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Quantitative analysis of the dynamic changes of ecological security in the provinces of China through emergy-ecological footprint hybrid indicators

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ABSTRACT

Historical evaluation and future projection of ecological security have become increasingly important during the past decades. In this study, we establish a framework on historical evaluation and future projection of ecological security. In particular, historical ecological security evaluation based on emergy-ecological footprint, ecological security projection based on emergy-grey model and an emergy-based evaluation indicator system. This framework is applied to China's provincial ecological security evaluation during 2006–2015. In parallel, a potential projection in the future 100 years for the same area is performed. Results show that (1) Ecological deficit exists in economically developed regions, with more developed and relatively concentrated industrial production in the local; (2) Most of China's western provinces are secure, while mid-eastern China provinces are less secure, with the exception of Tianjin (slightly insecure) and Shanghai (extremely insecure). Most of the "two-screens, three-belts" regions are secure or less secure; (3) fossil fuels are the main contributors to the emergy-ecological footprint. (4) Ecological coordination and diversity index cannot entirely reflect ecological security; (5) Based on the present knowledge, in the coming 100 years ecological security might get worse in 10 provinces: Shanxi, Shaanxi, Tianjin, Inner Mongolia, Anhui, Hainan, Yunnan, Qinghai, Ningxia and Xinjiang. Policy recommendations are, then, raised to improve China's ecological security state.

1. Introduction

Global ecological security, which depends on maintaining a dynamic equilibrium between humans and nature, has been hampered by rapid industrialization and urbanization, human population growth, economic development and growing demand for natural resources over the past 30 years (Carroll et al., 2014; Chu et al., 2017; Wen et al., 2017). The degradation of the Ecological Security State (ESS) gradually attracted worldwide attention, due to the recent outbreaks of new global security threats (e.g. ecosystem degradation and global warming). These, in turn, may foreshadow, for example, serious pandemics in the near future. A special attention has now focused on China. As the demand placed upon ecosystems exceeds their capacity to regenerate, China, similarly to many other countries, is starting to draw on ecological reserves. This fact has profound implications for ecosystem health, ecological security, and human well-being. Under the background of an "ecological credit crunch", national government in China is pointing to opportunities for changing direction and increasing both China's economic competitiveness and ecological security. This has profound implications not only for China's hopes of maintaining long-term economic development, but also for attempting to guarantee the security of the global environment.

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Abbreviation:

ESS	ecological security state
EEF	emergy-ecological footprint (ha)
eef	emergy-ecological footprint per capita (ha/cap)
PSR	pressure-state-response
EF	ecological footprint (ha)
ef	ecological footprint per capita (ha/cap)
EEC	emergy-ecological capacity (ha)
eec	emergy-ecological capacity (ha/cap)
NED	national emergy density (sej/ha)
WCED	the World Commission on Environment and Development
ED	ecological deficit (ha)
ed	ecological deficit per capita (ha/cap)
ES	ecological surplus (ha)
es	ecological surplus per capita (ha/cap)
EFI	ecological footprint intensity
H	ecological footprint diversity index
EECI	ecological and economic coordination index
Jing-Jin-Ji	Beijing-Tianjin-Hebei Region
Jiang-Zhe-Hu	Jiangsu-Zhejiang-Shanghai
GIS	Geographic Information System
RS	Remote Sensing

China's ESS already improved over the recent years, stimulated by an increasing awareness on this topic. In 2014, ecological security was included in the national security system for the first time. In fact, China's President Jinping Xi pointed out that it was a significant part of national security. In 2016, China's 13th Five-Year Plan pointed out the "two-screens, three-belts", which refer to Tibetan Plateau Ecological Security Screen, Loess Plateau-Sichuan-Yunnan Ecological Security Screen, Northeast Forest Belt, North Sand Prevention Belt, Southern Hilly and Mountainous Belt. These are crucial areas of environmental conservation to be preserved for complying with the ecological security strategy. In 2017, China launched 37 National Key Research and Development Programs on "Ecological restoration and protection in the typical ecological fragile zones" (Global change research, 2017), supported by the Ministry of Science and Technology. Besides, new databases (for example, China's ecosystem assessment and ecological security pattern database) were established and improved by the Research Center for Eco-Environmental Sciences, Chinese Academy of Sciences, to provide information support to policy-making on ecological conservation (dataset, 2010). This indicates that more attention was paid to ESS in China. Despite this, the definition of ecological security is still not unified (Chu et al., 2017). Moreover, its evaluation methods are not standardized and need to be improved. Here, considering the relationship between nature and human, ecological security can be regarded as a status under which ecosystem itself is diverse and stable, offering enough ecosystem services to support socio-economic development and human well-being.

Many studies evaluated ESS at different temporal and spatial scales, including cities (e.g. Xiamen (2003–2006), etc.), regions (e.g. Beijing-Tianjin-Hebei region (1995–2011), mining areas etc.), water bodies (e.g. Yellow River, etc.) and different artificial systems (e.g. biogas production systems, etc.) (Chu et al., 2017; Cook, 2005; Hodson and Marvin, 2009; Kislov et al., 2010; Qin et al., 2011; Wu et al., 2015). Among them, regional ESS evaluations provided theoretical and empirical basis for us to perform a long-term ESS evaluation at the macro scale in China, considering the increasing awareness on national ecological security as a new kind of security. To our best knowledge, evaluations of ESS at the macro (e.g. national) and long-term scale have been lacking in China and this paper aims at filling this gap.

The methods used in ESS evaluations mainly included ecological footprint (Chu et al., 2017; Huang et al., 2007; Li et al., 2014; Wang et al., 2011), pressure-state-response (PSR) modeling (Bai and Tang, 2010; Hua et al., 2011; Zhao et al., 2006), ecological network analysis (ENA) (Li and Xu, 2010) and cellular automata model (Gong et al., 2009). Among them, the ecological footprint method can better evaluate the gap between ecological carrying capacity and socio-economic development, supporting the identification of the constraint factors or components of ecological footprint excessing the capacity. Therefore, ecological footprint method is mainly discussed here.

Ecological footprint (EF) is a land-based indicator for assessing resource sustainability, through comparing the amount of bioproductive land needed to ensure supply for a given population or system with the amount of bioproductive land available in that population' territory (e.g. a country) (Wackernagel and Rees, 1998). EF can be used to analyze and evaluate the gap between human dependence on nature and biocapacity, through quantitative measurement of human demands (of different land types), as well as ecosystems capacity of supplying resources and assimilating wastes (Collins et al., 2018; Wang et al., 2017; Wiedmann and Barrett, 2010). As soon as it was proposed, EF was widely used to assess ESS and for sustainability evaluations (Klinsky et al., 2010). However, the EF has some drawbacks. For example, it lacks of consideration for resource's quality (Wu et al., 2015), it considers different environmental resources as substitutable with each other, it is inconsistent across scales, it only provides a "user-side" viewpoint (Pulselli et al., 2011), and it is mainly dependent on a single variable (Blomqvist et al., 2013).

To address these issues, there were some potential improvements proposed in the EF method (He et al., 2016), such as a modified approach based on EF and emergy analysis, namely the emergy-ecological footprint (EEF) proposed by Zhao et al. (2005). Emergy (see details in appendix 1) is the total available energy directly and indirectly involved in the processes of making a good or service (product) (Odum, 1996). Measures are, then, converted and expressed into a single standard energy unit, i.e. solar emergy, by using transformities. This enables the evaluation of the characteristics and the joint eco-economic benefits originating from the functions and structures of different systems (Zhao et al., 2005; Houshyar et al., 2018; Sun and An, 2018). This feature allows complementing the EF and overcoming some of its drawbacks. Also, EEF calculation is feasible, because biocapacity can be measured by renewable resources and consumption, while production data can be converted into emergy flows too (Pereira and Ortega, 2009). In addition, it provides a "supply-side" evaluation, which reflects quality differences of different inputs within one economic system (Geng et al., 2016; Yu et al., 2016).

