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Research paper

Imputing missing data in non-renewable empower time series from night-time lights observations

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ABSTRACT

Emergy is an environmental accounting tool, with a specific set of indicators, that proved to be highly informative for sustainability assessment of national economies. The empower, defined as emergy per unit time, is a measure of the overall flow of resources used by a system in order to support its functioning. Continuous time-series of empower are not available for most of the world countries, due to the large amount of data needed for its calculation year by year. In this paper, we aim at filling this gap by means of a model that facilitates reconstruction of continuous time series of the non-renewable component of empower for a set of 57 countries of the world from 1995 to 2012. The reconstruction is based on a 3 year global emergy dataset and on the acknowledged relationships between the use of non-renewables, satellite observed artificial lights emitted at night, and Gross Domestic Product. Results show that this method provides accurate estimations of non-renewable empower at the country scale. The estimation model can be extended onward and backward in time and replicated for more countries, also using higher-resolution satellite imageries newly available. Besides representing an important advancement in emergy theory, this information is helpful for monitoring progresses toward Sustainable Development and energy use international goals.

1. Introduction

Energy availability, management and use are crucial aspects to consider for achieving sustainability. The United Nations Sustainable Development Goal 7 is "*ensure access to affordable, reliable, sustainable and modern energy for all*" (http://www.un.org/sustainabledevelopment/; last accessed: March 2017). Specific targets to be reached by 2030 include ensuring universal access to affordable energy, expanding and upgrading energy infrastructures and increasing the share of renewable and clean energy in the global energy mix, among others.

The current energy model is largely based on non-renewable sources being "enabling" resources necessary to support the production processes of food and other goods (Fantazzini et al., 2011). As a consequence, economic growth is largely explained by variations in oil consumption alone (Murphy and Hall, 2011).

Mounting scientific literature shows how it is crucial to move away from non-renewable based models toward development based on renewable energies (Rogelj et al., 2013; Jarvis et al., 2012). This problem has also been tackled by a number of economists involved in designing a growth theory with exhaustible resources (see for example the debate fed, among others, by Robert , and John Hartwick, 1977, during the economic crisis in the 1970s), as well as by ecological economists (Daly, 1990) and other scientists interested in sustainable development (Bastianoni et al., 2009).

One of the main indicators used for assessing the level of sustainability of different energy use models is Emergy, a thermodynamics-based indicator, introduced by Odum (1988, 1996), that reflects the energetics of natural and human-driven systems and measures all the resource flows that feed the activity of a system, like a country or a production process. These resource flows are expressed in terms of a common unit: the equivalent solar energy that has been used, directly or indirectly, to obtain them. Emergy, in fact, represents the flow of solar energy that is "memorized" in a product or a resource, from direct solar radiation, rain, wind, wood, water, to non-renewable resources like oil, which is very old solar energy that has been stored in deep deposits, and other materials.

Emergy can be calculated as a flow per unit time (the empower) representing the environmental value of resources used to maintain a given system at a certain level of organization.

Sustainability has a global dimension and is related to global challenges. It is an extensive problem (Pulselli et al., 2008a) that needs to be solved by putting into relation the absolute consumption of resources

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and energy with the absolute availability of them at the global level, which has also implications at the national/sub-national level. To assist the sustainability transition, a monitoring system of energy availability and use is thus needed at the global scale.

Remote Sensing can be of great help in achieving this task, highlighting dynamics and effects of human action at the largest scale. Monitoring systems at different scales and in different fields, including temporal and spatial energy distribution and use, can be supported by satellite observations and Geographic Information Systems (e.g. Doll and Pachauri, 2010; Min et al., 2013; Amaral et al., 2005; Kiran Chand et al., 2009).

In this vein, night-light satellite observations represent an increasingly used product. Global scale images of nocturnal lights have been used to monitor energy consumption, but also population density, urban dynamics, carbon emissions, light pollution and anthropic impacts on the environment (Proville et al., 2017; Imhoff et al., 1997; Dobson et al., 2000; Doll, 2008; Ghosh et al., 2010a, 2010b; Oda and Maksyutov, 2011; Sutton et al., 2012; Frolking et al., 2013; Ceola et al., 2015; Bennie et al., 2015).

Coscieme et al. (2014) used nocturnal lights as a spatially related proxy of emergy. They found that the non-renewable component of emergy correlates with the sum of lights emitted within a territory, as detected by satellite imageries. This strict relationship confirms that large scale satellite-based measuring of nocturnal lights goes beyond the mere sum of bulbs turned on; on the contrary, it identifies urban, industrial and people aggregations and the consequent convergence of resource and energy flows in geographical areas. Investigating these phenomena at a systemic level allows the visualization of "*an alternative geography based on environmental resource use, in which a territory is interpreted as a continuum of physical and morphological elements, infrastructures and urban settlements, rather than a combination of separated systems*" or a "*thermodynamic geography*" (Pulselli, 2010).

In this paper, night-time lights observations are used, together with Gross Domestic Product (GDP) per capita, to estimate the annual non-renewable empower in 57 countries of the world from 1995 to 2012 continuously. Complete time series are useful to investigate variability in resource use, expressed in emergy terms, and possible trends in emergy-based indicators, which are useful tools for investigating sustainability (Brown and Ulgiati, 1997). However, emergy time series are only available for a limited number of countries and non-continuous years. For example, Lomas et al. (2008) provided emergy values for Spain for 1984, 1989, 1994, 2000 and 2002; Lei et al. (2012) for Italy and Sweden (and Macao) for different non-continuous years; similar analyses have been performed by Yang et al. (2010) and Lou and Ulgiati (2013) for China, and Giannetti et al. (2013) for Brazil, among others. Sweeney et al. (2007) and Brown et al. (2009) calculated emergy values for most of the world countries for the years 2000, 2004 and 2008. These gaps are due to the large amount of information needed for emergy assessments.

Time series estimation is here proposed by means of statistical reconstruction based on a multiple imputation strategy that is usually adopted to complete data affected by missing values. Beyond the main aim of the reconstruction of 1995–2012 time series for the non-renewable component of emergy for a large set of countries, the method enables calculation and visualization of the uncertainty involved in the reconstruction and further development of emergy representations at a more detailed spatial resolution.

Ultimately, this analysis facilitates time-series reconstructions that can be used to refine/monitor national and international policy goals.

2. Methods

2.1. DMSP-OLS time series of night-time emitted lights

Visible light emitted at night within a territory can be detected by satellites equipped with specialized sensors. A repetition of the observations is needed to exclude areas obscured by clouds and remove other sources of noise (Elvidge et al., 2001). A system of six satellites, the Operational Linescan System (OLS) flown by the U.S. Air Force Defense Meteorological Satellite Program (DMSP), has been providing time series of night-lights data available since 1992, archived at the NOAA National Geophysical Data Center (NGDC) (Elvidge et al., 2009). Each year, a global picture is composed by reporting the observational data on a latitude-longitude grid (Plate Carree projection) with a resolution of 30 arc seconds, or approximately 1 km^2 at the equator. Furthermore, a measure of the total brightness of nocturnal observed lights within each country of the world is calculated for each year as a Sum of Lights Index (SOL in digital brightness value) (Elvidge et al., 2001). The total brightness of night-time observed lights is expressed as the sum of the values of every 1 km^2 pixel in the nation's territory. Pixels are characterized by a digital number value that stretches from 0 (totally dark areas, e.g. wilderness settings) to 63 (maximum brightness detectable by the sensor; e.g. densely populated urban areas) (Tuttle et al., 2013). These values can be used as a proxy to describe and monitor patterns of resource consumption that are difficult to measure and map (Coscieme et al., 2014, 2017).

2.2. Emergy evaluation of territorial systems

Emergy is defined as the available energy of one type required in transformations to generate a flow or storage (Odum, 1988, 1996). Solar energy, being the fundamental energy for all biosphere processes, is used to express all energy flows in a common unit. Therefore, emergy is expressed in solar emergy joules (sej) and measures the convergence of different forms of energy flows into a final energy form, through a series of energy transformations, starting from solar radiation. Different energy forms are converted into sej by means of specific factors called Unit Emergy Values (UEVs).

Emergy is extensively used to study anthropic activity on a territorial basis (Pulselli et al., 2008b; Campbell and Ohrt, 2009; Campbell and Garmestani, 2012; Morandi et al., 2015; Giannetti et al., 2016; Agostinho et al., 2016; Tassinari et al., 2016). Emergy evaluations of territorial systems are informative to understand the environmental costs of the use of resources by humans. Thus, these analyses investigate the sustainability of territorial systems such as cities or entire countries (Giannetti et al., 2010, 2012, 2013; Sevegnani et al., 2016; Pulselli et al., 2008b; Pulselli, 2010; Bastianoni et al., 2005; Brown and Ulgiati, 1997).

