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Research article

A network-based frequency analysis of Inclusive Wealth to track sustainable development in world countries

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ABSTRACT

Using human (HC), natural (NC), and produced (PC) capital from Inclusive Wealth as representatives of the triple bottom line of sustainability and utilizing elements of network science, we introduce a Network-based Frequency Analysis (NFA) method to track sustainable development in world countries from 1990 to 2014. The method compares every country with every other and links them when values are close. The country with the most links becomes the main trend, and the performance of every other country is assessed based on its 'orbital' distance from the main trend. Orbital speeds are then calculated to evaluate country-specific dynamic trends. Overall, we find an optimistic trend for HC only, indicating positive impacts of global initiatives aiming towards socio-economic development in developing countries like the Millennium Development Goals and 'Agenda 21'. However, we also find that the relative performance of most countries has not changed significantly in this period, regardless of their gradual development. Specifically, we measure a decrease in produced and natural capital for most countries, despite an increase in GDP, suggesting unsustainable development. Furthermore, we develop a technique to cluster countries and project the results to 2050, and we find a significant decrease in NC for nearly all countries, suggesting an alarming depletion of natural resources worldwide.

1. Introduction

The world has changed dramatically since the end of the 20th century, and the pace of change shows no sign of slowing down. The global societal aspiration for development seems to systematically lead to the consumption of more resources, which not only puts additional pressure on the world's natural resources but it also jeopardizes the environment and plays a key role in altering the climate. According to several studies (Meadows et al., 1972; Rockström et al., 2009; Wackernagel et al., 2002), the depletion of resources, climate change, and the degradation of the environment bear clear signs of unsustainable development. Moreover, studies have also shown that standards of living can be on the rise even as stresses on the environment are increasing (DeFries, 2014; Johnson, 2000; Raudsepp-Hearne et al., 2010). Therefore, tracking progress (or lack of it) in sustainable development is critical (Bettencourt and Kaur, 2011; Clark and Dickson, 2003; Kates, 2001; Levin and Clark, 2010; Parris and Kates, 2003). The Gross Domestic Product (GDP), Human Development Index (HDI), and ecological footprint have long been used to track human development (Rees, 1992; UNDP, 2016; Wackernagel and Rees, 1996), but many have shown that these indices can fail to capture whether a development is sustainable or not (Dasgupta et al., 2015; Polasky et al., 2015). By contrast, the Inclusive Wealth (IW) index, also called Comprehensive Wealth or Genuine Wealth, was designed purposefully to track sustainable development (Arrow et al., 2004; UNU-IHDP and UNEP, 2014; World Bank, 2010). IW is defined as the sum of three capitals (defined in monetary terms) representing the triple bottom line of sustainability: human (i.e., society), produced (i.e., economy), and natural capital (i.e., environment); see supplementary information for details on what variables are included in the three capitals.

The main goal of this study is to capture and evaluate the main sustainable development trends and trajectories of world countries relative to every other using IW data from 1990 to 2014 (UNU-IHDP and UNEP, 2014; Urban Institute and UNEP, 2017). Traditionally, the arithmetic mean or median are used to capture the general trend, but both can be easily biased by the presence of extreme values in a

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dataset. For this study, we prefer to use and adapt Network-based Frequency Analysis (NFA) (Derrible and Ahmad, 2015), which is not affected by extreme values and which is able to capture general trends in a more robust way. Moreover, NFA allows us to measure the evolution of an entity relative to the evolution of other entities. More specifically, the objectives of this study are to: a) create a method to estimate the main human, natural, and produced capital trends in the world using concepts from network science; b) assess the relative performance of every country from the general trends captured; c) cluster countries based on their performance in all the three capitals; and d) project current trends up to 2050 to depict the potential future performance of every country. For this work, we use data from the 2014 and 2017 Inclusive Wealth Report (UNU-IHDP and UNEP, 2014; Urban Institute and UNEP, 2017). We selected human, natural, and produced capital for all the countries for our analysis.

One of the main contributions of this work is the deployment of the NFA method and extension to orbital NFA (oNFA), whose results can offer a significant contribution to current knowledge and complement traditional statistical approaches. Briefly, among 140 analyzed countries, 110 showed an increasing trend for human capital, whereas only 4 countries for natural capital and 6 countries for produced capital showed an increasing trend from 2000 to 2014. Moreover, based on the combined performance of human, natural, and produced capital, only 3 countries show an optimistic trend, whereas 18 countries show a decreasing trend, and the 119 remaining countries have not changed significantly from 2000 to 2014.

