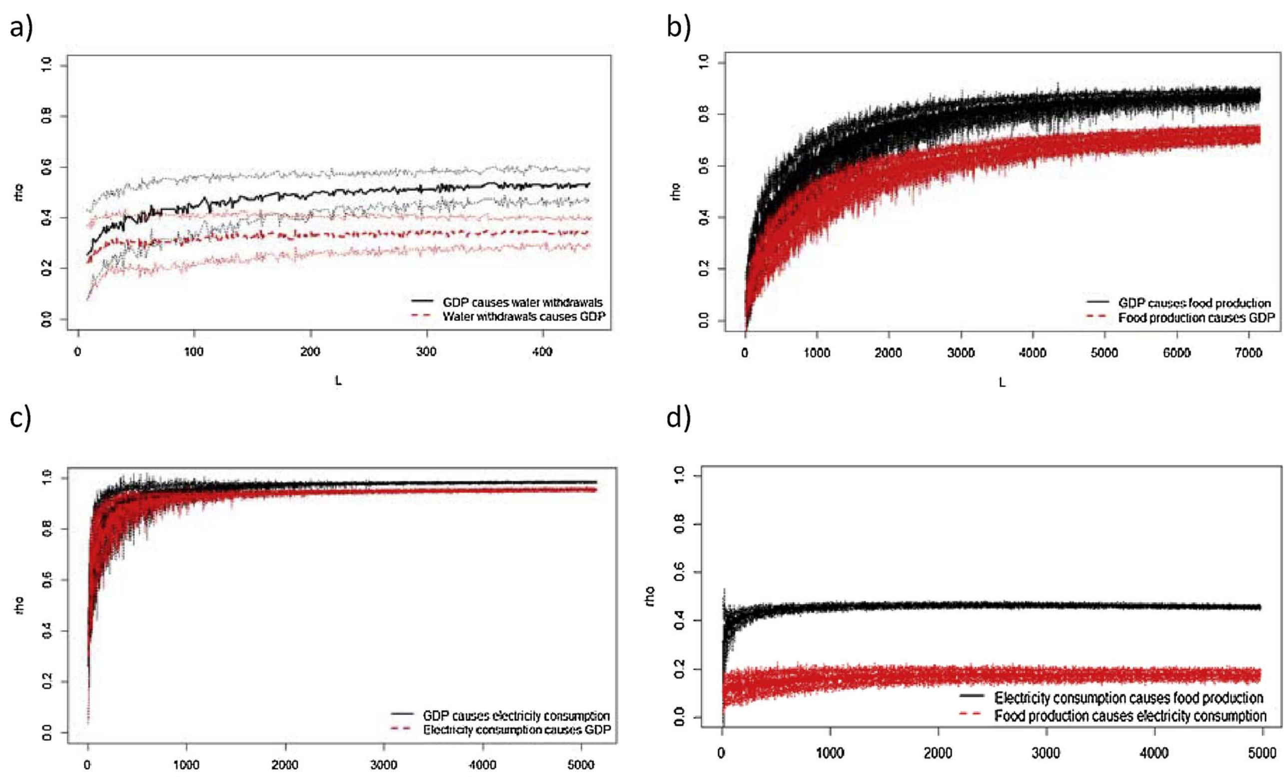

Fig. 4. Multispatial convergence cross mapping results for a) GDP and water withdrawals; b) GDP and food production; c) GDP and electricity consumption; and d) food production and electricity consumption. Rho values (y-axis) represent relative strength of causal influence. L (x-axis) indicates the length of the data series.

suggesting a stronger causal connection. GDP and electricity consumption are shown to be very tightly coupled, with strong causal influence (Fig. 4c). The very rapid rise to stability could indicate synchrony (Sugihara et al., 2012), which refers to a situation when one variable is so dominant that the other variable's behaviour is forced to follow it. Thus, there is no true two-way coupling, but a dominant driving mechanism in the system. Water withdrawals influence food production more than the other way round, while there is little difference in casual strength between water withdrawals and electricity consumption, indicating potentially strong coupling. The relationship between food production and electricity consumption shows asymmetry (Fig. 4d), with electricity consumption 'causing' changes in food production more than the other way round. The rho values are low, especially in the food → electricity direction, suggesting relatively weak coupling between these sectors.