The largest available database of emergy and empower data is the National Environmental Accounting Database (NEAD) hosted by the Center for Environmental Policy (University of Florida). The NEAD provides emergy data for a large set of world's countries in three different years, i.e. 2000, 2004 and 2008 (Sweeney et al., 2007; Brown et al., 2009). Total empower for every nation is calculated as the sum of renewable resources, non-renewable resources, and imported resources (data are available at http://www.cep.ees.ufl.edu/nead/; accessed March 2017). Imported resources are resources purchased from outside the national economy and include fuels, minerals, and finished goods. The services embodied in imported resources are also sometimes included. In this paper, we refer to the sum of non-renewable and imported resource flows as "non-renewable empower".

The Emergy baseline used in this paper is 15.2 E + 24 sej $year^{-1}$, which is also adopted within the NEAD framework.

2.3. Assumptions

Coscieme et al. (2014) showed that non-renewable empower, as calculated in the NEAD, is strongly correlated with the sum of lights emitted by countries in 2000, 2004 and 2008. On the other hand, renewable empower and sum of lights are not related. Night-time lights, in fact, help identify human settlements (both urban and industrial) that require a large convergence of resource flows, especially non-renewable, from raw material and minerals to a wide set of products coming from human-driven transformation processes (Proville et al., 2017); renewable energy flows, on the contrary, are properties of an area independently of human presence (sunlight, rainfall, geothermal heat, spring water sources, etc.).

This strong linear association of the sum of lights with non-renewable empower can be used to specify a regression model able to explain the

Table 1
The 57 countries investigated in this study have been divided into 4 Groups tuning up the non-renewable empower imputation model parameters (after Elvidge et al., 2014).

Group 1 Armenia; Austria; Botswana; Bulgaria; Croatia; Czech Republic; Denmark; Estonia; Finland; Germany; Hungary; Ireland; Latvia; Lithuania; Norway; Slovakia; Sweden.	Group 2 Cambodia; Egypt; El Salvador; Ethiopia; Jordan; Mali; Rwanda; South Africa; Tanzania; Tunisia.
Group 3 Albania; Australia; Azerbaijan; Belarus; Burundi; Cyprus; Greece; Guinea; Israel; Italy; Kazakhstan; Kenya; Malawi; Mauritania; Mexico; Pakistan; Poland; Portugal; Spain; Switzerland; Thailand; Venezuela; Vietnam.	Group 4 Canada; Japan; Moldova; Russia; Ukraine; United Kingdom; USA.

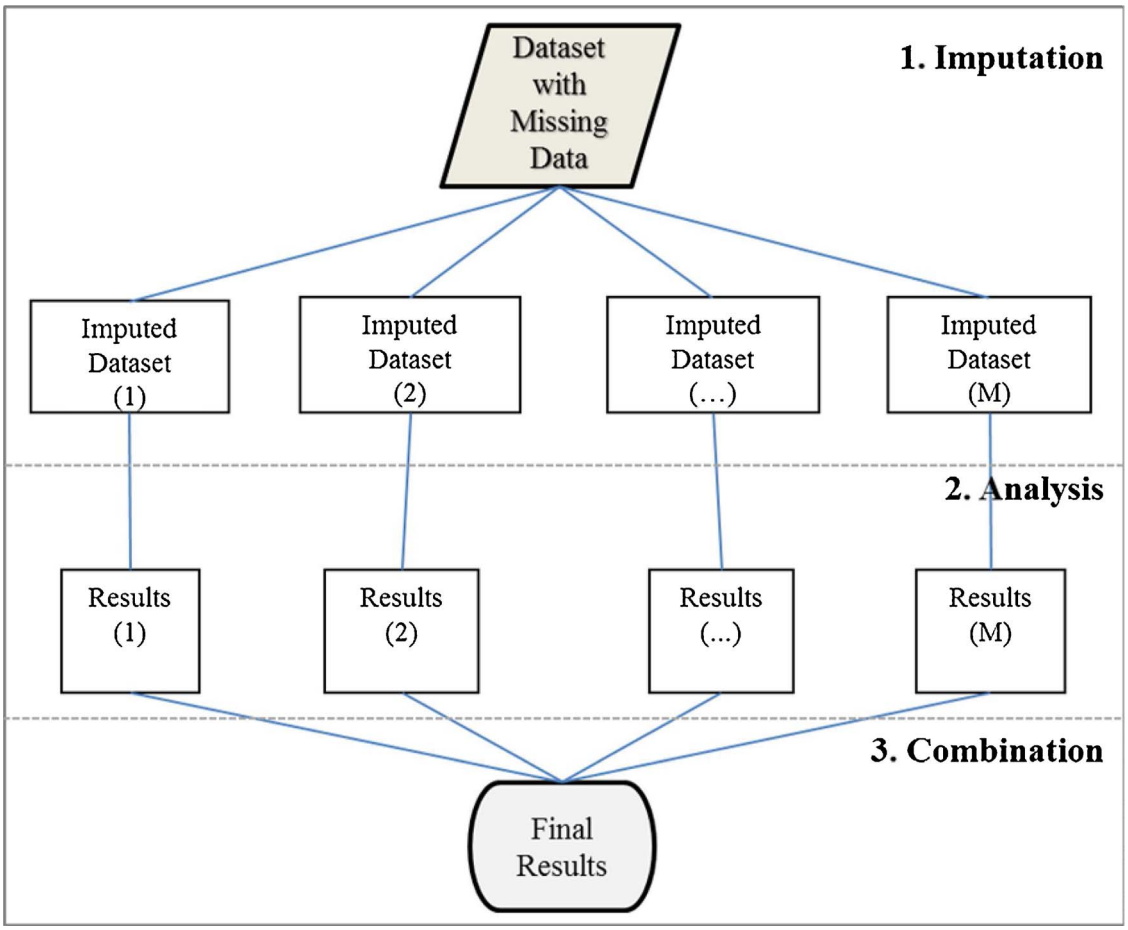

Fig. 1. Schematic representation of multiple imputation analysis and its phases.

variation of non-renewable empower and consequently provide estimations for years for which the NEAD does not provide emergy data. The basic idea is to deal with the not-computed non-renewable empower values as missing data (Little and Rubin, 1987) and to perform multiple imputations to estimate them. However, in order to define the best imputation technique, the structure of the data needs to be taken into account.

The night-lights data structure resembles a Time-Series–Cross-Section (TSCS): comparable time series data (for the period 1992–2012) observed on a variety of units (134 countries).

Emergy and empower, including renewable and non-renewable aggregates, have been only calculated for 2000, 2004 and 2008. The same are missing before 2000, from 2001 to 2003, from 2005 to 2007, and after 2008. Moreover, while empower has been calculated for the year 2000 for more than 100 countries, many of them show missing data for 2004 and/or 2008. In order to have a balanced number of observed empower values across countries, we decided to include just the countries presenting a complete series of 3 values (i.e. for the year 2000, 2004 and 2008) in the analysis. As a consequence, the number of countries considered in our analysis is equal to 57.

Given the data availability, the main objective of this paper is to estimate the non-renewable empower of countries using an imputation model relating the non-renewable empower to SOL. Moreover, since the imputation model aims at being predictive, any variable that would increase predictive power should be included. Because of that, and given the known strict relationship between measures of GDP and non-renewable resource use (Ward et al., 2016; Pulselli et al., 2015; Murphy and Hall, 2011; Henderson et al., 2009; Ghosh et al., 2010b; Xie and Weng, 2016; Sutton et al., 2012; Sutton and Costanza, 2002; Proville et al., 2017), GDP per capita in continuous time series (converted into 2005 US$ year^{-1} by purchasing power parity rates) has also been considered in the model. The GDP data have been collected from World Bank Open Data (available at: http://data.worldbank.org/last accessed: April 2017).

