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Evidence of causality between economic growth and vegetation dynamics and implications for sustainability policy in Chinese cities

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ABSTRACT

Integrating causal considerations into the process of decision-making is beneficial to predict the outcomes of the policy interventions for sustainability. Unfortunately, this type of causal approach is still lacking in policy-making process. Here, a panel Granger causality model was employed to explore causal relationships between vegetation change and gross domestic product per capita based on data covering 285 Chinese cities between 2001 and 2015. The results show that unidirectional Granger causality runs only from economic growth to vegetation change, and not vice versa. This one-way causality indicates that China's economic development is a driver of vegetation change, however vegetation change does not influence macroeconomic output. These results have implications for the limitations and uncertainties which are inherent in monetizing the value of ecosystem services provided by vegetation cover in which estimated monetary value cannot generate actual macroeconomic benefit. Another implication of our findings is that future sustainability policies need to address the continuity of external economic inputs to prevent negative policy outcomes caused by the economic inefficiency of ecosystem protection. The absence of a positive feedback loop between vegetation cover and economic growth could lead to a new economy–environment crisis whereby sustainability is put at ever greater risk due to a reduced motivation for pro-environmental resource (financial, human) allocations.

1. Introduction

Ecosystem protection and economic prosperity both contribute to sustainable development (Griggs et al., 2013; UN, 2015). However, ecosystem degradation caused by economic growth or economic compensation for environmental conservation and restoration is an obvious depletion of sustainable development. Therefore, sustainability all around the world is being compromised by the complexities of economy–environment dynamics (Fu et al., 2019). One of the main reasons for this is the general absence of causal considerations in decision-making processes, which reduces the likelihood of successful outcomes of sustainability policies.

To bridge this gap, this paper focuses on the potential relationship between per capita gross domestic product (PGDP) and the Normalized Difference Vegetation Index (NDVI). As the frontier of the interaction between the economy and ecosystem, the relationship between PGDP and NDVI is important for the realization of Sustainable Development Goals (SDGs) (Fu et al., 2019; UN, 2015). Economic growth contributes to the goals of eradicating poverty, ensuring employment, eradicating hunger, and ensuring good health and wellbeing; however, such growth often threatens the goals of life on land and climate system. Vegetation cover provides essential ecosystem functions at all possible spatial scales, yet it has become the frontier of the impacts of economic growth on ecosystem. Thus, establishing a positive causal relationship

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between PGDP and NDVI is key to fulfilling these integrated Sustainable Development Goals. Before that, examination of causal relationship is an essential procedure to make suitable sustainability policy.

To investigate this possible relationship, this study used the Granger causality model to obtain a better understanding of the underlying causality between economic growth and vegetation dynamics. The cities of China provide an excellent laboratory for our research objective. On one hand, Chinese cities are the world's hotspot of economic growth (Bai et al., 2014); on the other hand, they are disrupting vegetation dynamics in an unparalleled way (Chen et al., 2019; Song et al., 2018).

2. Literature review

2.1. Economic growth as a driver of vegetation dynamics

Economic-induced vegetation changes include vegetation degradation by urbanization (Liu et al., 2015; Song et al., 2015), deforestation to expand agricultural land (Song et al., 2018), and reforestation and afforestation through publicly funded programs (Bryan et al., 2018). For instance, in most developing countries (e.g., Brazil, Argentina, Myanmar, Vietnam, Cambodia, and Indonesia), in the pursuit of economic profits, natural vegetation is commonly removed to make way for export-oriented industrial agriculture (Song et al., 2018). A quantitative analysis of grasslands in China's Three-Rivers Headwaters region found that an increase in GDP of 149 million CNY is associated with a 0.093% decrease in the net primary productivity of grasslands due to the land-use change from grasslands to urban landscape (Han et al., 2018).

However, the impacts of economic growth on vegetation are spatiotemporally heterogeneous. Research has found that economic factors are the key drivers of vegetation growth, especially in China (Lü et al., 2015). Feng et al. (2019) found that an increase of rural per capita net income accounted for 11.1% of the NDVI increase in Yan'an city, China. Zhao et al. (2012) found that per capita GDP was the most important determinant of the extent of vegetation cover in Chinese cities. These findings have been reinforced by other studies (Chen and Hu, 2015; Dobbs et al., 2017) which demonstrated that economic growth was a driving force for the provision of urban vegetation. Increasing income may stimulate demand for environmental goods and services, not least a greater quality and quantity of vegetation coverage (Richards et al., 2017). Furthermore, economic growth promotes the development of rational and effective green strategies using local government revenues (Chen and Wang, 2013). The directions and magnitudes of the impacts of economic growth on vegetation dynamics vary remarkably across studies. However, the premise that economic development leads to changes in vegetation is widely accepted.