Unravelling such causal connections is extremely difficult. In the energy ⟵⟶ food case, it may seem intuitive that the dominant relation should be opposite to that found here. However, a growth in energy availability can drive food production in a number of ways including: i) reducing the human burden of agriculture, allowing more to be produced in a given time and over a given area by using electrical and/or mechanical energy; ii) energy allows for scale efficiency in agriculture, and can make agricultural processes more efficient; and iii) energy can be used for lighting and pumping water, greatly improving yields, cropped area and artificially lengthening growing seasons (e.g. greenhouses). There is of course a two-way relationship (more food production requires more energy), but it is suggested that the energy → food direction is dominant (Fig. 4d).

3.4. Quantifying the WEF-GDP system: historical validation

Results for the replication of the WEF-GDP system from 1961 to 2013 show reasonable agreement with historical observations (Fig. 5). The mean and median of the simulations are in agreement with historical values of total global water withdrawal, food production, electricity consumption and GDP (RMSE values of simulated data versus historical data are 1.9, 1.9, 0.4 and 1.6 for water, energy, food and GDP respectively). Electricity consumption and GDP are consistently overestimated (model mean and median), but are well within percentile limits. Water withdrawals are also overestimated, but not to the extent of energy and GDP. The difference between simulated and observed GDP values decreases over time. It is worth pointing out that the observed points are global aggregations of the national data for each year, thereby removing national-level variability. There is considerable variability around mean and median values when this variability is accounted for (10th and 90th percentile lines in Fig. 5). Accounting for this variability is important for tracking potential future trajectories of this system, and for recognising the vast difference between nations and regions.

3.5. Future pathways

Fig. 6 shows future projections of the water withdrawal and GDP sectors based on the GDP growth scenarios described in the Data and Methods section. The direction of growth and the magnitude of change are clearly guided by the forced changes to the GDP between 2020 and 2100. For example Scenarios 5 and 6 show decreasing trends in WEF sectors, while there are strong increases in Scenarios 4 and 7. These general trends are discussed in the next section. The variable amounts of scatter in the simulated data are the result of the pseudo-random Monte-Carlo sampling approach adopted in the SD modelling – no two runs produce identical results (i.e. there is no set seed in the SDM simulations).