2. Methodology

With the profusion of data and availability of virtually limitless computing power, new algorithmic solutions have been developed and applied since the early 2000s (Ahmad et al., 2017, 2016). In this study, we utilize Network-based Frequency Analysis (NFA) that is able to capture global trends in a dataset and measure the relative evolution of an entity (Ahmad and Derrible, 2015). Although not rooted in the general field of Network Science (Newman, 2010), the method essentially compares to forming a network. From a Machine Learning perspective, the foundation of the methodology is closest to kernel density estimation (KDE) (Parzen, 1962; Rosenblatt, 1956), where the critical challenge is to select the optimum bandwidth. The NFA method works as follows. First, we convert each dataset to a network by comparing the performance of all countries with every other. Formally, we connect two countries together when their values are within a certain range, ζ, of each other. A network is analytically represented by an adjacency matrix, A_{ij}, where the cells take a value of 1 if nodes i and j are connected and 0 otherwise. For this study, adjacency matrices are defined as:

$$A_{ij} = \begin{cases} 1 & if (x_i - \zeta) \le x_j \le (x_i + \zeta) \\ 0 & otherwise \end{cases} \tag{1}$$

where, x_i and x_j represent the value (e.g., HC) of countries i and j.

To form the network, the selection of an optimal ζ is critical. To find the optimal ζ, first, we create a network using a ζ as 1% of the median of the data and we then gradually increase it. We rapidly observe the evolution of a giant cluster, which includes a significant portion of the nodes of that network. Moreover, we also observe that the giant cluster increases gradually with the increment of ζ, but it then stabilizes after a certain value of ζ. The value of ζ for which the size of the giant cluster remains stable is selected as the optimal ζ. Detailed information about network formation can be found in Derrible and Ahmad (2015) and is recalled in the supplementary information, including details on how the optimal value of ζ is determined. After forming the network, the country with the highest degree (i.e., number of connections) in each dataset becomes the most representative country, thus capturing the main trend. We refer to it as the Network-based (N) mode since it captures the statistical mode of a frequency distribution.

The N mode is then used as a benchmark to evaluate each country's performance relative to the general trend. For this, we use the concept of geodesic distance in network science (Newman, 2010) by measuring how far a node is from the N mode. We then refer to this distance as the "orbital position" of a country. Because this distance is related to the cutoff ζ_t calculated (for more details, see the methodology section in the supplementary information), we can calculate the orbital position as:

$$O_{i,t} = \frac{x_{i,t} - M_t}{\zeta_t} + C \tag{2}$$

where, $O_{i,t}$ is the orbital position for country i in year t, $x_{i,t}$ is the corresponding value for country i in year t, M_t is the N mode in year t, and ζ_t is the cutoff in year t. The orbital position of the N mode is set at 100 (i.e., $C = 100$). Therefore, orbital positions with values less than the N mode will be less than 100, and conversely, orbital positions with values greater than the N mode will be greater than 100. Moreover, the change in orbital positions from one year to the next is computed by taking the difference between orbital positions in two consecutive years and is defined as "orbital distance." Equation (2) can be used to track the "orbital speed," that is the speed at which a country's orbital positions are changing.

$$O'_i = \frac{\sum_{2}^{T} O_{i,t} - O_{i,t-1}}{T_i} \tag{3}$$

where, O'_i is the orbital speed for country i and T_i is the number of available data points within the timeline of 1 (i.e. 1990) to T (i.e. 2014) for country i.

The evolution of the orbital positions of all the countries is visualized by plotting them in polar format and designated as an "orbital diagram." If a country went through significant changes from 1990 to 2014, considerable changes are observed in the orbital diagrams. Conversely, if a country did not go through significant changes from 1990 to 2014, no or few changes are observed in the orbital diagrams, regardless of their gradual increment in all the capitals (i.e., human, natural, and produced capital) during the analyzed period. The general method is referred to as orbital NFA (oNFA) and a Python script was made available in open access on the authors' website at http://csun.uic.edu/codes/oNFA.html and on the popular code sharing platform GitHub at https://github.com/csunlab/oNFA (accessed April 19, 2018).

Moreover, as IW is the summation of HC, NC, and PC, a high capital value (e.g., HC) can compensate for the losses in other capital values (e.g., NC). Therefore, to further supplement IW, we can compute the combined performance of all three capitals. While constructing the networks, we systematically observe the presence of a giant cluster (i.e., sub-network containing most countries) for each dataset, in which all countries (i.e., nodes) are directly or indirectly connected to one another (for more details, see the methodology section in the supplementary information). Therefore, for each capital and each year, a country can be either part of the giant cluster or not, thus yielding two distinct groups for each dataset. As we have three datasets (i.e., human, natural and produced) for each year, we have $2^3 = 8$ possible combinations per year, and therefore we can group all countries into 8 different clusters. To find the combination for each country, we assign a value of '2' if a country is in the giant cluster and a value of '1' if it is not.