2.2. Impact of vegetation change on economic growth

Research on impact of vegetation change on economic growth has tended to focus largely on ecological processes (e.g., land evapotranspiration, desertification, $PM_{2.5}$, land surface temperature) (Wang et al., 2018; Zhang et al., 2015; Zhang and Huisingh, 2018), and rarely on socioeconomic consequences of vegetation change (van Vliet et al., 2015). Hanewinkel et al., 2013 predicted that climate-induced shifts in the major tree species in Europe might reduce the local productivity of European forests, with consequences for the income of forest owners and the downstream timber industry. Additionally, a global panel regression analysis found that a 10% increase in vegetation cover, which can promote agricultural and environmental yields, could reduce the poverty headcount ratio in rural areas by 0.7% (Heger et al., 2018).

Introducing monetary valuation into ecological thinking is another way to investigate the socioeconomic consequences of vegetation change (Costanza et al., 2017; Silvertown, 2015; Yu et al., 2019). This is commonly conceived and operationalized in terms of the maximum amount of money a consumer would be willing to pay to increase vegetation cover or to avoid the loss of it (Choumert and Salanié, 2008). Such studies can then lead to the pricing of vegetation cover, so as to inform the public and governmental decision-makers about the importance of vegetation change (Costanza et al., 2017; Mullaney et al., 2015). In China, the monetary value of forest ecosystem services, as calculated using the Willingness to Pay Index, was estimated to be 33% of GDP in 2008 (Niu et al., 2012). However, despite this focus on monetization, whether and how economic gains are affected by ecosystem services provided by vegetation cover remains uncertain (Braat and Groot, 2012; Spangenberg and Settele, 2010).

2.3. Integrating causality into sustainability policy

The sustainable development goals of preserving ecological sustainability without harming economic interests, and achieving economic development without diminishing or degrading ecosystem, remain challenging (Lin et al., 2016). Effective policymaking must be based on a rigorous understanding of causal relationships (Hogwood and Gunn, 1984). Exploring the causality between vegetation change and economic growth could help to uncover the complexity and nonlinear nature of economy–environment systems, especially for designing effective policies to conserve vegetation cover and simultaneously avoid economic compensation. However, unfortunately, this causality has still not been sufficiently studied. Most extant research in this domain has focused on the unidirectional relationship between vegetation change and economic growth, and particularly the impacts of economic growth on vegetation change.

The inferential methodologies which are commonly employed in this area of research, namely correlation (Lü et al., 2015) or regression analyses (Chen and Hu, 2015; Feng et al., 2019; Zhao et al., 2012), are not based on frameworks which are applicable to dynamic systems with feedback loops, and are not designed to identify causalities. Besides using causality approach to enlighten policy-making process, considering causality in economic–vegetation dynamics is based on the assumption of payment for ecosystem services in which the monetary value of vegetation cover enables to project macroeconomic output. This study aims to determine whether the panel Granger causality test can be used to support or refute the assumption of monetarizing the value of ecosystem services provided by vegetation cover.

3. Material and methods

3.1. Panel Granger causality test

According to the rationale of causality proposed by Granger (1969), a variable X is said to Granger cause Y if at time t, Y_{t+1} is better predicted by using lagged values of X than by not doing so. In brief, it is a statistical hypothesis test for determining whether one time series is useful for forecasting another, and has been used to developed a mature econometric method for examining causality between economic variables, such as the causality between economic growth and tourism development (Aslan, 2014), energy consumption (Lin and Nelson, 2018; Zafar et al., 2019), carbon dioxide emissions (Hashmi and Alam, 2019), and financial development (Hyera and Mutasa, 2016). Recently, a few ecologists have utilized Granger causality test to examine relationships between ecosystem and economic system. For example, Uddin et al. (2017)

used panel Granger causality test to uncover a unidirectional causal relationship between real income and ecological footprints. From the above literature review, it can be seen that the variability in the relationships between economic systems and ecosystems hampers the credibility of sustainability policy. To the best of our knowledge, few studies have considered the causality in decision-making for sustainability policies. In an attempt to capture the flow of causal information between ecosystems and economic systems, we employed the panel Granger causality test developed by Dumitrescu and Hurlin (2012).