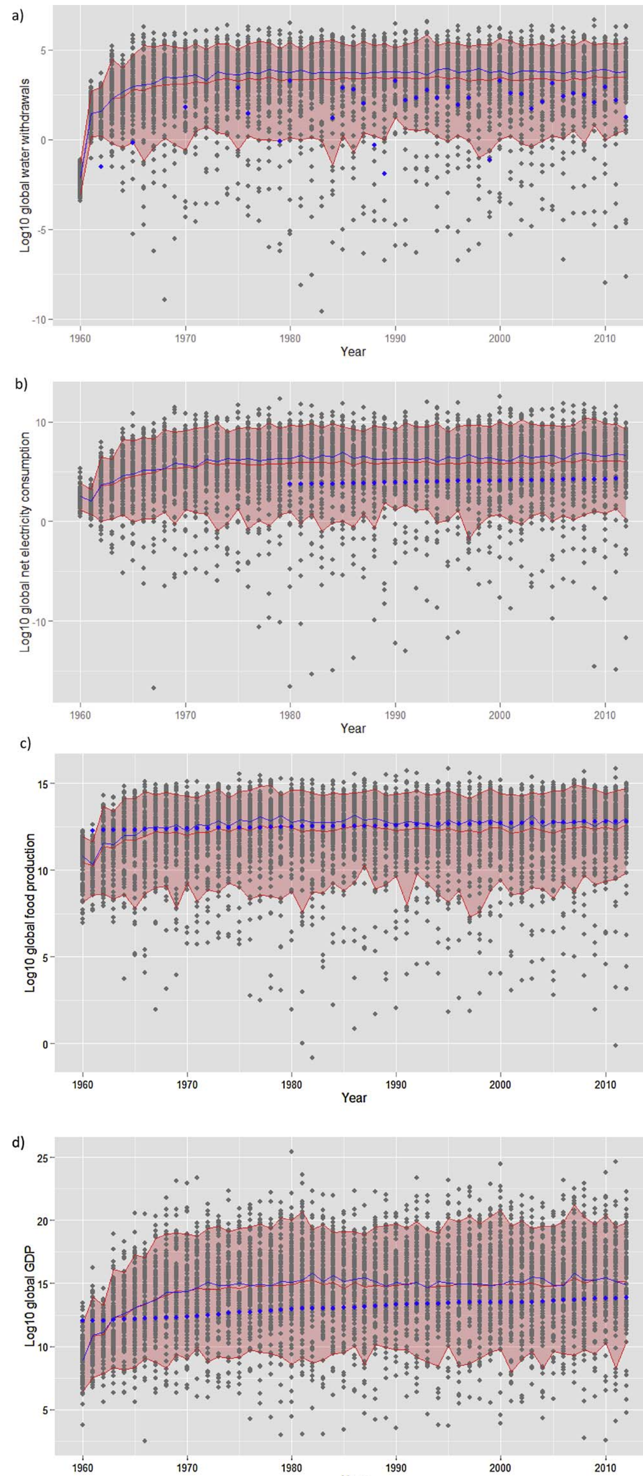

Fig. 5. Simulated figures compared with historical observations for a) total global water withdrawals; b) total global net electricity consumption; c) total global food production; and d) total global GDP. Blue dots represent historical observations, grey dots are simulated values (100 values for every year), red line indicates model average values, blue line indicates model median values and the red shaded area indicates the 10th (lower) and 90th (upper) percentiles of the simulations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4. Discussion