The variables considered in the analysis are observed over time within each cross-sectional unit (country) so they generally vary smoothly, however they may vary over time within any cross-section: there may be periods of growth, stability, or decline. In order not to force the model parameters to be fixed, independently of the trends of SOL and GDP per capita in each country, we decided to check the dynamics over time of these two variables to refine the model parameters (see Weng, 2014; Proville et al., 2017 for investigations of the relationships between the spatial distribution of a list of socio-economic indicators and night-time lights). Following the classification proposed by Elvidge et al. (2014), and further controlling for heterogeneity in the SOL and

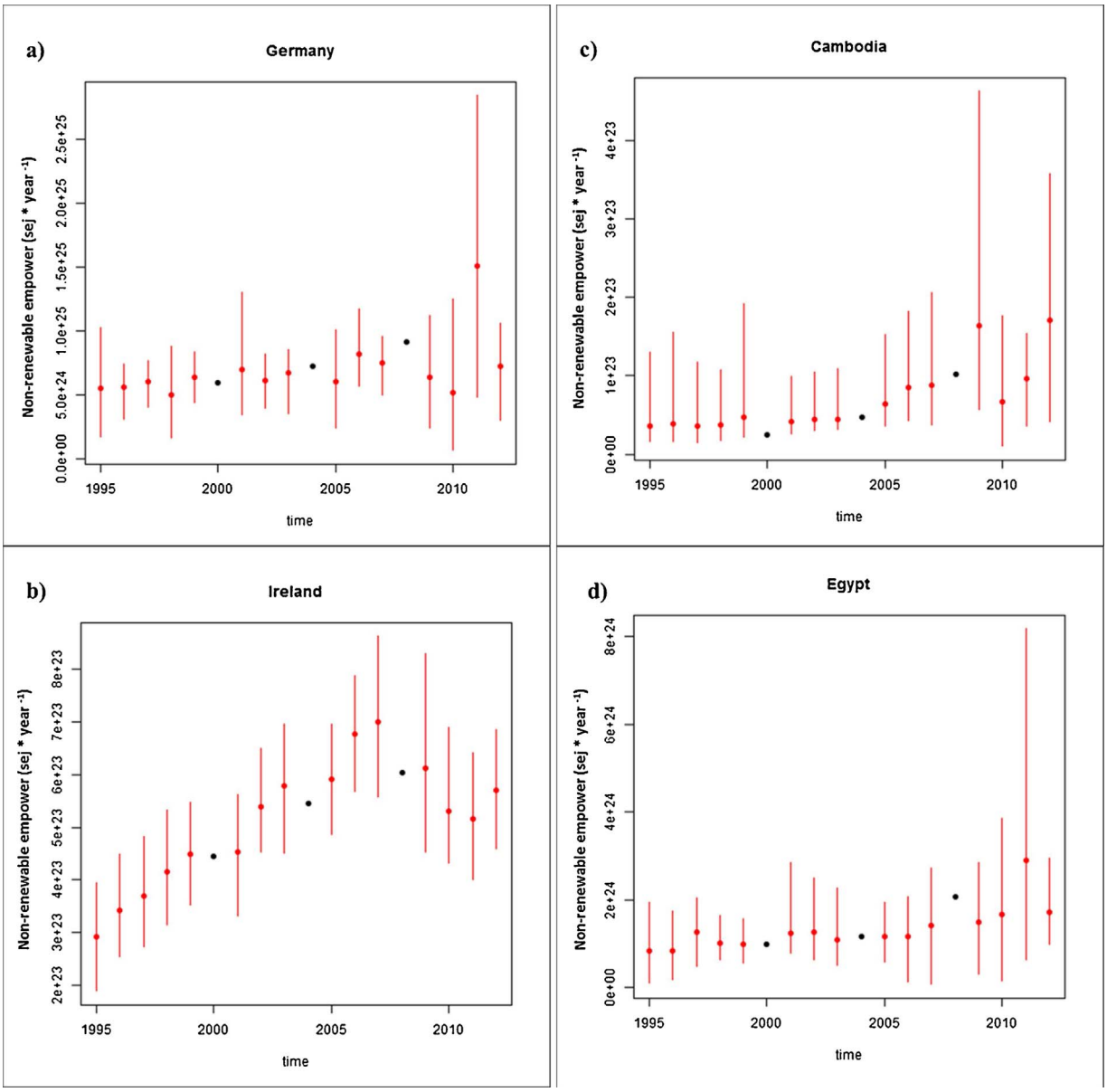

Fig. 2. Reconstructed 1995–2012 time-series of non-renewable empower (sej year^{-1}) for two representative countries of group 1 (a, b), group 2 (c, d), group 3 (e, f), and group 4 (g, h). Dark points (with no bars) are calculated values by NEAD (http://www.cep.ees.ufl.edu/nead/; accessed March 2017); red points (with bars) are the mean of the multiple imputations performed in this study, with 95% confidence intervals.

GDP per capita time series, we empirically developed an optimal grouping of countries into 4 groups, shifting countries from one group to another until reaching the best fitting model based on the available data. In other words, we tried to obtain a good compromise between maximum approximation (i.e. one single set of model parameters for all the countries) and maximum accuracy (i.e. one different set of model parameters for each country).

Despite it is of interest to fully understand the characteristics of these groups and the reasons why different relationships exist among SOL, GDP per capita and non-renewable empower for countries within each one of them, we are leaving this investigation to future research developments. However, a certain geographical homogeneity can be noted for Group 1, almost entirely composed by European countries (Table 1). On the other hand, Group 2 does not include any European country and Group 3 (and 4, which is however composed by a relatively limited number of countries) shows higher geographical heterogeneity (Table 1). The distribution of non-renewable empower per capita, the Emergy Yield Ratio (EYR, i.e. the ratio between all the resources used by a country in a year over the flow of imported resources), the Environmental Loading Ratio (ELR, i.e. the ratio between imported plus non-renewable resources used by a country in a year over the flow of renewable resources), and the Human Development Index (HDI) for the year 2008 within the 4 groups are reported in Appendix A. From this information, from a first analysis we can observe that groups cover a continuous range of non-renewable empower per capita, with increasing median values from Group 2 to Group 4, with Group 1 showing the highest value (Fig. A1). Regarding Emergy indicators (EYR and ELR; Table A1), the countries considered in this study largely correspond to only one of the two main categories globally represented, as classified by Giannetti et al. (2012). More specifically, we were able to impute non-renewable empower from SOL and GDP per capita only for countries with either medium or low EYR and, at the same time, high ELR (Table A1). Conversely, countries with high values of EYR and low values of ELR are not represented in our analysis despite being the most common worldwide (as highlighted by Giannetti et al., 2012). Regarding the HDI, Group 1 and 4 mostly include countries with very high and high human development levels, Group 2 mostly includes countries with medium or low human development, while Group 3 is the most heterogeneous (Table A2).

Given the TSCS structure of the data, the variables involved in the analysis recorded within each country are observed to vary smoothly

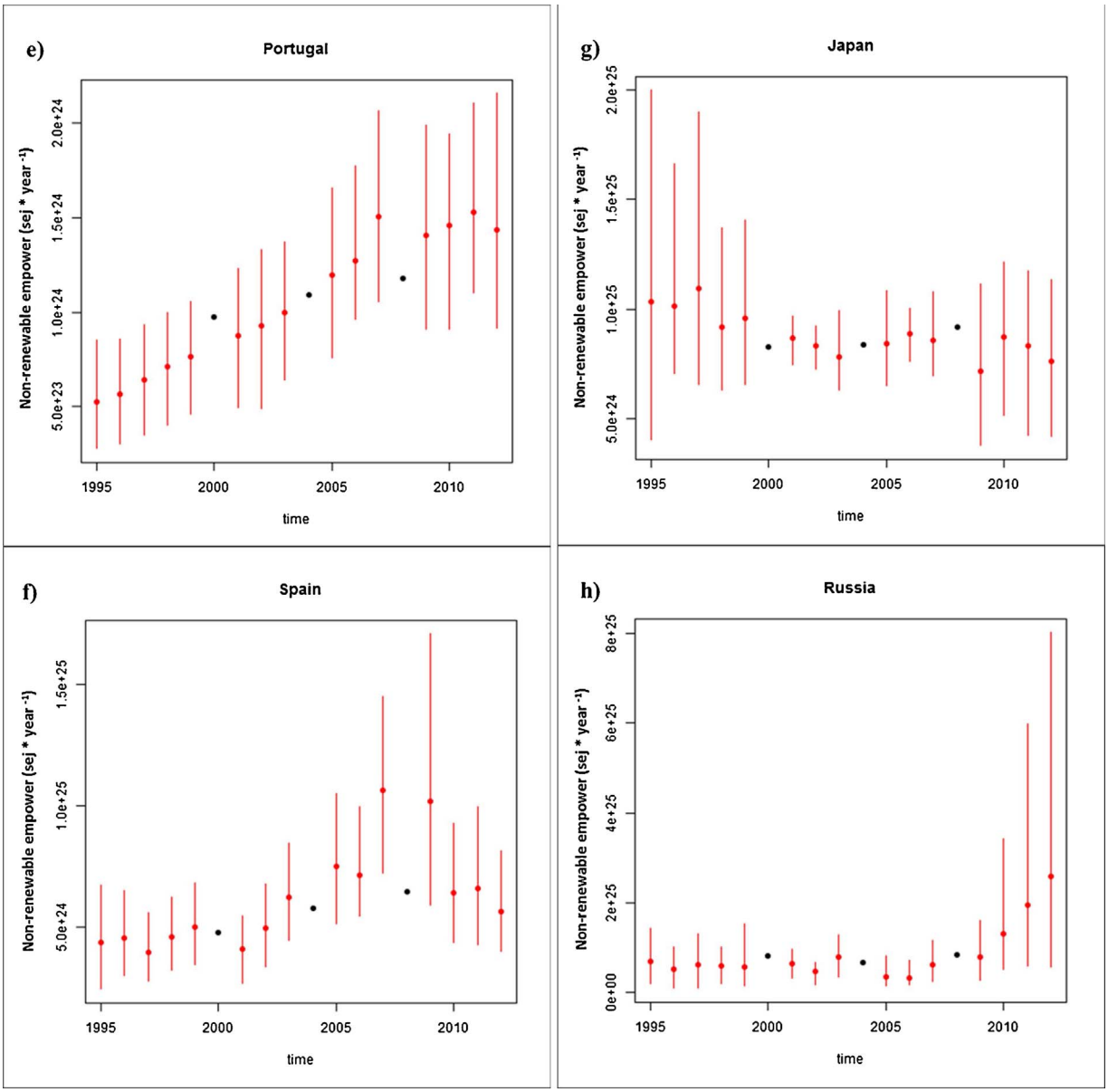

Fig. 2. (*continued*)

over time. Thus, knowing the calculated values of non-renewable empower (available for 2000, 2004 and 2008) close in time to any missing value may enormously aid the imputation of that value. For this reason, we narrowed down the time-series of our imputations to 1995–2012 (instead of 1992–2012) in order to start time series in a year closer to 2000, that is the first year with calculated empower.