3.1.1. Panel unit root test

Panel data contain both cross-sectional and longitudinal information. Thus, the possibility of nonstationarity must be investigated. The panel unit root test aims to examine whether the selected variables are stable in time. In this study, we applied the following panel unit root tests: LLC test (Levin et al., 2002), Breitung test (Breitung, 2000), IPS test (Im et al., 2003), the Fisher–ADF, and the Fisher–PP tests (Choi, 2001; Maddala and Wu, 2003) and Hadri test (Hadri, 2000).

3.1.2. Panel cointegration test

After determining whether the variables were nonstationary in time, we tested for the presence of cointegration. According to Pedroni's test (Pedroni, 2004, 1999), there are two alternative hypotheses: (1) the homogenous alternative, where the dynamics among individual members of the panel and the heterogeneity in the long-term cointegrating vectors are taken into consideration in the test; and (2) the heterogeneous alternative, which simply averages the individually estimated coefficients for each member.

3.1.3. Hurlin's Granger causality test

Once the existence of cointegration between variables has been confirmed, the issue of causal linkages arises. In this paper, we introduced a Granger non-causality test for heterogeneous panel data models developed by Dumitrescu and Hurlin under the Homogeneous Non-Causality (HNC) hypothesis to examine causality. The model is as follows:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t} \quad (1)$$

where x and y represent two stationary variables observed for N individuals during T periods; K, $K \in N^*$; and $\beta_i = (\beta_i^{(1)}, \cdots, \beta_i^{(K)})'$ is the lag length, which is identical for all individuals. Individual effects α_i are assumed to be fixed in the time dimension, while the autoregressive coefficients $\gamma_i^{(k)}$ and regression parameters $\beta_i^{(k)}$ can vary among individuals, and $\varepsilon_{i,t}$ is the residuals of the model.

The HNC hypothesis takes into account the heterogeneity in both the regression model and the causal relationship. Under the alternative, we allowed for a subgroup of individuals for which there was no causal relationship and a subgroup of individuals for which the variable x Granger-causes y. The null hypothesis of HNC is defined as follows:

$$H_0: \ \beta_i = 0 \ \forall i = 1, \cdots, N$$

The alternative hypothesis is:

$$H_1: \ \beta_i = 0 \ \forall i = 1, \cdots, N_1$$

$$\beta_i \neq 0 \ \forall i = N_1 + 1, N_1 + 2 \cdots, N$$

Considering the cross-sectional (N = 285) and time series (T = 14) panel data, we introduce the standardized average statistic $\tilde{Z}_N^{HNC}$, which converges to the distribution:

$$\tilde{Z}_N^{HNC} = \sqrt{\frac{N}{2K} \times \frac{N-2K-5}{T-K-3}} \times \left[\frac{T-2K-3}{T-2K-1} W_{N,T}^{HNC} - K\right] \rightarrow N(0,1)$$

where $W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T}$; $W_{i,T}$ is the standard Wald statistic for every individual of the panel associated with the individual hypothesis $H_0: \ \beta_i = 0$; and $W_{N,T}^{HNC}$ is the average Wald statistic. If the value of $\tilde{Z}_N^{HNC}$ is greater than the corresponding normal critical value for a given level of risk, then the HNC hypothesis is rejected.

3.2. Material

We tested for Granger causality between two variables: economic growth, which is represented by PGDP (per capita GDP), and vegetation cover, which is measured by the Normalized Difference Vegetation Index (NDVI). Despite the criticisms of PGDP in terms of the extent to which it is a reliable measure of economic welfare, it remains the mainstream economic index by which governments measure economicgrowth. PGDP data were collected from the *Statistical Yearbook of China's Cites, 2001–2016*. Here, we used nominal PGDP rather than real PGDP since inflation only exists in the economic system.

Numerous studies have demonstrated that NDVI derived from remotely sensed data is an effective indicator of vegetation status and ecological information, such as the spatial and temporal distribution of the vegetation fraction, vegetation biomass, carbon dioxide fluxes , biodiversity, desertification, and other ecosystem services (Peng et al., 2019; Pettorelli et al., 2005; Zhang and Huisingh, 2018). Thus, we used average annual NDVIs to explore the causality between economic growth and vegetation cover. Average annual NDVI data (spatial resolution: 1 km × 1 km) were provided by the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (http://www.resdc.cn/Default.aspx). These NVDI data span the total city, rather than only the municipal administrative area. A total of 285 Chinese cities at the prefecture level and above for the period 200–2015 were included in the panel Granger causality test. Descriptive statistics for PGDP and NDVI are summarized in Table 1.