4.1. Correlation and causation

Results show strong correlation and causal influence between many

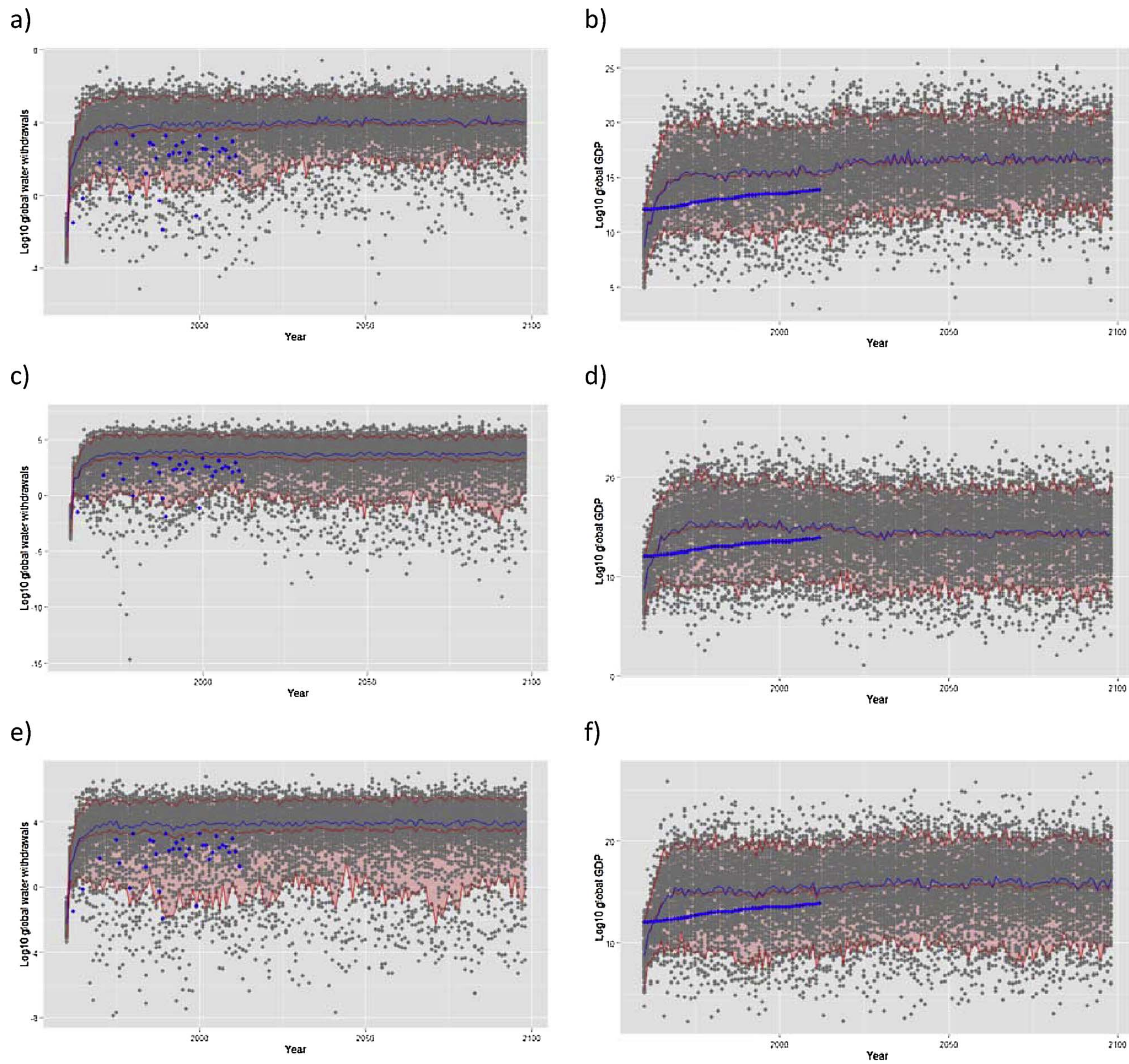

Fig. 6. Global projections of total water withdrawals and GDP under scenarios 1–7 (a, c, e, g, i, k, m and b, d, f, h, j, l, n respectively). See Data and Methods section for details about the growth scenarios. Blue dots represent historical observations, grey dots are simulated values (there are 100 values for every year), red line indicates model average values, blue line indicates model median values and the red shaded area indicates the 10th (lower) and 90th (upper) percentiles of the simulations. For water withdrawals, the log-axis masks the historical trend, which changed from 713 $km^3 yr^{-1}$ in 1975–1873 $km^3 yr^{-1}$ in 2000. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of the sectors. For the correlation between GDP and water withdrawals, higher GDP countries generally withdraw more water. Reasons for the variability in this relationship could include countries with lower GDP (potentially 'less well' developed) being more reliant on inefficient irrigation methods (leading to greater inter-annual variability in water demand for example) or higher GDP countries having large service sectors (with lower water demand than agriculture and more constant demand between years) and efficient water distribution systems, meaning lower variability in water withdrawals. It is acknowledged that GDP is also related to the size of the population, so GDP and 'developed' do not correspond exactly. Likewise, GDP and food show moderate correlation with variability. It is possible that lower GDP countries reliant on agricultural practices that result in lower yields and with greater inter-annual variability in production, while high production totals may result from compensation for inefficiencies in storage and distribution, or as a result on large quantities produced for export. Inefficient agricultural systems and/or unfavourable climatic and soil conditions could lead to low and variable yields and production totals. Higher GDP countries may be more reliant on service industries and import from lower income countries, having lower endogenous food production totals, or may produce large volumes for export in very efficient and/or intensive systems with lower variability in production (e.g. The Netherlands). When water withdrawal was correlated to food production, although the correlation was fairly strong, the relationship appears to strengthen at higher values of water withdrawal. One possible explanation is that nations with higher water withdrawal are, generally, wealthier in terms of GDP (shown in the correlation of water withdrawal and GDP). Agricultural practices in wealthy countries may be more efficient (e.g. The Netherlands) while lower income nations may be more reliant on traditional irrigation methods and cropping practices which are more exposed to local climatic conditions, with greater variability in food production. Another possibility is that higher