Following these settings, the imputation task was conducted via Amelia II, a well-suited imputation R-package (Honaker and King, 2010). Amelia II requires a multivariate normal distribution of the data. For this reason, we performed a *log* transformation on the non-renewable empower data before running the imputation model. However, note that the final imputations of non-renewable empower are then returned in the original untransformed data form.

Amelia II also requires a specific assumption on the process generating missing values: the "Missing At Random" (MAR) assumption. In order to clarify the meaning of this assumption we remind that the missing data mechanism describes the relationships between observed variables and the probability of missing data. Data are MAR if missingness is related to other measured variables in the analysis model, but not to the underlying values of the incomplete variable (in our case non-renewable empower for the periods 1995–1999, from 2001 to 2003, from 2005 to 2007, and after 2008). A special case of MAR mechanism is the "Missing Completely At Random" case (MCAR). Data are MCAR when the probability of missing data on a variable X is unrelated to other measured variables and to the values of X itself. In other words, missingness is completely unsystematic and the observed data can be thought of as a random subsample of the hypothetically complete data. We can argue that it is a very strict assumption that is unlikely to be satisfied in practice. In our application it holds, because missingness on non-renewable empower is not dependent on the data at all, just on the choice of calculating emergy for years 2000, 2004 and 2008. Amelia II implements joint multivariate normal multiple imputation, taking into account for the TSCS form of the data. The package implements different methods to model smooth temporal variation within cross-section units (Honaker et al., 2015). In this study, "*lags and leads*" of the explanatory variables have been included, since data for one period tend to be highly correlated with data for the previous or subsequent period.

2.4. Multiple imputation

The idea of multiple imputation is to impute a certain number of

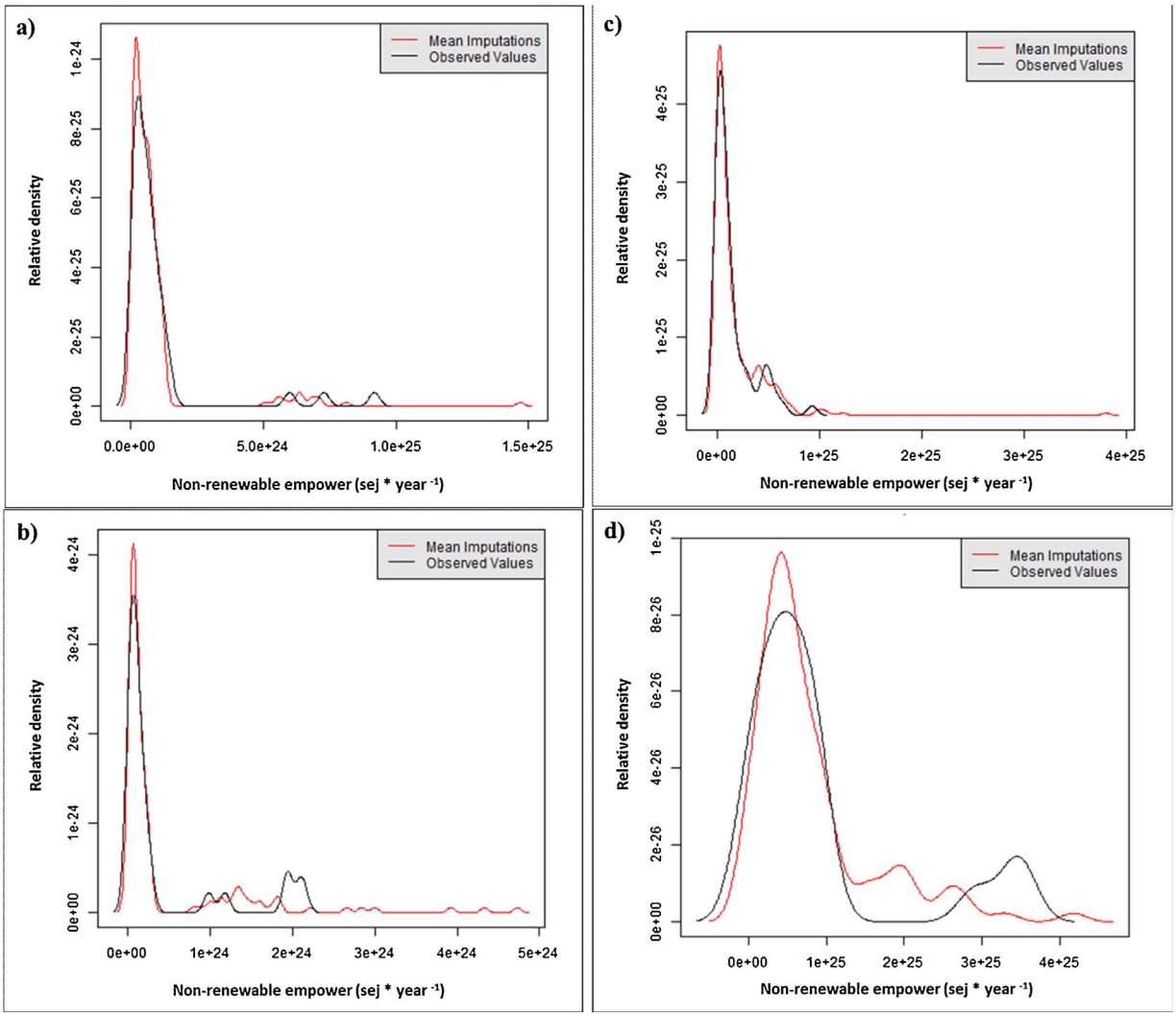

Fig. 3. Distribution of the observed non-renewable empowers (dark line; data from NEAD, http://www.cep.ees.ufl.edu/nead/; accessed March 2017) and imputed non-renewable empowers (red line; this study) in sej year^{-1} for the 57 countries investigated; a) group 1; b) group 2; c) group 3; d) group 4.

values (say M) for each missing value in the dataset, therefore creating M completed datasets (Fig. 1).

The imputations across these datasets are based on the same set of observed values (in our case, the values available in the NEAD for 2000, 2004 and 2008, and the SOL and GDP per capita across the whole period 1995-2012). The multiple values estimated for each unobserved non-renewable empower reflect the uncertainty of the imputation. In deeper explorations, the data analyst can apply any statistical method individually on each imputed dataset and then combine the results in a final dataset ("Final Results" in Fig. 1). This study aims at completing existing non-renewable empower time series, so the multiple imputation task stops at the first step ("Imputation" in Fig. 1), performing a total number of 10 imputations (i.e. M = 10), and thus obtaining 10 "Imputed Datasets" (Fig. 1).

2.5. The imputation model

To implement multiple imputations, an appropriate model incorporating random variation is needed. Amelia II imputes missing values by means of a linear regression model, i.e. modeling missing values as a linear function of the observed ones by also considering the following aspects:

1) if variables recorded over time within a cross-sectional unit are observed to vary smoothly, then knowing the observed values close in time to any missing value is enormously beneficial to the imputation of that value;
2) the imputation model can include an individual effect for each cross-section, resulting in a more flexible estimation.

Regarding the first aspect, Amelia II offers a number of methods to adapt the imputation model by extending the data according to smooth basis functions of time (Honaker et al., 2011). In this study, the smoothing task has been performed including "*lags and leads*" of the dependent and/or key explanatory variables into the imputation model. "*Lags*" are variables that take the value of another variable in the previous time period, while "*leads*" take the value of another variable in the next time period. This strategy seems to be particularly suited for our analysis, since both past and future values close in time of non-renewable empower, SOL, and GDP per capita are likely highly correlated with the present value.

Regarding the second aspect, the generation of multiple imputation values is performed through a bootstrap in combination with an expectation maximization algorithm named EMB (expectation maximization with bootstrapping): the algorithm first bootstraps a sample dataset with the same dimensions as the original incomplete data; on each bootstrap sample the algorithm estimates the sufficient statistics needed to generate multiple sets of parameters, finally imputing the missing values (for details see Honaker and King, 2010).