4. Results

4.1. Panel unit root tests and panel cointegration tests

Table 2 shows the results of the panel unit root tests. These tests provided strong evidence that NDVI did not exhibit a unit root. This indicates that NDVI is temporally stationary in level. Meanwhile, the Breitung, IPS, and Fisher–ADF tests on PGDP did not reject the null hypothesis in level. When we performed the tests on first differences, the results indicated that the hypothesis of a unit root was rejected at the 1% significance level, indicating that PGDP is temporally stationary in first difference.

Panel cointegration tests for PGDP and NDVI were necessary to examine whether the two variables were cointegrated in first difference. The results of seven statistical parameters obtained from the Pedroni's panel cointegration test are reported in Table 3. For a small time series, the group ADF test provides the best power properties, followed by the panel ADF test; meanwhile, the panel v-test and group rho-test tend to perform poorly (Wagner and Hlouskova, 2010). As shown in Table 3, except for the panel v-test, all tests rejected the hypothesis of no cointegration. The

Table 1
Descriptive statistics for PGDP and NDVI.

Variable	Unit	Mean	Median	S.D.	Max	Min	Variance	Kurtosis	Skewness
NDVI	(0,1]	0.71	0.75	0.13	0.70	0.09	0.02	8.15	−2.20
PGDP	billion RMB	27,952.77	19,933.00	27,118.64	46,7749.00	99.00	7.35E+08	27.69	3.24

Table 2
Results of panel unit root tests with individual intercept and trend.

	Variable	LLC	Breitung	Hadri	IPS	Fisher−ADF	Fisher−PP
Levels	NDVI	−30.81 (0.00)	10.49 (0.00)	30.19 (0.00)	−20.58 (0.00)	1385.68 (0.00)	1744.49 (0.00)
	PGDP	−11.03 (0.00)	21.68 (1.00)	35.75 (0.00)	0.78 (0.78)	538.98 (0.82)	828.57 (0.00)
First difference	NDVI	−59.72 (0.00)	−34.27 (0.00)	43.37 (0.00)	−43.22 (0.00)	2552.50 (0.00)	4330.15 (0.00)
	PGDP	−33.65 (0.00)	1.33 (0.90)	113.47 (0.00)	−22.53 (0.00)	1602.83 (0.00)	2887.39 (0.00)

Note: Numbers in parentheses represent the p-value; when the p-value is less than 0.01, the null hypothesis without unit root is significantly rejected, i.e., the variable is temporally stationary.

Table 3
Results of Pedroni's panel cointegration test.

Statistical parameters	Statistic	P-value
Panel v-Statistic	−12.10	1.00
Panel rho-Statistic	−17.32**	0.00
Panel PP-Statistic	−101.09**	0.00
Panel ADF-Statistic	−72.17**	0.00
Group rho-Statistic	−7.60	0.00
Group PP-Statistic	−128.28**	0.00
Group ADF-Statistic	−71.94**	0.00

Note: ** represents rejection of the null hypothesis at the 5% significance level.

statistically significant cointegration of PGDP and NDVI in first difference suggests that, overall, the relationship between both variables was stationary (or in equilibrium).

4.2. Panel Granger causality test

As shown in Table 4, the null hypothesis of HNC from PGDP to NDVI was rejected ($P < 0.01$), indicating a causal relationship running from PGDP to NDVI. However, we found no evidence for a causal relationship running from NDVI to PGDP ($P > 0.01$), suggesting that NDVI does not influence PGDP in our dataset.

5. Discussion

5.1. Reflections on research methodology

Research on integrated sustainable development goals faces one key analytical challenge: demonstrating causal connections between economic and ecological components (Fu et al., 2019; van Vliet et al., 2015). The exploration of causality is the most important prerequisite for discussing the effect caused by driving forces. Unfortunately, extant economy−environmental research facing confounding and ambiguous outcomes generally lacks a causality consideration. Taking economic growth and vegetation dynamics as an example, we computationally simplify the complex causality between economic system and ecosystem into a numerical representation based on the combining data of both cross-sectional and longitudinal information. The first result from our econometric approach is that economic growth causes changes in vegetation cover. This is consistent with existing literature which suggests that economic growth is the dominant driving force behind vegetation change (Chen and Wang, 2013; Geist and Lambin, 2004; Plieninger et al., 2016; Richards et al., 2017). The second result is that vegetation dynamics does not cause economic growth. This contradicts widely held assumptions of monetization of ecosystem services provided by vegetation cover.