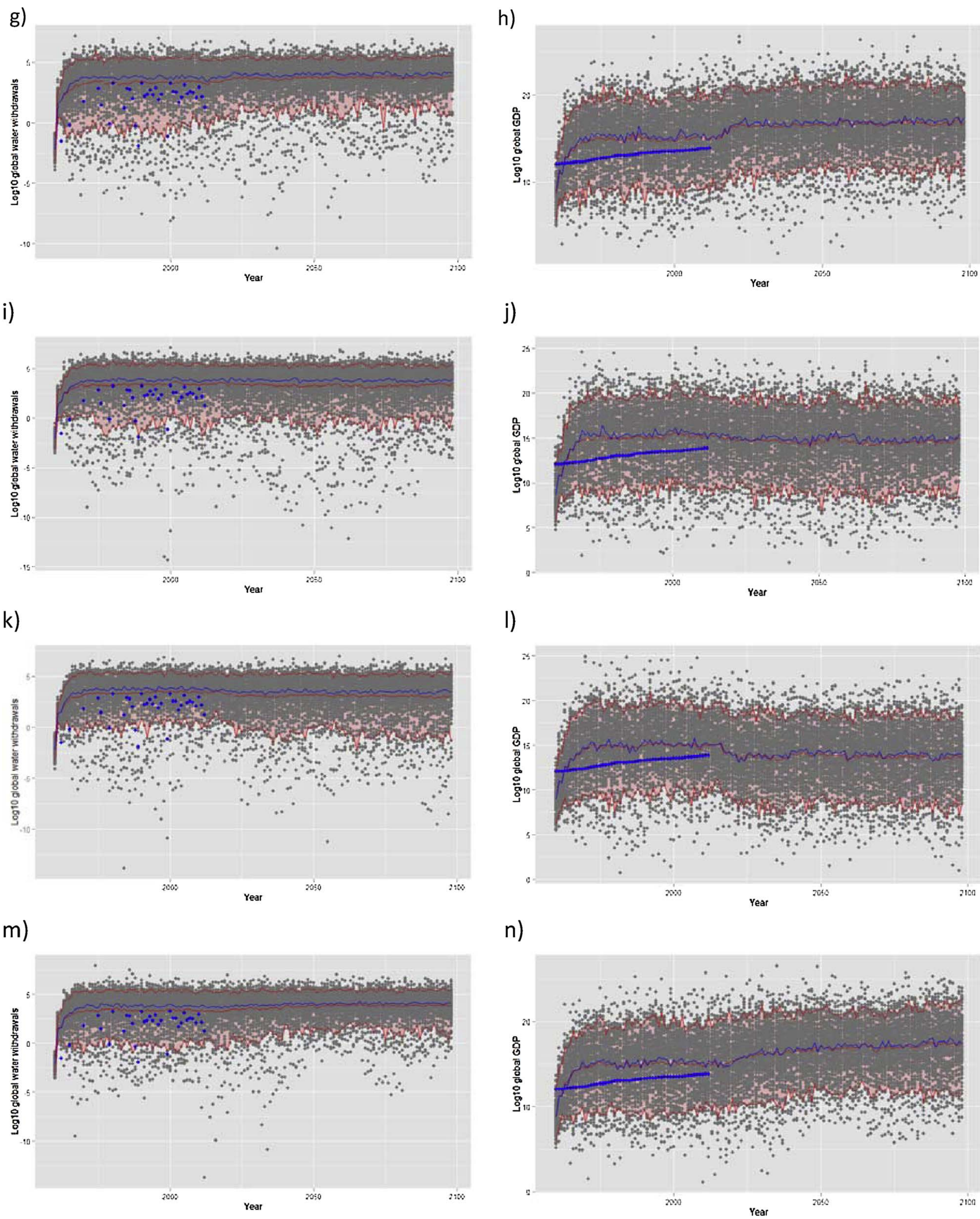

Fig. 6. (*continued*)

volumes of food production generally require higher water requirements, although this can be mediated to some extent by improvements in water use efficiency, The Netherlands being a case in point. While this may explain the correlation between increased food production and water withdrawals, it does not explain the stronger relationship (i.e. less scatter around the regression line) at higher water withdrawal values (i.e. higher-GDP nations), which is related to lower variability in production and water withdrawals. When food production and electricity consumption are correlated, considerable variability is shown, possibly suggesting a weaker 'nexus' connection between these sectors at national level.

Causal analysis shows which variable pairs are subject to stronger or weaker causal interaction, and which direction of causality is stronger, if any. The GDP-water and GDP-food correlations had similar