In the analysis conducted here there is indeed a large amount of missing data. However, no established cutoff exists from literature regarding an acceptable percentage of missing data to being possible to deal with.

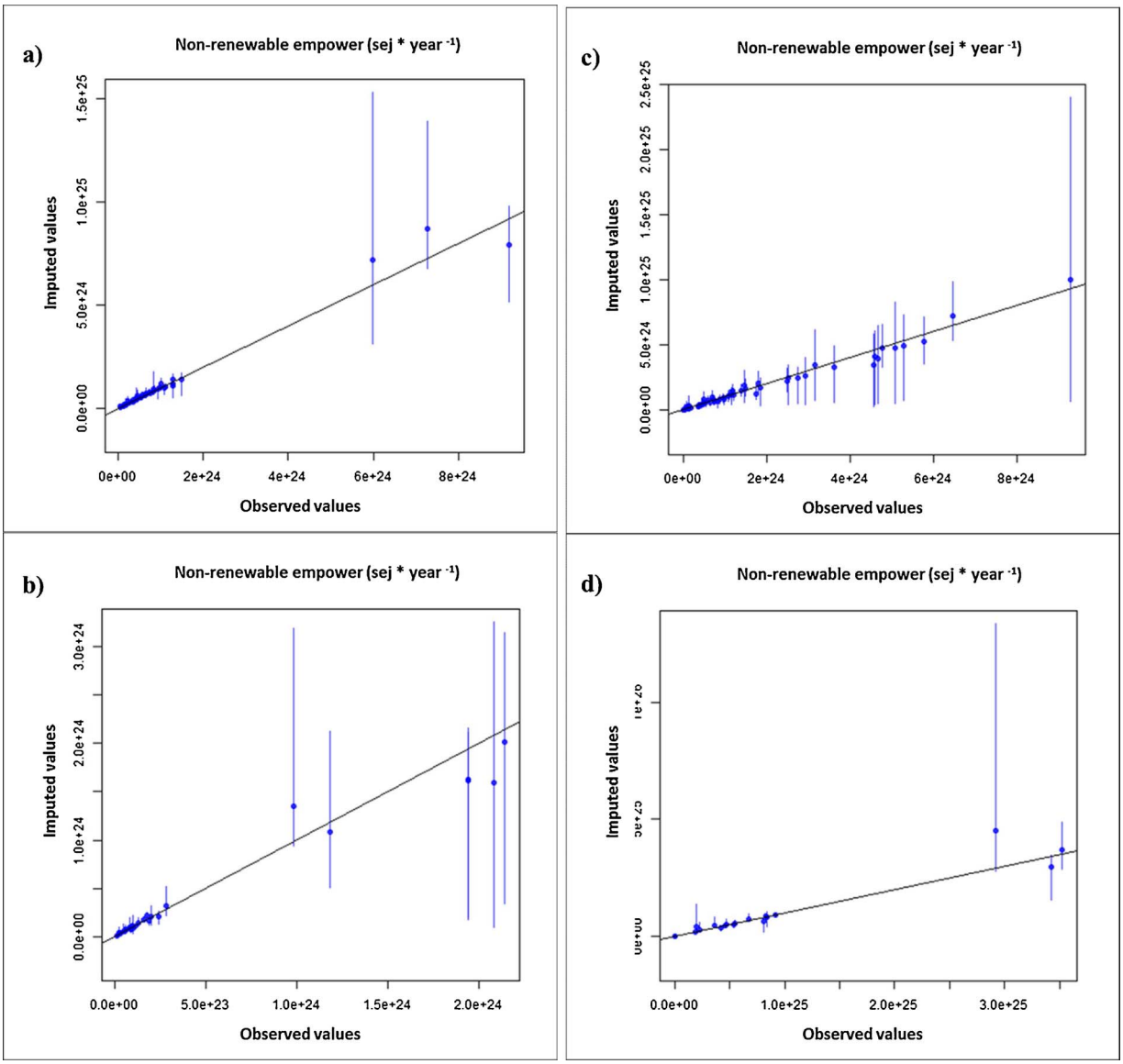

Fig. 4. Observed versus imputed values of non-renewable empower (sej year^{-1}) for the 57 countries investigated; a) group 1; b) group 2; c) group 3; d) group 4. 95% confidence intervals are shown for imputed values.

Furthermore, the amount of missing data is not the sole criterion by which a researcher assesses the missing data problem. Tabachnick and Fidell (2012) posited that missing data mechanisms and patterns have greater impact on research results than does the proportion of missing data. With respect to these issues our task is not problematic because the missing data mechanism is MCAR, as required by Amelia II, and the missing data pattern is univariate, that is the easiest pattern to handle with, computationally. Another important issue influencing the performance of the imputation model is the variance of the variable/variables to be imputed. As already mentioned, the variables considered in the analysis are recorded over time within each cross-sectional unit so they generally vary smoothly over time. As a consequence, the model considering temporal approaches, within Amelia II, have the potential to offer good forecasts.

3. Results

3.1. Reconstruction of continuous non-renewable empower times series

In this paper, non-renewable empower 1995–2012 continuous time-series have been reconstructed for a set of 57 countries divided into 4 groups, starting from 3 calculated values and using imputation models based on GDP per capita and the sum of emitted lights. Some illustrative results of this analysis are shown in Fig. 2, where observed and imputed non-renewable empower values are reported over time for two representative countries in each group (similar graphs for all the 57 countries investigated are shown in Fig. S1). In Fig. 2, the dark points (with no bars) represent non-renewable empower in 2000, 2004 and 2008, as calculated by NEAD (http://www.cep.ees.ufl.edu/nead/; accessed March 2017); the red points (with bars) represent the mean imputations for all the missing values along the time series. Due to the multiple imputation strategy used, we get the imputation distribution for each mean imputation, and we can draw the 95% confidence bands, giving us a measure of the uncertainty associated with the imputations in different years.

In Fig. 2 we can see the reconstructed time-series of Germany and Ireland (group 1; Fig. 2a, b); Cambodia and Egypt (group 2; Fig. 2c, d), Portugal and Spain (group 3; Fig. 2e, f), Japan and Russia (group 4; Fig. 2g, h).

From the majority of these graphs, it is notable that imputations are characterized by a smaller dispersion in the central part of the time-series (between 2000 and 2008). This is a prevalent trait of the time-series reconstructed (Fig. S1), highlighting how the availability of a larger set of non-renewable empower observed values could improve the efficacy of the imputation strategy.

Table 2
Average values of non-renewable empower time-series reconstruction (in 1E + 24 sej year^{-1}) for the 57 countries, divided into 4 groups, investigated in this study. Values for the year 2000, 2004 and 2008 are from NEAD (http://www.cep.ees.ufl.edu/nead/; accessed March 2017). Emergy baseline is that used by the NEAD: 15.2 E + 24 sej year^{-1}.