Table 4
Results of the Dumitrescu−Hurlin Granger non-causality test with Akaike Information Criterion (AIC) option for lags.

Cause → Result	Zbar statistic#	Lag
PGDP → NDVI	−1.75*	1
NDVI → PGDP	−1.52	1

Note: * represents rejection of the null hypothesis at the 10% significance level; # represents the $\tilde{Z}_N^{HNC}$ statistic using Hurlin's Granger causality test for heterogeneous panel data models.

5.2. Causality from PGDP to NDVI

The causal relationship from PGDP to NDVI suggests that the former plays a role in changing the latter. This finding is not surprising, since economic systems have repeatedly been shown to drive landscape change, including vegetation dynamics (Plieninger et al., 2016). Literature review indicated that the impact of economic growth on vegetation change varied across a spectrum from positive to negative direction. The causal direction from PGDP to NDVI highly depends on the specific political, historical, and biogeographic context at the local level. Economic causes of vegetation change are related to urbanization, agricultural activities, market growth and commercialization, and economic structures. These related factors form a complex economic system which affects vegetation cover at several spatial and temporal levels, and finally bring out different outcomes. For instance, rising wealth stimulates public demand and governmental policies for ecological sustainability, which requires a high quality and quantity of vegetation coverage (Chen and Wang, 2013; Richards et al., 2017). Conversely, economic incentives may become an important driver of vegetation degradation such as agricultural expansion/abandonment or the loss of cultivated land (Plieninger et al., 2016; Song et al., 2018). Our study verifies the existence of causality from PGDP to NDVI; however, it does not identify a general causal direction, which is not suitable for context-sensitive sustainability policies. More interesting is the challenge for sustainability policy that how to transform this causality into positive one.

5.3. No causality from NDVI to PGDP

The lack of a causal linkage from NDVI to PGDP suggests that, in the context of the spatiotemporal framework of our data set, there are no discernable consequences of vegetation change on PGDP. Previous studies have (intentionally or unintentionally) neglected to examine the causal linkage from NDVI to PGDP. This study provides the first examination of the causal relationship from NDVI to PGDP. If vegetation change does play an important role in China's economic development, feedback from vegetation change to macroeconomic metrics should be evident. Practical experience from sustainability programs has proved that environmental protection decouples from economic growth. For example, the maintenance of household incomes is a significant challenge once initial program investments have ceased. Households with a lower economic interest in ecological protection either require long-term support or they are likely to return to the previous livelihood (Bryan et al., 2018). Thus, the promotion and protection of environmental goods and services may not be conducive to local economic development.

5.4. Policy implications

5.4.1. Pitfall of monetarizing ecosystem services

The implication of the missing causality from NDVI to PGDP is the need to rethink the monetization of ecosystem services. Sustainability policies tend to overestimate the importance of placing monetary values on ecosystem services. Some ecological economists are enthusiastic about estimating the economic prices of environmental goods and services, not least because doing so can provide quantifiable and comparable indices that can be readily understood by governments and other stakeholder groups. However, the underlying assumptions that are used to monetarize the value of environmental goods and services, including vegetation cover, are questionable in terms of the extent to which they are realistic and robust. Put differently, can subjective surveys of paying for ecosystem services adequately gauge the contribution of ecosystem services to the macroeconomic system? Our results and the wide diversity of monetary value estimates for ecosystem services in the literature could suggest that the answer to this question is *No* (de Groot et al., 2010; Häyhä and Franzese, 2014; Spangenberg and Settele, 2010). Monetarizing instruments encourage sustainability policy to prioritize ecosystem protection over economic growth. However, without considering the causality from ecosystem protection to economic growth, monetarizing ecosystem services may be of little practical use.