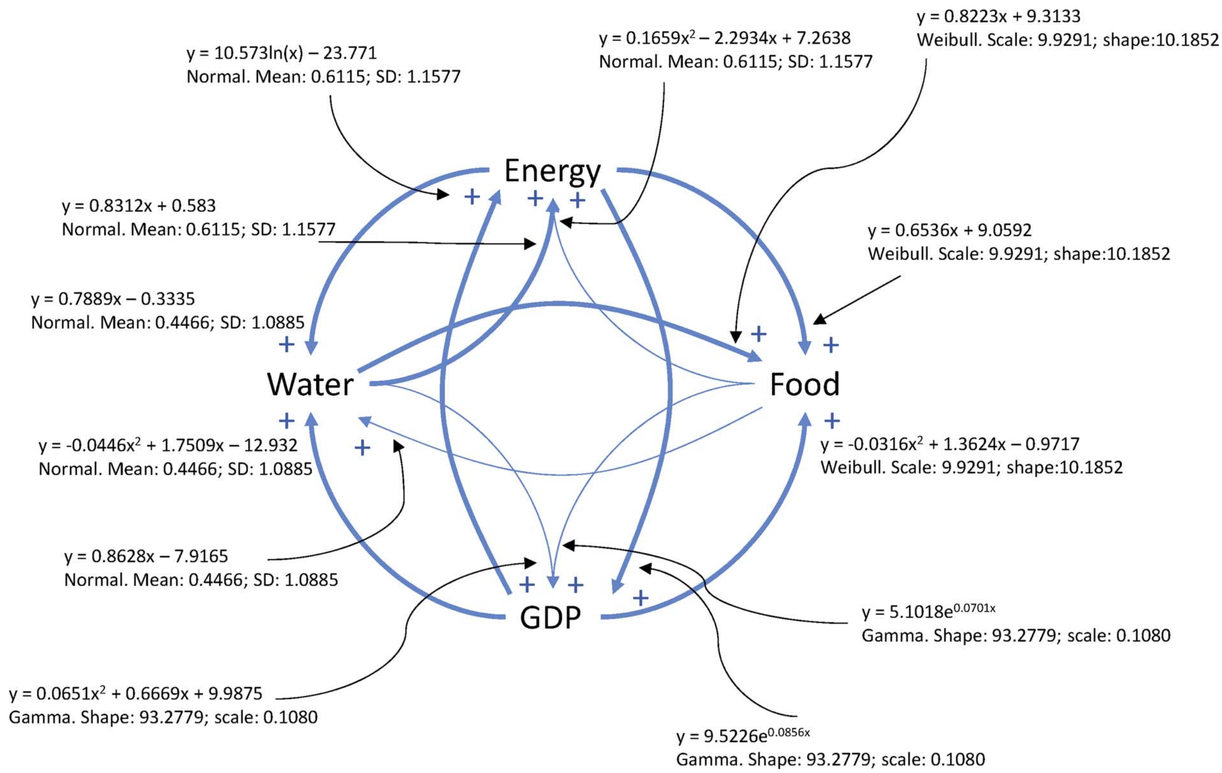

Fig. 7. The quantified WEF-GDP system.

correlation coefficients (c. 0.55) but show different apparent causal behaviour, demonstrating that correlation does not imply causality. GDP and electricity are strongly correlated and show strong causal influence. Similarly, water and food are shown to be strongly correlated and exhibit strong bi-directional causal influence. Electricity and food are weakly correlated and show considerable asymmetry in the causal relationships. Some of the causal analyses show very rapid rise in the 'rho' value, meaning that either: i) there is a strong bi-directional causal influence between the two sectors or; ii) the system is subject to synchrony. It is not possible to determine which of these possibilities is correct. This analysis does indicate those sectors that appear to have strong bi-directional causal influence (such as GDP and electricity) and those where the causality in one direction is strong than the other.

4.2. Towards quantifying the global WEF-economic system

The work presented in this paper quantifies the previously qualitative WEF framework (Fig. 1), and allows for the questions in the Introduction to be answered, at least at the global level. Fig. 1 is updated in Fig. 7, with each WEF-GDP link now quantified. With respect to historical observation, model simulations show reasonable agreement although electricity consumption and GDP, and water to a lesser extent, are overestimated (model mean and median; Fig. 5) at the globally-aggregated level. Model performance is good considering the vast complexity of this system. The overestimation in the electricity sector is c. 2–3 orders of magnitude (Fig. 5b), with a similar level of overestimation for GDP (Fig. 5d). As the observations are consistently overestimated over time, bias-correction could be employed to force model results to better fit the data. It was chosen not to do this in order to show raw simulation results.