country	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Group 1																		
Armenia	0.11	0.15	0.13	0.11	0.12	0.14	0.16	0.23	0.21	0.19	0.28	0.31	0.36	0.23	0.27	0.34	0.37	0.32
Austria	0.86	0.91	1.00	1.10	0.96	0.94	0.95	0.98	0.97	1.30	1.20	1.20	1.30	1.50	1.30	1.10	1.10	1.20
Botswana	0.09	0.09	0.10	0.11	0.11	0.06	0.09	0.10	0.11	0.12	0.11	0.11	0.12	0.14	0.11	0.11	0.12	0.14
Bulgaria	0.25	0.22	0.24	0.31	0.26	0.37	0.31	0.33	0.31	0.37	0.41	0.44	0.61	0.47	0.51	0.53	0.50	0.51
Croatia	0.13	0.15	0.14	0.16	0.13	0.14	0.16	0.16	0.18	0.20	0.22	0.20	0.23	0.26	0.23	0.18	0.20	0.21
Czech Republic	0.66	0.71	0.74	0.70	0.67	0.70	0.77	0.79	0.84	1.10	1.10	1.10	1.20	1.30	1.30	1.00	1.20	1.10
Denmark	0.46	0.44	0.56	0.60	0.52	0.55	0.48	0.65	0.72	0.64	0.67	0.74	0.70	0.75	0.93	0.72	0.53	0.73
Estonia	0.06	0.08	0.10	0.08	0.08	0.07	0.11	0.12	0.13	0.18	0.16	0.18	0.19	0.21	0.17	0.16	0.14	0.21
Finland	0.36	0.42	0.43	0.46	0.42	0.52	0.54	0.54	0.57	0.57	0.60	0.61	0.70	0.76	0.65	0.60	0.70	0.60
Germany	5.60	5.70	6.40	5.10	6.40	6.00	6.80	6.30	6.80	7.30	6.00	8.10	7.10	9.20	6.30	5.50	15.00	7.10
Hungary	0.43	0.43	0.43	0.49	0.48	0.43	0.55	0.60	0.64	0.65	0.81	0.71	0.83	0.85	0.74	0.71	0.70	0.85
Ireland	0.29	0.34	0.38	0.42	0.47	0.45	0.47	0.54	0.56	0.55	0.60	0.70	0.72	0.60	0.64	0.51	0.54	0.61
Latvia	0.04	0.05	0.05	0.05	0.05	0.06	0.07	0.08	0.09	0.11	0.12	0.12	0.15	0.16	0.14	0.14	0.10	0.14
Lithuania	0.10	0.12	0.11	0.12	0.10	0.12	0.15	0.20	0.17	0.22	0.24	0.25	0.30	0.29	0.32	0.35	0.22	0.28
Norway	0.73	0.74	0.81	0.92	0.90	0.83	0.92	0.91	0.91	1.10	1.10	1.10	1.10	1.00	1.10	0.95	0.97	1.00
Slovakia	0.26	0.25	0.29	0.34	0.29	0.33	0.34	0.35	0.36	0.45	0.52	0.49	0.64	0.68	0.67	0.74	0.66	0.69
Sweden	0.64	0.66	0.75	0.67	0.76	0.87	0.77	1.10	0.93	0.99	1.10	1.10	1.20	1.30	1.20	0.95	1.20	0.94
Group 2																		
Cambodia	0.03	0.04	0.05	0.04	0.05	0.03	0.04	0.05	0.05	0.05	0.06	0.09	0.09	0.10	0.18	0.06	0.10	0.18
Egypt	0.89	0.80	1.30	1.00	1.00	0.98	1.20	1.30	1.10	1.20	1.10	1.10	1.40	2.10	1.40	1.60	3.00	1.70
El Salvador	0.07	0.09	0.09	0.07	0.09	0.08	0.10	0.11	0.10	0.08	0.09	0.11	0.09	0.10	0.09	0.12	0.10	0.11
Ethiopia	0.07	0.07	0.09	0.07	0.07	0.06	0.10	0.07	0.07	0.09	0.09	0.11	0.11	0.13	0.14	0.19	0.15	0.20
Jordan	0.14	0.13	0.16	0.14	0.17	0.19	0.17	0.17	0.15	0.16	0.18	0.18	0.18	0.18	0.19	0.21	0.23	0.24
Mali	0.03	0.02	0.03	0.03	0.03	0.03	0.04	0.03	0.04	0.03	0.04	0.04	0.04	0.06	0.06	0.06	0.07	0.08
Rwanda	0.01	0.01	0.02	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.03	0.03	0.03
South Africa	1.30	4.70	2.80	2.70	1.40	1.90	1.50	1.30	1.50	1.90	2.20	1.80	1.80	2.10	4.30	1.60	1.80	3.90
Tanzania	0.06	0.06	0.10	0.07	0.08	0.06	0.09	0.07	0.09	0.08	0.10	0.09	0.09	0.12	0.09	0.10	0.12	0.10
Tunisia	0.17	0.16	0.23	0.19	0.21	0.20	0.25	0.24	0.26	0.24	0.29	0.23	0.25	0.28	0.26	0.27	0.26	0.27
Group 3																		
Albania	0.06	0.06	0.03	0.03	0.06	0.03	0.11	0.11	0.19	0.09	0.25	0.26	0.25	0.13	0.48	0.38	0.52	0.63
Australia	2.50	2.60	2.30	2.60	2.50	2.50	2.00	2.50	2.70	2.90	2.60	3.10	3.60	3.60	3.50	3.10	3.80	4.10
Azerbaijan	0.11	0.12	0.10	0.12	0.13	0.14	0.09	0.14	0.20	0.17	0.25	0.34	0.54	0.47	0.55	0.61	0.68	0.79
Belarus	0.26	0.23	0.34	0.63	0.34	0.36	0.38	0.36	0.30	0.41	0.39	0.51	0.63	0.56	0.61	1.80	2.40	3.30
Burundi	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02
Cyprus	0.04	0.05	0.04	0.05	0.06	0.06	0.06	0.06	0.07	0.07	0.07	0.08	0.09	0.09	0.09	0.10	0.10	0.09
Greece	0.32	0.31	0.36	0.43	0.47	0.65	0.59	0.68	0.71	0.74	0.83	0.91	1.00	0.49	0.88	0.71	0.69	0.59
Guinea	0.04	0.04	0.03	0.05	0.07	0.04	0.06	0.07	0.06	0.06	0.06	0.05	0.05	0.07	0.07	0.06	0.07	0.09
Israel	0.30	0.33	0.39	0.44	0.39	0.39	0.42	0.38	0.40	0.48	0.41	0.48	0.49	0.49	0.49	0.60	0.64	0.62
Italy	4.00	3.70	3.50	4.30	4.20	4.70	4.50	4.10	6.00	4.60	5.90	4.00	6.10	5.10	6.00	5.20	3.90	5.70
Kazakhstan	1.30	1.00	0.86	0.84	0.52	0.84	0.59	1.10	1.60	1.20	0.96	1.10	1.90	1.50	2.40	2.80	4.70	4.20
Kenya	0.24	0.28	0.24	0.20	0.32	0.37	0.19	0.18	0.19	0.08	0.19	0.20	0.19	0.13	0.27	0.27	0.36	0.42
Malawi	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.04
Mauritania	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.02	0.02	0.02	0.03	0.03	0.03	0.10	0.04	0.04	0.05	0.09
Mexico	5.10	3.80	3.20	5.50	4.20	9.30	5.80	4.30	6.10	4.60	5.20	3.80	4.20	5.30	6.40	4.70	10.00	5.60
Pakistan	1.10	1.30	0.80	1.20	1.00	0.70	0.88	0.90	1.20	1.80	1.50	1.80	2.40	1.20	2.00	1.10	1.40	1.30
Poland	2.30	1.50	1.00	5.60	1.90	1.50	2.70	5.70	2.70	1.80	5.10	6.70	2.00	2.50	4.40	38.00	3.80	12.00
Portugal	0.53	0.60	0.59	0.72	0.75	0.97	0.95	0.92	1.00	1.10	1.20	1.20	1.50	1.20	1.30	1.40	1.50	1.60
Spain	4.90	4.70	4.20	4.10	4.90	4.80	4.00	4.90	5.60	5.80	7.40	6.20	10.00	6.50	9.80	6.70	7.00	5.50
Switzerland	0.69	0.58	0.51	0.72	0.79	0.61	0.72	0.60	0.92	0.75	0.92	0.73	0.75	0.97	0.84	1.30	0.87	0.93
Thailand	2.00	2.20	1.60	1.90	1.70	1.90	1.40	1.90	2.50	2.80	3.10	2.80	3.70	3.20	1.60	11.00	7.00	7.50
Venezuela	1.50	1.30	0.91	1.30	0.93	1.10	1.10	1.00	0.79	1.20	1.00	1.10	1.00	1.40	2.00	1.30	1.50	2.30
Vietnam	0.04	0.04	0.06	0.12	0.15	0.19	0.22	0.29	0.46	0.49	0.59	0.63	0.85	0.88	1.00	1.40	1.70	1.90
Group 4																		
Canada	9.90	6.60	6.50	4.90	5.70	3.60	4.50	3.80	4.20	4.30	2.30	1.90	3.40	4.70	2.90	3.10	3.70	2.90
Japan	14.00	11.00	10.00	9.20	8.60	8.30	8.70	8.20	7.80	8.40	8.50	8.90	8.70	9.20	7.20	9.80	8.40	7.80
Moldova	5.70	3.00	2.40	0.17	0.41	0.03	0.07	0.06	0.23	0.04	0.07	0.06	0.11	0.06	0.14	0.32	1.20	1.60
Russia	6.50	5.30	5.70	5.40	5.40	8.10	6.50	4.70	8.00	6.70	3.60	3.20	6.30	8.40	7.80	15.00	20.00	19.00
Ukraine	22.00	11.00	6.10	2.70	3.70	1.90	2.60	2.50	2.80	2.00	2.00	3.00	2.60	2.30	2.20	3.80	9.40	11.00
United Kingdom	5.30	4.50	5.00	5.10	4.90	4.60	4.40	4.10	4.50	5.40	4.70	4.70	4.90	5.40	3.80	5.40	5.00	3.50
United States	28.00	26.00	18.00	20.00	28.00	29.00	20.00	16.00	42.00	34.00	16.00	11.00	33.00	35.00	26.00	26.00	20.00	17.00

3.2. Diagnostic checks

At the end of the imputation process some checks on the imputations performed have been conducted to inspect the plausibility of the imputation model and, afterwards, to assess how well it predicts missing values in the TSCS. It is worth specifying that while the number of imputed values (M) is generally equal to five or ten in many applications (10 in our analysis), in the diagnostic task M is much higher (i.e. several hundreds of imputations). The large number of imputations is necessary to build confidence intervals around the imputed values.