5.4.2. Political priority: economic growth versus ecosystem protection

As originally conceived to sustainability, a proactive approach to ecological sustainability is essential for achieving sustainable economic development. Sustainable economic development will further promote ecological sustainability, as shown in Fig. 1. Policies around the world put more and more emphasis on ecosystem protection. However, the norm is that economic growth is the key ingredient determining the success or failure of ecosystem-oriented sustainability policies. For decades, successive governments in China have been committed to ecological protection. One of the key characteristics of China's success is long-term financial investment (Bryan et al., 2018), which benefits from rapid economic growth. In the event that external payments to ecosystem protection cease, China's sustainable land development programs would be at risk and land degradation may resume as households return to farming to supplement incomes (Bryan et al., 2018). Our empirical results follow this norm and raise the question of how to promote sustainability when there is no essential support from economic development. There is a disconnect between ecological protection to economic growth, and therefore a proactive approach to ecological protection is not necessarily able to create economic benefits (breaking "A" in Fig. 1).

Recognizing the potential disconnect from ecosystem protection to economic development has important implications for political priority. The current policy (not just sustainability policy) pursues the goal of ecosystem protection, but is not fully aware that ongoing resource (financial, human) inputs play an important role in the success of sustainability programs. Non-causality evidence which shows that ecosystem services cannot necessarily create economic profit demonstrates that these ongoing resources must come from external economic system. In the future, political priority must be given to addressing the deeper causality between economic system and ecosystem, i.e., to address how to establish a positive loop between the two systems. The absence of causality from vegetation change to economic development could lead to new ecological–economic crises. The socioeconomic foundation of ecological protection will be ceaselessly eroded if ecological protection does not generate adequate material and financial support for itself. If things continue this way, the viability of ecological systems will be seriously threatened.

6. Conclusions

Integrating causal considerations into decision-making processes is important for maximizing the likelihood of successful outcomes for sustainability policy. To conclude, this study employed a panel Granger causality test to identify and explore causal relationships between vegetation change and economic growth using data for 285 Chinese cities between 2001 and 2015. Only unidirectional Granger causality was found, running from

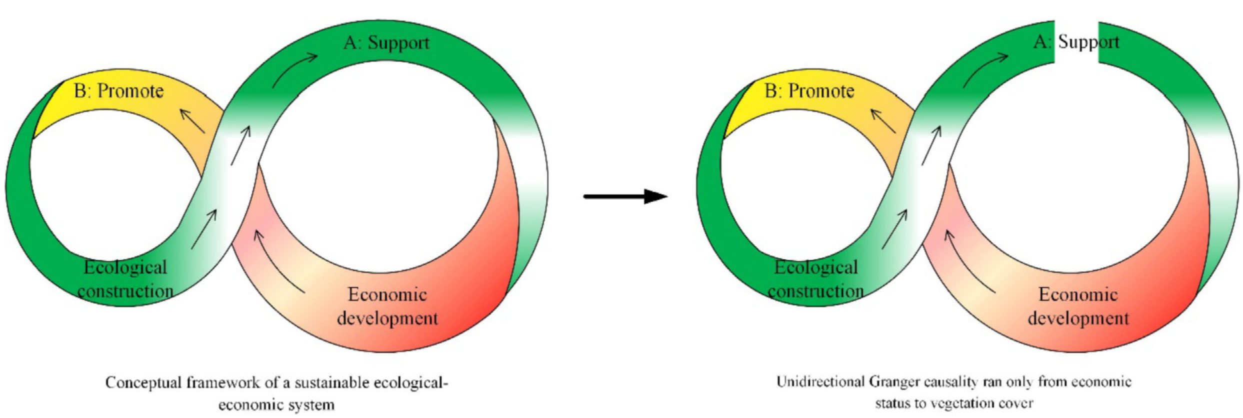

Fig. 1. Conceptual framework of a sustainable ecological–economic system. When a positive feedback loop between vegetation cover and economic growth has been established, a "win-win" for people and nature can be achieved. However, our empirical model confirmed a breakpoint in part "A".

economic growth to vegetation change. It is not surprising that the economic system is a detrimental driver of ecological change. One challenge that is faced by sustainability policy is how to establish a positive, rather than a negative causality from economic growth to vegetation change. The assignment of a monetary value to vegetation cover has long been a basis for environmental decision-making; however, our findings suggest that this approach may not be beneficial. Moreover, the absence of a positive feedback loop between vegetation cover and economic growth could lead to a new ecological–economic crisis whereby the sustainability of environmental goods and services is put at ever greater risk due to reduced motivation for pro-environmental resource (financial, human) allocations. An important question is whether, and the extent to which, this finding transfers beyond our sampling frame—i.e., to other countries beyond China and to other time periods. Consequently, there is ample scope for future research in this domain to explore the interrelationships between ecological and economic metrics in different case-study contexts.

Declaration of competing interest

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

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