Future projections depend strongly on the GDP growth scenario (see Data and Methods section and Fig. 6). Across all sectors, scenarios four and seven show the greatest growth while scenario six shows the greatest contraction (on average). These projections could have important implications regarding resource consumption, especially if resource consumption is as closely related to GDP as is suggested in this work. Considering water withdrawals, Steffen et al. (2015) place the 'safe planetary boundary' for water withdrawals at 4000 $km^3 yr^{-1}$, which is suggested as the maximum volume of water that can be withdrawn globally without causing potentially irreparable damage to the resource and associated ecosystem services (the current global estimate is c. 2600 $km^3 yr^{-1}$). In this context, the projections in this paper give a view of how likely this threshold may be exceeded by the end of the century. The threshold value of 4000 $km^3 yr^{-1}$ is exceeded in 48% of results (out of 13900 in total – 100 simulations over 139 years) in scenario 5, but by as much as 61% in scenario 1. These values must be taken in the context of the variability that is accounted for in the simulations. Considering simulation means in 2017, in scenario 5 the model mean is 2900 $km^3 yr^{-1}$ (close to the estimate of Steffen et al., 2015), while in 2100 it is 2700 $km^3 yr^{-1}$, the decrease being driven by the negative GDP growth. Conversely, in scenario 1 in 2017, the model mean is 3700 km^3 yr−1, close to the 3200 $km^3 yr^{-1}$ of Hanasaki et al. (2013a,b), and to the 4000 $km^3 yr^{-1}$ of Wada and Bierkens (2014), and by 2100 it is 6700 $km^3 yr^{-1}$ which is slightly higher than the c. 6000 $km^3 yr^{-1}$ estimated by Wada and Bierkens (2014) and Hanasaki et al., (2013a,b), but well below the estimate of Hejazi et al. (2014); 13300 $km^3 yr^{-1}$ in 2095) who overestimate water withdrawals compared with other studies. All exceedance values reported here are higher than those in Sušnik (2015), who took a more simplistic approach to modelling the WEF system, not accounting for inter-sectoral linkages. This work implies that neglecting these interlinkages could lead to over-/underestimation of potential water resource consumption globally. Considering the very different approaches to deriving future estimates, this study, and the cited studies all suggest that by the end of this century, humanity will likely be exceeding what is considered a sustainable level of water withdrawals globally.

For net electricity consumption, the US Energy Information Administration has derived a recent set of future projections to 2050 (EIA, 2017; dataset available at https://www.eia.gov/analysis/projection-data.cfm). In 2017, the EIA (2017) estimates total global net electricity consumption at c. 37100 × 10^9 kWh. The SD model means in 2017 range from 570000 × 10^9 to 1900000 × 10^9 kWh (scenarios 2 and 1 respectively), reflecting the overestimation of model results for this sector (Fig. 5). In 2050, the EIA estimate global electricity consumption at c. 45000×10^9 kWh, with the SD model estimates in 2050 ranging from 237000×10^9 to 6400000×10^9 kWh (scenarios 6 and 7 respectively). It is noted that there is considerable variability around these mean values as a consequence of the Monte-Carlo sampling (Fig. 5) and that the GDP scenario drives the overall trend of electricity consumption. Even though this model overestimates electricity generation, demand (and therefore generation) will increase to the end of the century, leading to an increase in CO_2e emissions and concomitant climate impacts, unless there is a drastic improvement in generating efficiencies, or a significant and rapid switch towards low/zero fossil-fuel based generating technologies, for which there is significant global potential (Deng et al., 2015; Possner and Caldeira, 2017).

For global food production, the Food and Agricultural Organisation (FAO) of the United Nations have developed a series of production estimates to 2050 (Alexandratos and Bruisma, 2012; FAO, 2017). In 2013, the total global crop production in the FAOSTAT database (see Sušnik, 2015 for the crops included in this category) was 5080×10^9 kg. In the same year, model means in this study range from 1450×10^9 to 4158×10^9 kg, thereby slightly underestimating the FAOSTAT total. By 2050, FAO estimate that the required global food production to meet estimated demand will be 7548×10^9 kg (FAO, 2017). Using a different method based on average annual food production growth rates between 2007 and 2050, Alexandratos and Bruisma (2012) estimate total global food production in 2050 as 7147×10^9 kg. By 2050, this work estimates global food production between 1680×10^9 (scenario 5) and 7120×10^9 kg (scenario 1). This leads to the possible suggestion that if global GDP shrinks, there could be a large impact on global food production. Given that at present around 795 million people are malnourished (FAO, 2017), and with this expected to remain a global challenge to 2050, any potential drop in overall production (possibly linked to economic performance) could be damaging to the lives of millions of people. Maintaining, and potentially increasing yields, perhaps through intensification or through a considerable reduction in wastage, is therefore paramount. It is essential to decouple food production from GDP. However this may only be possible for crops with lower commercial value.