A first diagnostic check is performed by analyzing the density plots of the observed values and the mean values of the M imputations (Fig. 3). In Fig. 3, the dark line represents the distribution of the 57 non-renewable empower values extracted from the NEAD, while the red line

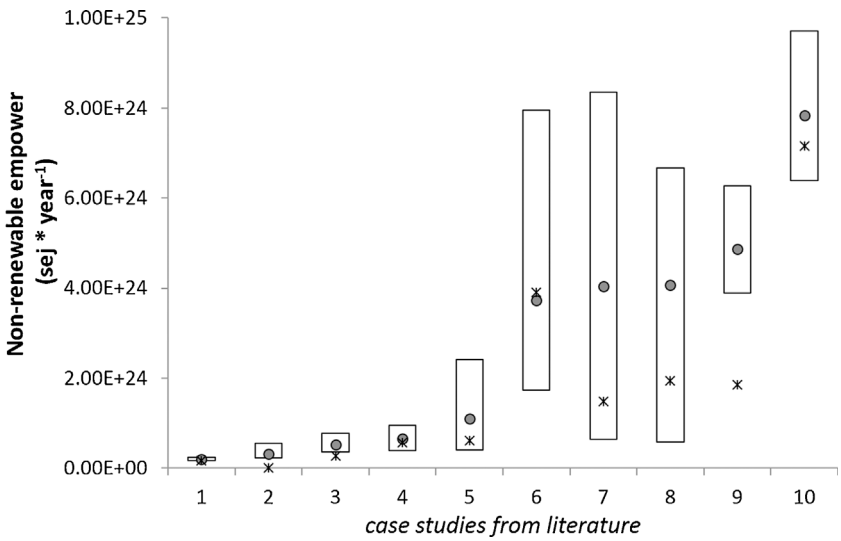

Fig. 5. Comparison of non-renewable empower (in sej * year^{-1}) calculated in 10 case studies from literature (*) with the range (□) and the average value (●) of the imputations based on the sum of lights and Gross Domestic Product per capita. 1 - Croatia (2011) from Lugaric and Krajcar (2016); 2 - Kenya (1999) from Cohen et al. (2006); 3 - Denmark (1999) from Rydberg and Haden (2006); 4/5 - Sweden (1996/2002) from Lei et al. (2012); 6 - Canada (2011) from Hossaini and Hewage (2013); 7/8 - Italy (1995/2002) from Lei et al., (2012); 9 - Spain (2002) from Lomas et al., (2008); 10 - Japan (2003) from Gasparatos and Gadda (2009).

represents the distribution of the mean value of the imputations obtained in this study for each missing data in the 57 countries investigated (divided into 4 groups; Fig. 3a–d).

Looking at Fig. 3 it can be noted that the distribution of the mean of the imputations largely overlays the distribution of the observed values.

A further diagnostic check that has been run to judge how accurate the imputed values were is the *overimputing*. It is based on the fact that there is no way to compare the mean prediction of the imputation model with the unobserved value, the latter being not available by definition. Accordingly, in order to assess the accuracy of the imputations, *overimputing* treats each of the observed values (i.e. non-renewable empower calculated by NEAD) as if it had actually been missing; in a sort of cross-validation. Several hundred imputed values are generated for each observed value, the large number of imputations allows the computation of a confidence interval representing what the imputed values would have been for non-renewable empower in the years 2000, 2004 and 2008.

In Fig. 4, the results of the *overimputing* check are shown. The x axis reports the observed values of non-renewable empower, while the y axis shows the imputed values when treating observed values as temporarily missing and impute them from the model.

In Fig. 4, $y = x$ line indicates perfect agreement; i.e. the imputation model is a perfect predictor of the observed value. Each vertical line/dot represents a country/year for which the non-renewable empower observed value is dealt as a missing value. The dots in the figure represent the mean of the imputations. For each mean imputation, the 95% confidence interval is also plotted, allowing an inspection of the accuracy of the imputation model.

The mean values of the multiple imputations along the 1995-2012 time-series are reported in Table 2, for the overall dataset of countries investigated. The set of all the imputed values is available in Table S1.

In order to perform an external check, or validation, on the reliability of the results reported in Table 2, the imputations of non-renewable empower were compared with case studies from literature (Fig. 5). A total of 10 case studies were identified by searching for the keywords "country name" (for each of the 57 countries investigated; Table 1) and "*emergy*" in Scopus (http://www.scopus.com; Fig. 5). Only emergy accounting applications at the national scale within the 1995–2012 period were considered. Studies referred to the years 2000; 2004 and 2008 were not considered because estimation through multiple imputation was not performed for these years; where calculated data were available.

In Fig. 5, stars indicate the values derived from literature; boxes are built based on the minimum (bottom of the box) and maximum (top of the box) imputation value (Table S1); dots indicate the average value of the imputations (i.e. the non-renewable empower values listed in Table 2). The non-renewable empower calculated in 8 out of 10 case studies identified falls within the range of the imputations for that country and year. The limited number of case studies found reflects the difficulties of performing national emergy accountings and highlights the relevance of proxy-based reconstructions of continuous time-series.

4. Discussion and conclusion

Energy availability and use is extremely relevant for sustainability as highlighted by the United Nations Sustainable Development Goals (i.e. Goal 7 and relative Targets). Sustainable development is a continuous and dynamic phenomenon that thus requires to be continuously studied over time. Sustainability indicators largely inform snapshots of a more or less sustainable/unsustainable state of the system under study. Emergy evaluation provides systemic information on flows of resources and, through appropriate computation, suitable indicators to detect the level of sustainability. However, a worldwide collection of punctual national accounting reports based on emergy seems not systematically feasible at the moment, especially because of difficulties in data collection and heterogeneity in data quality and availability in different contexts and countries of the world. More complete and organic pictures of development would emerge if continuous time series of these resource use measures and indicators were available.

A trade-off exists between the accuracy of calculated values and producing continuous observations over time. This is the case of emergy accounting: the application of this methodology needs a large amount of information and data processing, and, furthermore, still requires complete standards and guidelines for homogeneous implementation. These aspects explain why continuous time series of emergy are largely missing from literature.

By stressing the relationship between the non-renewable component of emergy and the sum of lights emitted at night at the country scale, we reconstructed continuous emergy time series from 1995 to 2012 for 57 nations. Estimation of continuous emergy time series is relevant as a starting point for a complete database at the international level, with implications for emergy theory and application at the national and global scale.

Calculation of encompassing systemic indicators, like emergy, can be of great importance to detect the development pattern of different countries, enabling comparisons and multidimensional investigations (i.e. not only based on economic measures). For example, Pulselli et al. (2015) proposed an input-state-output analysis framework based on the simultaneous evaluation of environmental, social and economic indicators to detect sustainability, and classify national socio-economic systems. They adopted emergy as an environmental (input) indicator, using information from the NEAD as a reference point. Due to the lack of continuous data for the three different kinds of indicators (namely, environmental, social and economic ones), the authors carried out a snapshot for 2008, but without studying in depth development over time. Now, the reconstruction of emergy time series could solve this

problem, at least from the environmental viewpoint, enabling applications of the input-state-output framework to study evolutionary behavior and development trajectories of national systems. Due to the global scale coverage of satellite imagery, the method here proposed overcome national boundaries and the different ability or possibility of countries to provide statistical information in different fields. In other words, the estimation of non-renewable emergy (in other cases, we can also refer to other measures) is possible for both rich and developed countries as well as poor and underdeveloped ones, contributing to erode disparities at least in the information system.

4.1. Limitations and further developments

The proposal here presented can be further refined including, for example, the countries that we excluded from the analysis because data were missing for at least one of the three years considered by the NEAD (i.e. 2000, 2004, or 2008). A step forward in this sense could be the punctual calculation of the complete set of emergy flows for those countries in a specific year.

As recently demonstrated (Coscieme et al., 2014), non-renewable emergy is correlated with total emitted lights at night. This relationship depends on the fact that, though non-renewable emergy is composed by a wide set of heterogeneous flows of resources, the concentration of light in an area indicates the presence of a system that stimulates convergence of flows of energy and matter to operate. In order to complete the picture (and the emergy inventory) at the country level, the flow of renewable resources can be easily included and added to the results of our estimation. This may also facilitate calculation of some emergy indicators, e.g. the emergy areal density (expressed in sej/m^2) or the Environmental Loading Ratio (ELR). Further specifications and indicator calculations are possible if appropriate disaggregation of the estimated non-renewable emergy is made, discriminating, for example, between local flows of non-renewable resources and resources imported from outside the national boundaries.