In this paper, an EEF framework is introduced to provide a more comprehensive assessment of historical and current ecological security in the provinces of China. The framework is also applied for monitoring and predicting national or regional ESS in a long-run as a form of potential early warning system. Furthermore, it is applied for investigating space and temporal disparity of the ESS in China's provinces, inspiring ESS improvement policies by considering local

realities within the entire China.

2. Methods

2.1. Emergy-based ESS evaluation theory and framework

Human activities are strongly related to ecosystems. Relative measures of ESS at the provincial scale should reflect the anthropogenic effects on the ESS generated by human decisions and activities (e.g. by impacting the ecosystem services and functions), as well as the long-term persistence and relative prevalence of both human-dominated socioeconomic subsystems and ecological systems. Therefore, ESS assessment needs to rely on different indicators, which are capable of detecting significant changes in the large-scale socioeconomic metabolism. In particular, they should include changes in energy flows, intensities, pathways and their consequences. The concept of emergy may account for the supporting ecosystem services, as well as for their convergence through a chain of energy and matter transformations in both space and time into final services (Brown and Ulgiati, 2004a). Hence, much can be gained from investigating ESS at the provincial scale. For such a purpose, transformities should be used together with the specific emergy of some among the main emergy flows, which drive ecological processes. This allows to account the direct, indirect and cumulative impacts, which often result in variation of ecosystem health. Planning and managing for ESS should follow some principles, which include: 1) a positive balance between ecological supply and demand should be preserved; 2) no major ecosystem stress should be suffered from socio-economic system; 3) the diversity and coordination of ecosystem and socio-economic system components should be maintained; 4) long-term monitoring and projection methods should be implemented; 5) evaluation methods, accounting for the multidimensionality of ESS (that cannot be simply evaluated by a single physical, chemical or biological parameter), should be implemented (He et al., 2016; Liu et al., 2009; Wu et al., 2015). In addition, ESS evaluation should be scalable, in order to allow comparisons among different evaluations at different scales.

Fig. 1 shows the emergy-ecological footprint ESS evaluation framework proposed in this paper. This includes the Emergy-Ecological Capacity (EEC) and EEF historical evaluation, emergy-GM (1, 1) projection model, which will be introduced later, and the ESS evaluation indicator system, composed of four indicators. EEC is the local renewable resources. GM (1,1) is derived from fuzzy mathematics. It features a high simulation accuracy, when applied both at small sample time sequences (Tabaszewski and Cempel, 2015; Yao et al., 2009) and for systems when information is only partially known (Wang et al., 2010).

First, 10-years span *eec* and *eef* in the study can be calculated by using emergy-ecological footprint model. Then, they can be partially forecasted, based on available data, through emergy-GM (1, 1) in the future 100 years. After that, the *ED* or *ES* can be calculated by the difference between *eec* and *eef*. However, since both *ED* and *ES* can be affected by population, areas, GDP and so on, *EFI* is selected to evaluate and classify the ESS level. In particular, if $0 < EFI < 1$, it means that the case under study is secure. In parallel, for the insecure study case, the coordination and diversity of that area are further evaluated. The four indicators, described in Section 2.2.3, have the following features: (1) They are mutually independent; (2) They can comprehensively and systematically reflect ecological security from different perspectives, and reflect the quality difference of the ecosystem's contribution to the socio-economic system; (3) All of them can be calculated to conduct feasible and standard evaluations.

2.2. Emergy-based ESS evaluation methods

2.2.1. Emergy-based historical EEC and EEF accounting

The four indicators of the ESS evaluation framework are based on the two variables in the EEF model: EEC and EEF.

The formula of EEC per capita is as follows:

$$eec = (1 - 0.12) \cdot (R/NED) \tag{1}$$

where *eec* is the emergy-ecological capacity per capita (ha/cap), measured as the area related to the maximum flows of renewable resources: sunlight, wind kinetic, rain chemical potential, rain geopotential, earth cycle. NED is the National Emergy Density (sej/ha) (i.e.: the total emergy used in a country divided by the area of that country). The factor 0.12 accounts for the recommendation of the World Commission on Environment and Development (WCED, 1987) to set aside 12% of the overall national area as biodiversity conservation area (Rees, 1992). Boundaries for each item coincide with the provincial borders, which means that renewable resources are measured at provincial level. For example, the sunlight, earth cycle, wind and so on in formula (2) are the local renewable resources. According to the Emergy theory:

$$\begin{aligned} \mathrm{R} = &\text{sunlight} + \text{earth cycle} + \text{Max}\{\text{wind kinetic}, \\ &\text{rain chemical potential}, \text{rain chemical potential}\}. \end{aligned} \tag{2}$$

where *R* is emergy of renewable resources per capita (sej/cap), resulting by the amount of equivalent solar emergy used, directly or indirectly, in all the energy transformation processes needed to obtain the resource.

The formula of EEF per capita follows:

$$eef = (U/pop)/NED \tag{3}$$

U is the emergy of all items of production or consumption, calculated as:

$$U = p_i(c_i) \times E_i \times UEV_i \tag{4}$$

where: pop is the population of that area; $p_i(c_i)$ is the production or consumption of the *ith* item; E_i is the energy conversion coefficient of the *ith* item, which means the equivalent joules per t (J/t); UEV_i is the unit emergy value of *ith* item. The specific E_i and UEV_i used in this study can be found in Table A1.

Similar to the classical EF calculation, EEF is constituted of six biologically productive land types, which are presented in Table 1.

Raw data, such as land areas and production and consumption data, are from the "China Energy Statistical Yearbook 2007–2016, Statistical Yearbook 2007–2016" of China's 30 provinces (except for Tibet, Hong Kong, Macao and Taiwan due to lack of raw data of these four provinces).

2.2.2. Emergy-based ESS evaluation indicator system

Based on our approach for ESS evaluation (Fig. 1), four indicators are selected, i.e., Flux (*F*), Intensity (*I*), Diversity (*D*) and Coordination (*C*). F is the difference between emergy-ecological footprint capacity (*eec*) and emergy-ecological footprint demand (*eef*). It indicates changes on ecosystem's support to socio-economic system, thereby reflecting ESS from an absolute value changes perspective. F is the equivalent of the ecological balance, calculated through classic EF approach, from an emergy-ecological footprint perspective. Ecological Footprint Intensity (EFI), as a substitute for I, is the pressure level on the ecosystems generated by a given socio-economic system. It is defined as the ratio of emergy-ecological footprint per capita (*eef*) to emergy-ecological capacity per capita