Throughout this work, a number of assumptions and shortcomings are recognised. First, the analysis is at global level and as such national and regional differences and variations are unaccounted for in detail, although variability is captured in the best-fit distribution and sampling approaches. A future avenue for research is to carry out a similar analysis at national or regional resolution. This will help characterise global hotspots of critical resource use, and will better define the variability at the global level. This will allow for regional and 'cluster' (e.g. OECD-countries) comparisons. Second, while the model incorporates water, energy, food and GDP in an integrated manner, other sectors are neglected including the climate sector, an explicit representation of socio-economic-political developments (see the next point), and the influence of technological developments and human 'capital' as drivers of the GDP system. All these issues are likely to play a crucial role in future resource use and consumption patterns. Third, although GDP is integrated within the model and estimated as part of it, the GDP values in the future scenarios were also forced by potential long-term directions of GDP growth. The assumption is that GDP accounts for socio-economic developments in the broadest sense. After 2018, the direction of GDP (socio-economic) growth is determined by the growth scenarios and is not endogenously derived. The assumption is that in some way GDP (growth) drives the WEF system. Fourth, this study assumes stationarity of this global system. That is, it is assumed that the relationships identified between the WEF-GDP sectors for the last c. 50 years will continue to hold, broadly speaking, over the coming 50 years and beyond. Given that global change is advancing at ever-greater rates, this may not necessarily be the case, and abrupt as-yet unknown transitions ('phase' or 'critical' transitions; Scheffer, 2009) in the system could occur. In the absence of knowing for certain when, how, and to what extent change will take place, assuming system-wide stationarity is a reasonable first approximation. The seven GDP scenarios act to partially capture most likely global-scale trajectories of socio-techno-political-economic development in a broad sense.

Despite the shortcomings and assumptions, this work has advanced previous efforts by integrating water, energy, food and GDP in an integrated and consistent modelling and analysis framework. It uses freely-available, widely recognised global datasets as the fundamental basis on which analyses are carried out, avoiding prohibitively expensive proprietary data or software. It provides a platform on which to build, allowing this work to be refined in the future to be more comprehensive and account for more sectors, influences and interactions (e.g. zooming in to national-level analysis; analysing the influence of human capital and technological progress on wealth and GDP). While there is potential for improvement, this work takes a considerable step towards quantitative modelling of the global water-energy-food-economic system, something that until now has largely been a qualitative exercise, or which has considered only one or two sectors.

5. Conclusions

There is increasing interest in the global water-energy-food system, and how it relates to the global economy. Studies have investigated aspects of this system using different methodologies and datasets. Despite growing efforts, there remain a number of shortcomings including: not incorporating all WEF-GDP sectors; inconsistency between data; and inconsistency between modelling approaches. These shortcomings mean it can be hard to identify system-wide impacts, and can make comparisons between studies difficult. This work sets out a global scale analysis of the WEF-GDP system, using consistent, widely recognised datasets for each sector, and integrating the sectors into a single, coherent analysis and modelling framework, offering consistency where it has been previously lacking. Correlative and causal analysis suggests historical links between the WEF-GDP sectors with varying strength. Subsequent causal analysis revealed that 'correlation does not imply causation'. For example GDP is more strongly correlated to water withdrawals than food production, but causal analysis suggests that the food-GDP sectors have stronger causal influence than the correlation suggests. There are noticeable asymmetries in causality, for example between the food production and electricity consumption sectors. Following initial analysis, a system dynamics modelling approach was used to represent the WEF-GDP system in an integrated framework with a pseudo-random Monte-Carlo sampling approach adopted to characterise variability in the global system. Historical values of WEF-GDP sectors were estimated reasonably well given the complexity of the system and the assumptions and simplifications made in this study. Electricity consumption and GDP were consistently overestimated, something that could be addressed with bias-correction.

Future trajectories of the WEF-GDP system were assessed with seven GDP growth scenarios aimed at covering a range of potential socio-economic developments to 2100. Trajectories of WEF-GDP sectors depend strongly on the GDP growth scenario. WEF sector projections are compared with those from other studies. Water withdrawals are close to other values estimated by 2100 and suggest that humanity is at risk of exceeding the 'safe operating space' of humanity, something echoed by other studies. Food production estimates are close to other studies by 2050, while electricity consumption estimates are overestimated. It is suggested that water withdrawals and food production should be decoupled from GDP and similar economically-based performance indicators.

Future work could involve a national-level re-analysis to be able to compare nations, regions and country-clusters (i.e. OECD nations), and could attempt to incorporate other factors such as human capital and the influence of technological progress, although these latter developments could take a considerable effort. This work is a valuable early step in providing a quantitative modelling framework to the previously qualitative descriptions of the water-food-energy-economic system, and offers a consistent platform on which to build.

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