At this stage, the analysis performed presents several limitations. One main limitation is that non-renewable empower has been estimated only up to 2012. This limits possible emergy-based applications aiming to be relevant for defining timely policies. More recent estimations can be provided, but the accuracy is much worse after 2012; more specifically, the uncertainty of an imputed value is generally smaller around the observed value and larger far from the observed value, because in this case the value to be imputed have fewer neighbors from which to draw predictive power. This limitation can be overcome by relying on more recent high-resolution nighttime data such as images collected by VIIRS (https://ngdc.noaa.gov/eog/viirs/; see Steele et al., 2012 for an analysis of the characteristics of VIIRS images; see Coscieme et al., 2014 for an analysis of relationships between VIIRS and non-renewable empower at the sub-national level). VIIRS images are in fact available from 2011 onwards and published monthly with an approximated delay of 1 month (e.g. January 2017 data were available in February 2017). However, further developments in this sense depend on the availability of an updated emergy national accounting database, with more recent calculated values that can be used to refine night-time based estimations of continuous series. This is a call for emergy researchers and research institutions in order to be relevant for policy-making. Advances in this direction will therefore maximize the value and use of updated emergy datasets, highlighting the crucial role of calculated values within them and largely increasing their relevance and applicability at the global scale. Estimations are also influenced by the way in which reference values are punctually calculated. In our case, to estimate non-renewable emergy in time series, we considered the NEAD values as reference points, thus implicitly acknowledging the way in which these values have been calculated. To update time series and obtain estimate values for more recent years, analogous reference points are necessary which must be as much consistent as the NEAD values, and referred to a wide set of countries for different years.

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Appendix A

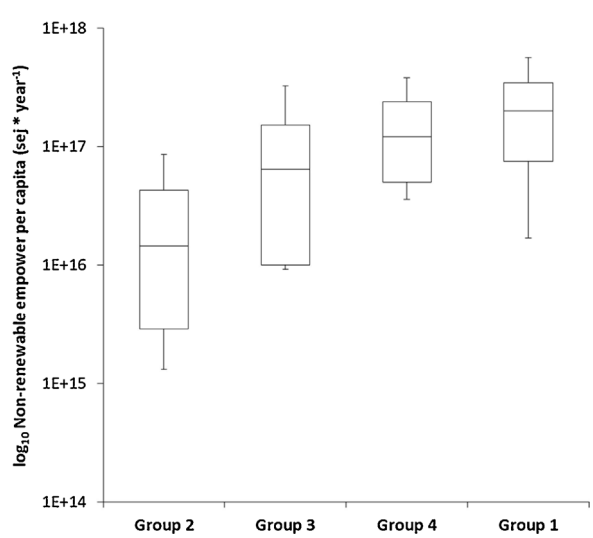

Fig. A1. Non-renewable empower per capita (sej * year^{-1}) for the year 2008 for the 4 groups of countries considered in this study (Table 1). On the x-axis, groups are ordered from lower to higher median value. Data are from the NEAD (http://www.cep.ees.ufl.edu/nead/; accessed June 2017).

Table A1
Emergy Yield Ratio (EYR, i.e. the ratio between all the resources used by a country in a year over the flow of imported resources), and Environmental Loading Ratio (ELR, i.e. the ratio between imported plus non-renewable resources used by a country in a year over the flow of renewable resources) for the 57 countries considered in this study (Table 1). Data are from the NEAD (http://www.cep.ees.ufl.edu/nead/; accessed June 2017). EYR and ELR classification into low, medium and high is based on Ulgiati and Brown (2002); see also Giannetti et al. (2006; Giannetti et al. (2006; 2012).

country	Emergy Yield Ratio (EYR)	EYR class	Environmental Loading Ratio (ELR)	ELR class
Group 1				
Armenia	4.205	MEDIUM	300.37	HIGH
Austria	1.152	LOW	230.46	HIGH
Botswana	3.589	MEDIUM	14.47	HIGH
Bulgaria	1.422	LOW	109.42	HIGH
Croatia	1.167	LOW	97.28	HIGH
Czech Republic	1.410	LOW	705.18	HIGH
Denmark	1.054	LOW	50.18	HIGH
Estonia	1.740	LOW	145	HIGH
Finland	1.031	LOW	171.79	HIGH
Germany	1.079	LOW	539.45	HIGH
Hungary	1.102	LOW	550.75	HIGH
Ireland	1.515	LOW	2.93	LOW
Latvia	1.267	LOW	52.8	HIGH
Lithuania	1.100	LOW	183.33	HIGH
Norway	1.760	LOW	12.85	HIGH
Slovakia	1.258	LOW	419.29	HIGH
Sweden	1.170	LOW	129.97	HIGH
Group 2				
Cambodia	1.521	LOW	5.53	MEDIUM
Egypt	4.527	MEDIUM	119.14	HIGH
El Salvador	1.365	LOW	6.38	MEDIUM
Ethiopia	2.517	MEDIUM	2.06	LOW
Jordan	1.154	LOW	144.19	HIGH
Mali	1.701	LOW	3.62	MEDIUM
Rwanda	2.592	MEDIUM	16.2	HIGH
South Africa	3.155	MEDIUM	38.01	HIGH
Tanzania	2.148	MEDIUM	2.35	LOW
Tunisia	1.429	LOW	34.03	HIGH
Group 3				
Albania	2.579	MEDIUM	64.47	HIGH
Australia	3.556	MEDIUM	4.63	MEDIUM
Azerbaijan	6.297	HIGH	233.23	HIGH
Belarus	1.060	LOW	176.68	HIGH
Burundi	2.603	MEDIUM	7.23	MEDIUM
Cyprus	1.213	LOW	606.57	HIGH
Greece	1.534	LOW	109.59	HIGH
Guinea	5.947	HIGH	1.6	LOW
Israel	1.961	LOW	1961.37	HIGH
Italy	1.148	LOW	287.04	HIGH
Kazakhstan	3.695	MEDIUM	40.6	HIGH
Kenya	1.516	LOW	4.89	MEDIUM
Malawi	1.466	LOW	5.18	HIGH
Mauritania	5.250	HIGH	8.78	MEDIUM
Mexico	1.740	LOW	48.34	HIGH
Pakistan	2.718	MEDIUM	31.98	HIGH
Poland	1.670	LOW	334.03	HIGH
Portugal	1.851	LOW	74.03	HIGH
Spain	1.918	LOW	239.71	HIGH
Switzerland	0.909	LOW	227.25	HIGH
Thailand	2.256	MEDIUM	59.38	HIGH
Venezuela	5.365	HIGH	14.58	HIGH
Vietnam	1.370	LOW	8.78	MEDIUM
Group 4				
Canada	2.358	MEDIUM	2.36	LOW
Japan	1.299	LOW	99.92	HIGH
Moldova	1.060	LOW	117.76	HIGH
Russia	4.423	MEDIUM	6.3	MEDIUM
Ukraine	1.756	LOW	97.58	HIGH
United Kingdom	1.494	LOW	6.58	MEDIUM
United States	2.284	MEDIUM	40.78	HIGH

Table A2
Human Development Index (HDI), for the 57 countries considered in this study (Table 1). Data available at http://hdr.undp.org; accessed July 2017.

country	Human Development Index (HDI)	HDI group
Group 1		
Armenia	0.722	HIGH
Austria	0.868	VERY HIGH
Botswana	0.656	MEDIUM
Bulgaria	0.766	HIGH
Croatia	0.801	VERY HIGH
Czech Republic	0.856	VERY HIGH
Denmark	0.896	VERY HIGH
Estonia	0.832	VERY HIGH
Finland	0.878	VERY HIGH
Germany	0.902	VERY HIGH
Hungary	0.814	VERY HIGH
Ireland	0.902	VERY HIGH
Latvia	0.813	VERY HIGH
Lithuania	0.827	VERY HIGH
Norway	0.937	VERY HIGH
Slovakia	0.824	VERY HIGH
Sweden	0.891	VERY HIGH
Group 2		
Cambodia	0.564	MEDIUM
Egypt	0.667	MEDIUM
El Salvador	0.648	MEDIUM
Ethiopia	0.394	LOW
Jordan	0.746	HIGH
Mali	0.385	LOW
Rwanda	0.432	LOW
South Africa	0.623	MEDIUM
Tanzania	0.451	LOW
Tunisia	0.706	HIGH
Group 3		
Albania	0.703	HIGH
Australia	0.922	VERY HIGH
Azerbaijan	0.724	HIGH
Belarus	0.764	HIGH
Burundi	0.362	LOW
Cyprus	0.844	VERY HIGH
Greece	0.858	VERY HIGH
Guinea	0.377	LOW
Israel	0.877	VERY HIGH
Italy	0.868	VERY HIGH
Kazakhstan	0.744	HIGH
Kenya	0.508	LOW
Malawi	0.395	LOW
Mauritania	0.466	LOW
Mexico	0.739	HIGH
Pakistan	0.536	LOW
Poland	0.817	VERY HIGH
Portugal	0.805	VERY HIGH
Spain	0.857	VERY HIGH
Switzerland	0.903	VERY HIGH
Thailand	0.704	HIGH
Venezuela	0.758	HIGH
Vietnam	0.617	MEDIUM
Group 4		
Canada	0.896	VERY HIGH
Japan	0.881	VERY HIGH
Moldova	0.652	MEDIUM
Russia	0.770	HIGH
Ukraine	0.729	HIGH
United Kingdom	0.890	VERY HIGH
United States	0.905	VERY HIGH

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolind.2017.08.040.

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