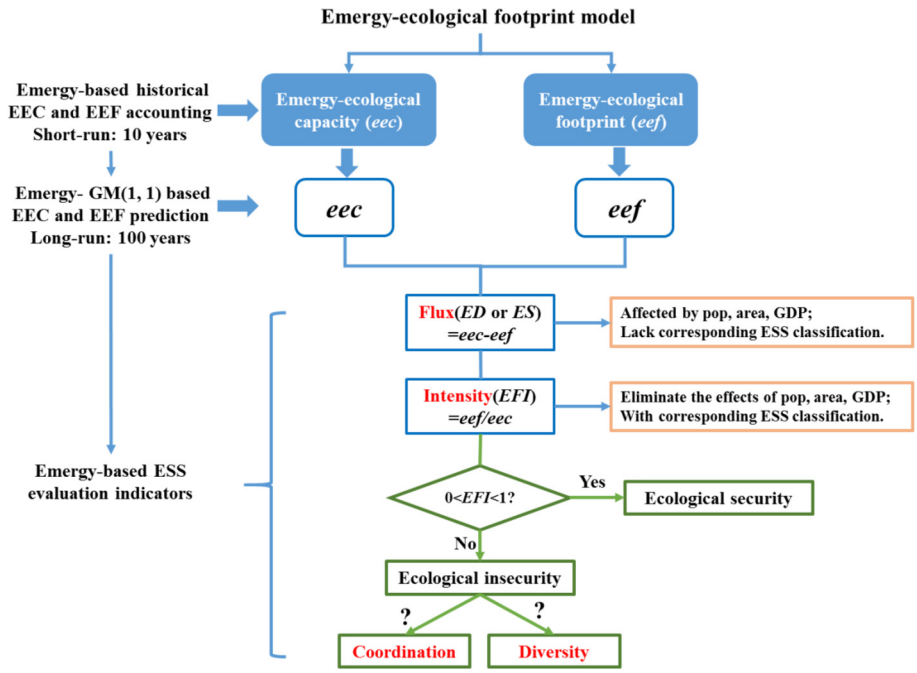


Fig. 1. Emergy-based ecological security status evaluation framework. The question mark "?" means that, if provinces are ecological insecure, their ecological coordination and diversity should be further investigated.

Table 1
Biologically productive land types considered in the emergy-ecological footprint accounting.

Land type	Production or consumption items
Cropland	grain, wheat, corn, soybean, cotton, vegetables, etc.
Forest	fruits and timber
Pasture	pork, beef, eggs, honey, etc.
Water	aquatic products
Fossil fuels	coal, crude oil, gasoline, diesel, natural gas, etc.
Built-up area	electricity and heat

(*eec*). EFI reflects ESS by analyzing stress suffered by ecosystem per unit of ecological capacity. Diversity expresses both the amount and the distribution of the different EEF components, which reflects ESS from an EEF composition and structure perspective. Finally, Coordination is used to measure the coordination degree between socio-economic development and ecosystems.

Flux is affected by population, area and Gross Domestic Product (GDP), among other variables. To eliminate the effect of these variables and directly reflect the ESS through specific indicators, the relative variable EFI is selected to classify the specific ecological security levels (Wang et al., 2011, 2017). After identifying ecological insecure areas, ecological diversity and coordination index are chosen to further analyze the reasons for ecological insecurity. In order to evaluate EES, the four parameters (i.e.: F, I, D and C) are determined in the way, which follows.

(1) Flux (ecological deficit or surplus):

The emergy-ecological footprint deficit or surplus is the ecological capacity per capita (*eec*) minus the emergy-ecological footprint per capita (*eef*), according to the following formula:

$$flux = eec - eef \tag{5}$$

This parameter can be used to obtain the absolute value change of the ecological flux in the province. If the result is negative, it represents an ecological deficit (*ed*), indicating that the consumption of resources exceeds sustainable levels (Chu et al., 2017). If the result is positive, it represents an ecological surplus (*es*).

(2) Ecological Footprint Intensity (EFI):

EFI is the ecosystem stress suffered from socio-economic system, expressed as the ratio between the *eef* and the *eec*. EFI values are determined through the formula:

$$\mathrm{EFI} = eef/eec \tag{6}$$

When $eef>0$, $eec>0$ and $0<\mathrm{EFI}<1$ (i.e. $eef<eec$), EFI indicates that the pressure suffered by the ecosystem is small and the province is ecologically secure. If EFI>1 (*i.e.* $eef>eec$), the pressure suffered by the ecosystem is larger than the ecological capacity of the province. Therefore, the ecological security is threatened. Under this case, the larger the EFI the heavier the degree of ecological insecurity. ESS can be classified according to its associated EFI (Table 2) (Yan, 2012).

(3) Ecological footprint diversity index (H):

Ecological footprint diversity can be measured by the Shannon - Wiener formula (Wackernagel and Rees, 1998):

Table 2
ESS Classification ESS based on the EFI values.

ESS level	ESS	Range of EFI
1	Security	0–1
2	Sub-security	1–10
3	Slight insecurity	10–18
4	Moderate insecurity	18–24
5	High insecurity	24–30
6	Extreme insecurity	≥30

$$H = -\sum_{i=1}^{n} p_i \ln p_i \quad (\mathrm{n} = 1, 2, 3.....) \tag{7}$$

where, H is the EF diversity index, p_i is the proportion of the *ith* land type in the total EEF.

Ecological footprint diversity can be divided into two components: (1) abundance (the number of the different land types that contribute to the footprint); (2) distribution (the distribution of emergy-ecological footprint over the different land types). The more equally the emergy-ecological footprint is distributed among the different land types in a system (e.g. a province or a country), the higher is the diversity of that system's footprint (Wang et al., 2011).

(4) Ecological and economic coordination index (EECI):

The EECI, introduced to measure the coordination degree between regional socio-economic development and the environment (Wang et al., 2017), is defined by the following formula (Chen, 2017):

$$\begin{aligned} \mathrm{EECI} &= (eef + eec) \Big/ \sqrt{eef^2 + eec^2} = \left(\frac{eef}{eec} + 1\right) \Big/ \sqrt{\left(\frac{eef}{eec}\right)^2 + 1} \\ &= (EFI + 1) \Big/ \sqrt{EFI^2 + 1} \end{aligned} \tag{8}$$

Being $eef>0$ and $eec>0$, $1 < EECI \leq 1.414$. The closer the $EECI$ is to 1, the worse the regional ecological coordination; the closer the EECI is to 1.414, the better the regional ecological coordination. When EECI = 1.414, the demand and supply of environmental resources are close to each other.

2.2.3. Emergy-GM (1, 1) model-based EEC and EEF data projection

Many methods can be applied to develop times series data projections. These are based, for example, on moving average (Bayer et al., 2017), exponential smoothing (Sbraba and Silvestrini, 2014), trend extrapolation (Glaeser and Nathanson, 2017), regression analysis(Fan et al., 2018), grey forecast (Cui et al., 2013) and so on. In particular, The GM (1, 1) model can be used to project in the future the existing behavior of non-linear time series. This is a non-statistical method, that is particularly effective when the amount of sample data is limited. It can be used to convert the original irregular series to more regular ones. The latter can be, then, used to establish the projection equation (Xu, 2002). In our case, this matches the features of the investigated 10-year time series. Therefore, GM (1, 1) is used to create a EES future projection based on the assessed behavior, through predicting EEC and EEF over time. Due to the page constraints, more details about GM (1,1) model data projection process is introduced in Appendix 2.

3. Results and discussions

3.1. ESS evaluation indicator system

3.1.1. Ecological deficit (ed) or ecological surplus (es)

Fig. 2 shows the ecological deficit (*ed*) or surplus (*es*) status, calculated by using the emergy-ecological footprint for the 30 provinces of China and their relative ranking, from largest to smallest flux. According to Fig. 2, most of the provinces displayed a change. Data span of Fig. 2 only included the results for the years 2006 and 2015.

Across the 30 provinces, *ed* or *es* values varied widely, from −1.49–14.63 ha/cap. Qinghai shows the largest *es* (11.71–14.63 hm^2/cap), followed by Xinjiang (4.17–5.09 ha/cap), Inner Mongolia (1.52–2.13 ha/cap), Gansu (1.09–1.18 ha/cap), Yunnan (0.47–0.70 ha/cap), Sichuan (0.17–0.22 ha/cap) and Guangxi (0.11–0.18 ha/cap). All these provinces have large land area. For example, Xinjiang and Inner Mongolia are the first and the third largest province in China. This partly explains the high ecological capacity of these provinces. Ecological deficit mainly exists in four regions of China: Northeast (Liaoning, Jilin and Heilongjiang) (−1.11 to −0.26 ha/cap), Jing-Jin-Ji (Beijing, Tianjin and Hebei) (−0.83 to −0.23 ha/cap), North China (Shanxi) (−1.49 to −0.72 ha/cap), Jiang-Zhe-Hu (Jiangsu, Zhejiang and Shanghai) (−0.70 to −0.24 ha/cap). Shanxi is characterized by the largest coal production in China, the Northeast is characterized by heavy industry, Jing-Jin-Ji and Jiang-Zhe-Hu are central areas for the Chinese economy: all of these socioeconomic factors are contributing to the regional ecological footprint.

As for the *ed* or *es* changes in rank in the past ten years, Ningxia's *ed* (−0.13 to −0.61 ha/cap) experienced the biggest change, moving from the 13th to 25th rank, followed by Hainan (−0.06 to −0.24 ha/cap), from 11th to 17th. The Beijing *ed* (−0.57 to −0.23 ha/cap) moved from 23rd to 15th. Regarding Ningxia, the *eec* decreased 13% while *eef* increased 65% from 2006 to 2015. Regarding Beijing, even though its *eec* decreased by 29%, its *eef* decreased by 56%, resulting in a decreasing *ed*. This may be related to the formation of the Jing-Jin-Ji metropolitan area, which caused increasing consumption of imported resources and materials in Beijing, thus causing a declining local *eef*.

3.1.2. Ecological Footprint Intensity (EFI)

According to the range of EFI of the 30 provinces, we classified them into two groups (Table 3).

From 2006 to 2015, 90% of the provinces remained under the same ESS. From Table 3, it can be noted that changes in ESS only happened for Guizhou and Shaanxi. This indicates that during 2006–2015, most of China's provinces maintained a stable ESS. Accordingly, Fig. 3 shows the ESS distribution in the Chinese provinces only for 2015 as an illustrative case. From Fig. 3, it can be noted that most ecologically secure provinces are located in western China, while less secure provinces are mostly located in mid-eastern China. Tianjin and Shanghai are in a status of slight and extreme insecurity. This might depend on their developed economy and larger ecological footprint, developed in very small areas to support the need of economic growth. Therefore, the difference between EEF and EEC is much larger than other provinces.

The spatial representations of the ESS for the 30 provinces was also overlaid with the “two-screens, three-belts” in Fig. 3. This shows that the majority of the Screens and Belts are secure, while only parts of them are less secure, such as the Northeast Forest Belt, Southern Hilly and Mountainous Belt.

A major goal of “two screens and three belts” policy is to limit inappropriate development activities, while offering protection for implementing ecological barriers, ecological networks, natural and cultural heritage areas. All of this is integrated with the grand strategy of long-term survival and development in China (Hu, 2014). Therefore, according to Fig. 3, the current ESS of “two screens, three belts” indicates that the above goal has been reached for now. Yet, in other countries, such as the U.K., a weakening in the protection stringency level of Green Belts (similar to “two screens, three belts” areas in China) was observed, allowing for an increased number of houses, securing full planning approvals in the Green Belts (Campaign to Protect Rural England, 2015). Green belts possess a huge environmental value with respect to climate change policies, by, for example, storing carbon, protecting soil from erosion, preventing flooding, and providing vital economic

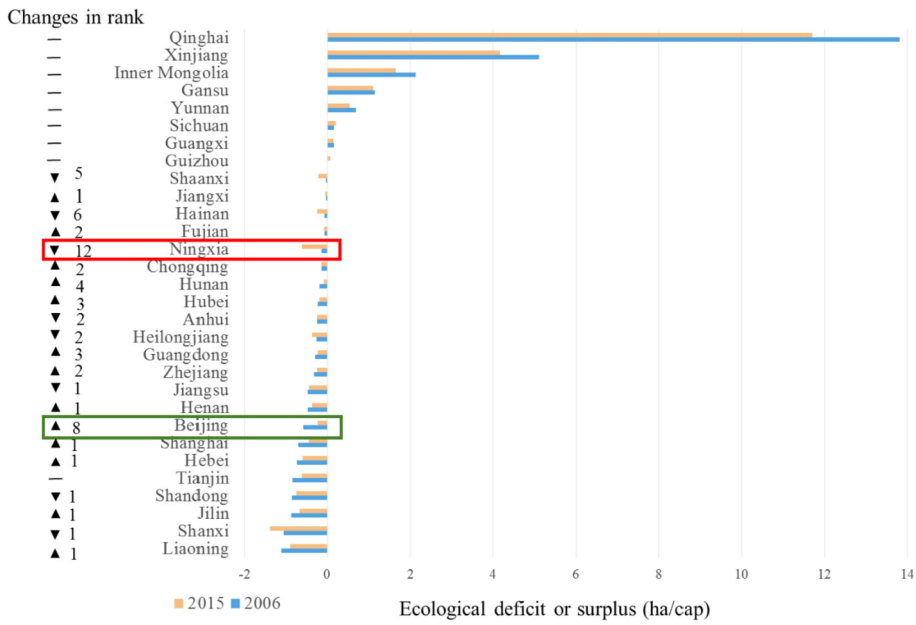


Fig. 2. Ranking and values of ecological deficit *(ed)* or ecological surplus *(es)* of the 30 provinces of China in years 2006 and 2015. The values in the second column indicate the rank change. The symbol "-" means no rank change. The symbols "▲" and "▼"indicate increases/decreases in rank, respectively.

Table 3
ESS type of the 30 provinces of China.

Ecological security types	Provinces
No changes in ESS	
Security	Inner Mongolia, Guangxi, Sichuan, Gansu, Qinghai, Xinjiang
Sub-security	Beijing, Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Hainan, Chongqing, Yunnan, Ningxia
Slight insecurity	Tianjin
Extreme insecurity	Shanghai
Changes in ESS	
Security to sub-security (2012) to security	Guizhou
Sub-security to security (2008) to sub-security	Shaanxi

Note: The number inside the brackets represents the year in which the changes occurred. For example, Guizhou is secure from 2006 to 2011, and changes into sub-security in 2012, then is secure during 2013–2015.

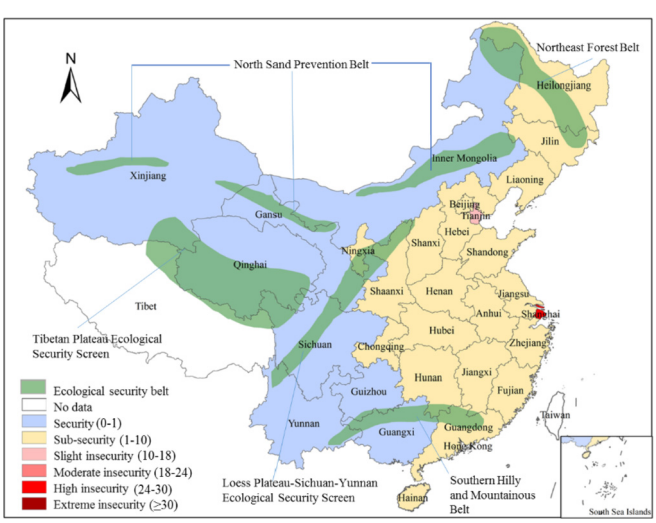


Fig. 3. Ecological security state in 2015 for the 30 provinces of China and the ecological security screens and belts *(i.e.* the "two-screens and three-belts"). The number followed by the ESS are the corresponding EFI values.

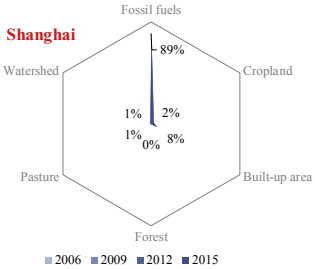
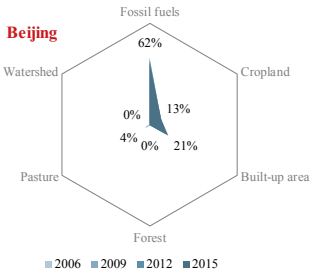
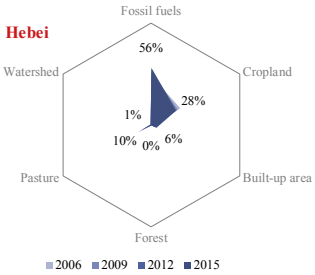
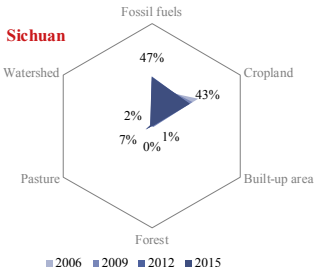
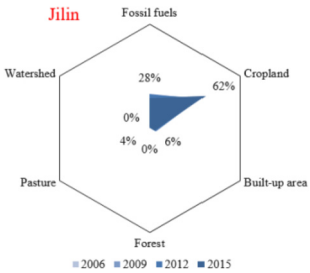
resources such as food, wood and other raw materials, medicinal resources and others. Therefore, it is critical for sustainable development in China to keep and expand "belts and screens" to enhance ecological security.

3.1.3. Ecological footprint diversity index (H)

(1) Emergy-ecological footprint components:

Using the six components EF and dividing it by the total ecological footprint, we can obtain the proportion of each component. Then, by drawing the radar figures of the components in China's 30 provinces, these provinces are divided into 5 models, according to the radar figure shapes and the proportions of the six components (Table 4). In particular, the provinces belonging to the same model will have a similar components proportion. Table 4 shows the 5 most recurrent composition models of the EEF observed in the 30 provinces investigated for the 2006–2015 period. The Shanghai and Beijing models are observed in ecologically insecure provinces. They are characterized by a prominent contribution of fossil fuels to the total EFF (e.g. 88–91% for Shanghai; 67–74% for Tianjin). On the other hand, the Sichuan and

Table 4
Different emergy-ecological footprint models observed in China's provinces.

Models	Components breakdown figure	Provinces	Explanation
Shanghai Model		Shanghai	”Needle-shape” composition. Only Shanghai belongs to this model characterized by shares of fossil fuel contribution higher than 88%.
Beijing Model		Beijing, Tianjin, Shanxi, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan, Guizhou, Shaanxi, Gansu, Qinghai, Ningxia	“Obtuse triangle” composition. Model characterized by a fossil fuel contribution higher than 60%, and close to zero forest land and water contributions.
Hebei Model		Hebei, Inner Mongolia, Liaoning, Anhui, Jiangxi, Shandong, Hubei, Hunan, Chongqing, Xinjiang	“Acute triangle” composition. Model characterized by a fossil fuel contribution between 50% and 60%, less than and close to zero forest land and water contributions.
Sichuan Model		Henan, Guangxi, Sichuan	“Isosceles triangle” composition. Model characterized by an equal share of fossil fuel land and cropland contribution and close to zero forest land, water, and built-land contributions.
Jilin Model		Jilin, Heilongjiang, Yunnan	“Acute triangle” composition. Cropland contribution higher than 60% and close to zero forest land and water contributions.

Jilin models are characterized by large contributions from cropland (e.g. 39% in 2011 for Henan; 61% in 2015 for Jilin). However, the EEF composition of Jilin and Henan constitute an exception among secure are sub-secure provinces, where fossil fuels are again the main footprint contributors (e.g. 85% in 2015 for Shanxi). In general, cropland constitutes the second most important contributor to footprint, with the exception of Beijing, Tianjin, Shanghai and Zhejiang, where built-up land is the second most impacting land type. The third most important contributor is pasture land in all the provinces besides Beijing, Tianjin and Jiang-Zhe-Hu. Forest land is the least contributor in all the provinces (e.g. 0–0.5% in Guangxi) except for Shanxi and Gansu, where water is the least contributor. Water is the second smallest contributor to footprint for most provinces.

In conclusion, for most provinces, the ecological footprint composition is as follows: fossil fuel land > cropland > pasture > built-up area > water > forest. For provinces in ecological insecurity, i.e. Shanghai and Tianjin, fossil fuel shares are much higher than in sub-secure and secure provinces, indicating that reducing fossil fuel use and improving utilization efficiency are effective ways for improving the ESS.

(2) Ecological footprint diversity index (H):

Fig. 4 shows the distribution of the ecological footprint diversity index of the 30 provinces during 2006–2015. The ecologically insecure province of Shanghai has the lowest diversity, followed by Shanxi, indicating an uneven distribution of the EEF components in these two provinces. For both of them, their very large share of fossil fuels accounts for the poor ecological footprint diversity. The slightly insecure province, i.e. Tianjin, also shows a very low H-value. Among the sub-secure provinces, Shanxi, Shaanxi, Guizhou, Ningxia, Jilin and Guangdong have the lower H-values. Some of the secure provinces, for example Gansu and Qinghai, have lower diversity than the majority of sub-secure provinces. This indicates that diversity only partially reflect ESS, having a diversity, which partially reflects the EEF composition, without considering the EEC.

In Fig. 4, smaller "boxes" (characterizing more or less one third of the overall set of provinces, such as Jiangsu, Henan, Heilongjiang, Zhejiang, etc.) indicate that ecological footprint diversity remained stable over the time series. The H-value of Hainan in 2006 is much higher than that of the following years because of the more even EEF component ratio distribution: cropland 25%, forest 0.45%, pasture 13%, watershed 25%, fossil fuels 36% and built-up area 0.68%. After 2006, the proportion of fossil fuels increases up to more than 55%, leading to worse diversity.

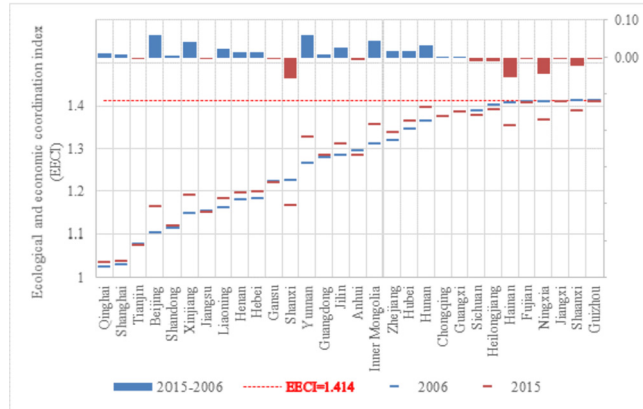


Fig. 5. The ecological coordination state of the 30 provinces of China in 2006 and 2015. The bars above the dotted line mean the differences between EECI in 2015 and 2006 and the right vertical axis indicates the specific differences scale. The blue bars indicate the larger values in 2015 than that of 2006, while the red bars mean the smaller values in 2015 than that of 2006. The red and blue bars below the dotted line mean the EECI values in 2015 and 2006 respectively.

3.1.4. Ecological and economic coordination index (EECI)

The EECI of the 30 provinces was calculated for the years 2006 and 2015. Fig. 5 and Table 3 show that, for the ecologically insecure provinces Shanghai and Tianjin, the EECI is very low, ranging from 1.030 to 1.038 and 1.068–1.079, respectively. However, the lowest EECI (1.024–1.045) is observed for a secure province, i.e. Qinghai. This is because the EFI-value is the lowest (0.024–0.046), leading the corresponding EECI lowest.

As shown in Fig. A2, the EECI is the function of EFI. When the EFI is between 0 and 1, and close to 0, the corresponding EECI value is close to 1, which means poor ecological coordination in Qinghai.

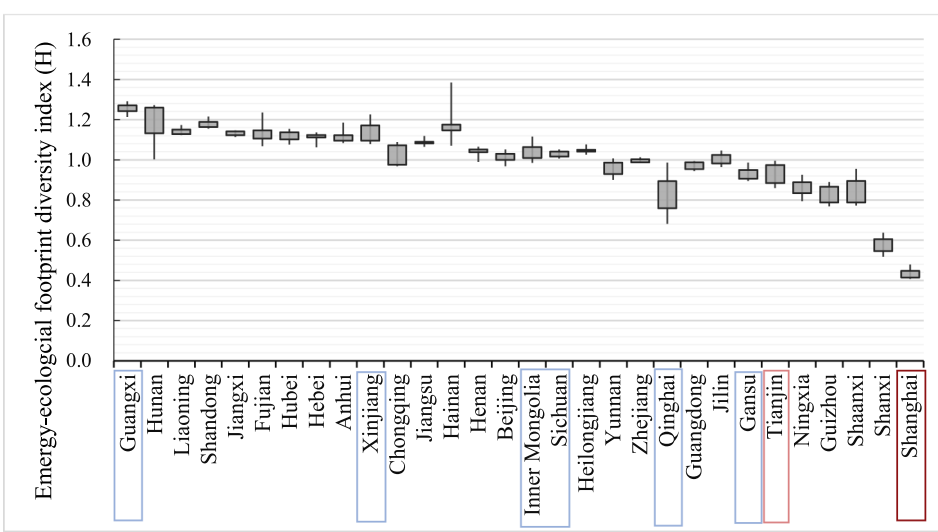


Fig. 4. The ecological footprint diversity index of the 30 provinces during 2006–2015. The provinces marked in dark-red, light-red and blue are classified as "extreme insecurity", "slight insecurity" and "security", respectively; The other provinces are classified as "sub-security".

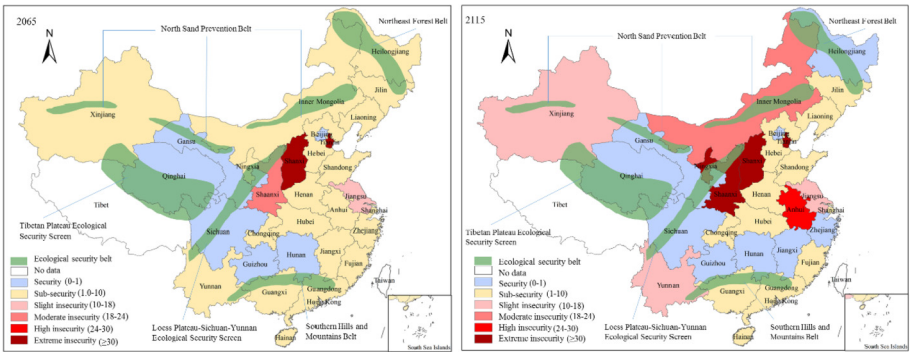


Fig. 6. The ESS of the 30 provinces in the future 50 year and 100 year.

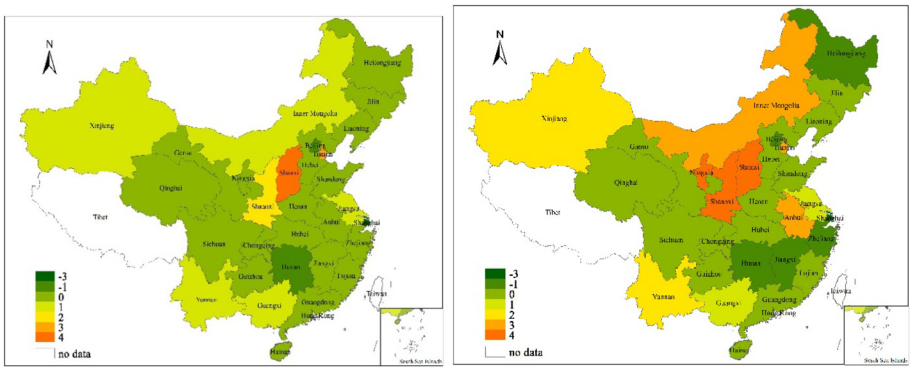


Fig. 7. Projected potential changes in ESS of 30 provinces in future 50 years (2015–2065) and 100 years (2015–2115). The positive number x in legend means the ESS would change worse for x levels. The negative number y in legend means the ESS would change better for y levels. 0 means no changes in ESS.

Table 5
ESS of China's 30 provinces in the future 100 year.

Changes in ESS	Provinces
"No changes" group	Security: Sichuan, Gansu, Guangxi and Guizhou Sub-security: Jiangsu, Fujian, Shandong and Guangdong
"Getting better" group	Sub-security to security: Beijing(2040), Hebei(2107), Liaoning(2088), Jilin(2088), Heilongjiang(2085), Zhejiang(2046), Jiangxi(2025), Henan(2105), Hubei(2065), Hunan(2025), Chongqing(2088) High insecurity to sub-security: Shanghai (high insecurity (2016–2017), moderate insecurity (2018–2026), slight insecurity (2027–2051), less secure (2052–2115))
"Getting worse" group	Security to sub-security: Inner Mongolia (2014), Yunnan (2040), Qinghai (2096) Sub-security to slight insecurity: Hainan (2104), Anhui (2103) Several ESS changes: Xinjiang: secure (2016–2051), less secure (2052–2105), slightly insecure (2106–2115) Ningxia: less secure (2016–2069), slightly insecure (2070–2087), moderately insecure (2088–2096), high insecurity (2097–2103), extreme insecurity (2104–2115) Tianjin: slightly insecure (2016–2033), moderate insecurity (2034–2054), high insecurity (2055–2070), extreme insecurity (2071–2115) Shanxi: less secure (2016–2024), slightly insecure (2025–2033), moderate insecurity (2034–2037), high insecurity (2038–2041), extreme insecurity (2042–2115). Shaanxi: less secure (2016–2053), slightly insecure (2054–2065), moderate insecurity (2066–2071), high insecurity (2071–2076), extreme insecurity (2077–2115)

Note: numbers in brackets indicate in which year the changes in ESS level is predicted to happen.

However, Qinghai is a secure province according to Fig. 3. Therefore, when applying EECI to analyze the coordination state, the range of EFI has to be identified first. If the EFI>1, the closer the EECI is to 1, the worse the regional ecological coordination; the closer the EECI is to 1.414, the better the regional ecological coordination. If 0 < EFI<1, provinces with the corresponding EFI are considered secure. The majority of ecologically secure provinces have EECI-values close to its maximum, i.e. 1.414. This is the case, for example, of Guizhou (1.411–1.414), Shaanxi (1.390–1.414), Sichuan (1.376–1.389) and Guangxi (1.381–1.401). From the time series results it can be noted that the EECI values do not change much, which means that the ecological coordination of the study area remained practically constant during the past 10 years.

3.2. Ecological security projection

GM (1,1) model can not only support the development of macroscopic long-term projections, but also short-term and

microscopic forecasts. The present long-term projection model is based on random factors processing. In particular, data are analyzed and dataset patterns are identified (Xu, 2002). In this study, the projection is performed over 100 years.

The emergy-GM (1.1) model is used to project *eec* and *eef* data in order to obtain infer some potential evolution for both the EFI of the 30 provinces for the future 100 years and for the ESS for years 2065 (after 50 years) and 2115 (after 100 years). Fig. 6 shows how the number of ecologically secure areas is expected to decrease, while the number of insecure areas is expected to increase. In particular, based on present data, projections show that Tianjin, Shanxi, Shaanxi and Jiangsu might become extremely and slightly insecure, respectively, during the coming 50 years. However, this would not pose a threat to the "two-screens, three-belts" areas. During the future 100 years the entire ESS of the 30 provinces would be much worse than the current condition, especially regarding Ningxia, Anhui, Inner Mongolia, Xinjiang and Yunnan, featuring extreme, high, moderate and slight insecurity respectively. Consequently, with the exception of the Tibetan Plateau Ecological Security Screen, the other four ecological security belts and screens would become increasingly insecure.

To be more specific, according to the development trends, the ESS of the provinces can be classified into four groups: "no change", "getting better" and "getting worse". The projected specific changes in ESS for the future 50 and 100 years are shown in Fig. 7 and Table 5. Preserving the present coupled human-ecosystem dynamics, while it is crucial to improve ESS for the whole set of provinces in China, this is particularly urgent in Shanxi, Shanxi, Ningxia, Tianjin, Inner Mongolia, Xinjiang and Yunnan, otherwise not only China's ecological security belts, but also the entire China, would face ecological security threat. Appendix 4 shows a detailed example on how EES is evaluated and predicted step-by-step. The same process was conducted for all provinces.

China's 12th Five-Year Plan states that the ecological security strategy of "two screens, three belts" will be further developed over the next two decades. The layout of the "main functional areas" will be defined by 2020. By 2030, the national ecological security barrier system will be completed. Thus, China should be characterized by an intensive, highly efficient production space, a comfortable living space, a high quality ecological space, where demographic and economic settings should be coordinated with the environment (Hu, 2014). However, according to the current developmental model, the above goal is still hard to achieve. Therefore, to achieve China's long-term ecological security goal, industrial and commercial land use should be tightly restricted or prohibited in many key ecological function areas, including the northeast forest, southern hilly and mountainous zones, the Tibetan and Loess plateaus, the Sichuan-Yunnan ecological protection areas and others (Hu, 2014).

4. Policy implications

China is experiencing a rapid industrialization and economic growth, leading to tremendous pressure on the ecosystem (Chu et al., 2017; Wen et al., 2017). In 2014, ecological security was first selected as the critical part of national security. In 2016, China established the national ecological security strategic pattern: "two-screens, three-belts". Therefore, evaluating and predicting China's ecological security is recognized as of great importance. Based on the analysis presented in this paper, policy implications are briefly discussed, in order to support the achievement of a more stable national ecological security.

First, there is a need to establish appropriate ecological security evaluation methods and tools, as well as associated early warning mechanisms. We found that most mid-eastern provinces are less secure, some being even slightly and extremely insecure. In addition, according to the current developmental trends, the ecological security state of around one third of the provinces might get worse in the future. Therefore, assessing and predicting national ecological security is urgent to have a clear understanding of the ecological condition of China and to provide policy implications to decision-makers. Ecological security metrology should be developed, integrating the use of appropriate remote and proximal sensing and computer technologies and tools, such as Geographic Information System (GIS). These could support the quantification of variables associated to environmental scenarios at local scale, which might constitute the basis for a dynamical assessment of ecological security threats (Lega et al., 2010; Gargiulo et al., 2013; Lega and Persechino, 2014; Errico et al., 2015; Wang et al., 2016). To achieve this goal, collaboration among all the relevant organizations, including universities, research institutes, information technology companies, and the government should be encouraged. By analyzing and evaluating ESS and its dynamics, national both ESS and its time and space distributions can be forecasted. Meanwhile, early warning and protection systems of local ecological safety levels should be established and improved, based on the regional and provincial ecological features. In addition, local monitoring platforms should support the communication and dissemination of ecological security assessment, so that the whole society can intuitively understand the local and national security state, enhancing people's attention to the ecological condition.

Second, there is a need to regulate land development. Every province should develop a functional area planning in order to determine the development direction, based on the local ecological capacity and environmental features. For example, Southern Qinghai, which represents 54.6% of the whole Qinghai province, was selected as National Ecological Protection Experimental Zone, because three rivers originate in this zone. Envisioning crucial areas for provisioning of vital ecosystem services, supported an improved distribution of economic activities and population in the northern part of the same province. Management policies should adapt to such a main functional area planning, so that the relationship between economic development and environmental protection can be dealt, starting from the planning phase. A good example of such a good practice in policy-making is given by the China's 11th Five-Year Plan, where it was required to establish national main functional area planning. The same goal was remarked later, during the 17th National Congress of the Communist Party of China, were the goal to define the main functional areas was fixed to year 2020. Therefore, every region should take advantage of this policy to form a reasonable spatial development structure.

Third, reasonable ecological compensation mechanisms should be set up. Our research results indicate that ecological deficit mainly exist in Jing-Jin-Ji and Jiang-Zhe-Hu (the economic core areas of China) the Northeast (heavy industrial region), Shanxi (the largest coal production area in China). All of these regions are relatively developed. However, the need for more resources to meet the economic and social development demands cannot be supplied by local environmental resources. Moreover, ecological capacity cannot support a rapid economic growth in these regions. This is why the generated ecological deficit leads to an increasing import of resources from other regions. This has environmental and fairness implications, with regions benefiting from production processes located elsewhere in China, while not dealing with pollution and other environmental problems raised by intensive production. We would, therefore, propose to establish novel ecological compensation mechanisms to coordinate regional development aimed at improving regional ecological security too. Specifically,

these efforts would be directed from downstream to upstream, from developmental to protected areas, and from use to production regions.

5. Conclusions

China has become the second largest economy in the world, pursuing a rapid economic development. Yet, this success also brings many problems, such as ecosystem degradation, resources waste and so on. This is why, in recent years, ecological civilization and ecological security were taken into consideration to remediate to the existing risks for human and ecosystem health. In recent years, for example, “two-screens, three-belts” were proposed as an ecological security policy and planning pattern. Due to an imbalanced development, different regions have different challenges, which need appropriate and specific security evaluation and projection. This is why accurate temporal and spatial assessment and projections are required, in order to support the development of middle and long-term policies on ecological security. Under such circumstances, emergy analysis method is selected to integrate the traditional ecological footprint model and to identify the embodied resource flows among different regions. Further, a novel ESS evaluation framework is established, which includes the emergy-based historical EEC and EEF accounting, a current EEC and EEF data projection based on emergy-GM (1, 1) model, as well as an ESS evaluation indicator system. This framework was applied to evaluate the ESS of China's 30 provinces, from 2006 to 2015, and to give a projection of current available information about ESS for the next 100 years.

Results show that ecological deficit mainly exists in Jing-Jin-Ji and Jiang-Zhe-Hu, with developed economy, and Northeastern China and Shanxi, known as industrial areas. In fact, in these areas, a more developed economy and intensive industrial development is still causing a larger ecological footprint. Except that Tianjin and Shanghai, that are slightly and extremely insecure, mid-eastern China provinces are less secure, while most of China's western provinces are in ecological security state. That means that most of the “two-screens, three-belts” areas are in security or sub-security. However, in order to further identify the factors leading to the existing insecurity, the EEF composition is calculated. It is possible to demonstrate that the use of fossil fuels is the main contributor to the EEF for most of the provinces, particularly in the ecological insecurity areas: Tianjin and Shanghai. This fact depends on their smaller area, in which a developed economy and large emergy-ecological footprint insist. Consequently, only an insufficient supply of renewable resources is available to meet the needs for economic growth. A 10-years ESS projection indicates that EES might get worse for 10 provinces, if present dynamic patterns are preserved. The results refer to the following provinces: Shanxi, Shaanxi, Tianjin, Inner Mongolia, Anhui, Hainan, Yunnan, Qinghai, Ningxia and Xinjiang, among which the former three are the most critical areas. However, due to lack of data the whole China's EES has not been evaluated. Furthermore, due to lack of import/export data at the provincial scale, the import and export factors are not included in this research. This is why appropriate monitoring tools and methods are required as a basis for further studies.

Based on the research findings, policy recommendations are raised, including establishing ecological security evaluation and early warning mechanisms, regulating land development and setting up reasonable ecological compensation mechanisms. These recommendations can help China to improve its ESS and to provide valuable policy insights to other countries facing similar challenges.

Acknowledgements

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Appendix 1

Some steps are necessary to perform an emergy analysis. Here, they will be simply introduced. First, determine the study boundaries, which can be associated either to the economic system or the ecosystem or the specific production process under study. Second, collect and classify data. For example, data can be classified according to some classes: Renewable (R); Non-renewable (N); Imported (F); labor and services date. Third, draw the emergy diagram (like in Fig. A1). Fourth, make emergy analysis table. Fifth, calculate and evaluate emergy flows. The evaluation indicators are shown in Table A1.

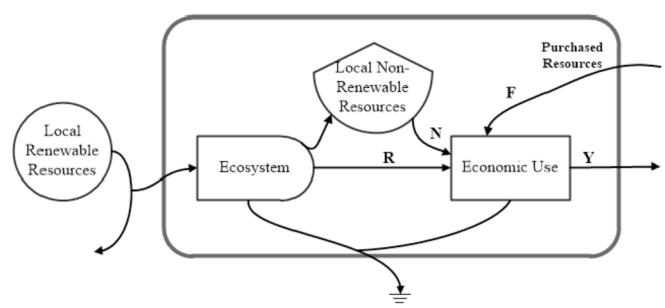

Fig. A1. A simple emergy diagram of regional economy that imports purchased inputs (F), and use local renewable and non-renewable resources. (Brown and Ulgiati, 2001).

Local renewable resources include sunlight, deep heat, wind, rain (chemical and geopotential) and so on. The ecosystem can provide renewable and non-renewable resources to economic use, such as water, coal, crude oil and so on. Economic system also needs to input materials and resources from the outside of the system boundary.

Table A1
Part of the emergy evaluation indictors (Brown and Ulgiati, 2004b).

Indicators	Formula	Explanation
Environmental loading ratio (ELR)	ELR=(N + F)/R	ELR is a measure of the disturbance to the local environmental dynamics, generated by the development driven from outside.
Emergy yield ratio (EYR)	EYR=(R + N + F)/F	EYR is a measure of the ability of a process to exploit and make available local resources by investing outside resources. It provides a measure of local resources by a process, which can be read as a potential additional contribution to the economy, gained by purchased resources.
Empower density (ED)	ED = U/S	U is the total emergy used in system. ED measures the emergy required per unit area and suggests land be a limiting factor to development or process.

Appendix 2

In this paper, UEVs are based on the latest geobiosphere emergy baseline (GEB) of 12.0E+24 seJ/yr (Brown et al., 2016). The UEVs, which are not initially based on this GEB, were modified based on the latest GEB.

1.Sunlight energy = province area (m^2) (Statistical Yearbook)xAvg. annual solar radiation (J/m^2) (http://www.docin.com/p-104082105.html)x(1-albedo)(70%); UEV = 1.00 seJ/J by definition
2.Wind kinetic energy = province area (m^2) (Statistical Yearbook)xair density (1.29 kg/m^3) xdrag coefficient (0.001) (Miller, 1964)x(Avg. annual wind velocity)^3 (Statistical Yearbook); UEV = 8.00E+02 seJ/J (Brown and Ulgiati, 2016)
3.Rain chemical potential energy = province area(m^2) (Statistical Yearbook)xannual rainfall (m) (Statistical Yearbook) xEvaporation rate (60.0%) (Lou and Ulgiati, 2013) xwater density (1000 kg/m^3) xGibbs free energy (4.94 J/g); UEV = 7.00 E+03 seJ/J (Brown and Ulgiati, 2016)
4.Rain geopotential energy = province area (m^2) (Statistical Yearbook)xannual rainfall (m) (Statistical Yearbook) xRunoff rate (40%) (Lou and Ulgiati, 2013)xwater density (1000 kg/m^3) xaverage elevation (m) (Statistical Yearbook)xgravity (9.8 m/s^2); UEV = 1.28E+04 seJ/J (Brown and Ulgiati, 2016)
5.Earth cycle = province area (m^2) (Statistical Yearbook)xheat flow (1.45E+06 J/(M2*yr))(Odum, 1996); UEV = 7.32E+04 seJ/J

Table A2
Energy conversion coefficients and transformities of production or consumption items.

Items	*E (J/t)*	Unit	Transformities (sej/unit)[a]	Reference
Cropland				
Rice	1.64E+10	J	6.53E+04	(Odum, 1996)
Wheat	1.57E+10	J	5.35E+04	(Odum, 1996)
Corn	1.65E+10	J	9.72E+05	(Brandt-Williams, 2001)
Millet	1.58E+10	J	6.53E+04	(Odum, 1996)
Sorghum	1.63E+10	J	6.53E+04	(Odum, 1996)
Potatoes	1.67E+10	J	1.63E+03	(Odum, 1996)
Cotton	8.37E+09	J	1.79E+06	(Brandt-Williams, 2001)
Soybeans	2.07E+10	J	4.83E+05	(Brandt-Williams, 2001)
Oil crops	2.55E+10	J	6.99E+04	(Odum, 1996)
Hemp	1.63E+10	J	1.09E+05	(Zhong, 2013)
Vegetables	2.50E+09	J	2.12E+04	(Odum, 1996)
Beet or sugar cane	2.50E+09	J	6.68E+04	(Odum, 1996)
Tobacco	1.75E+10	J	3.56E+04	(Zhong, 2013)
Pork	2.00E+10	J	1.34E+06	(Odum, 1996)
Egg	5.50E+09	J	5.33E+06	(Brandt-Williams, 2001)
Honey	1.34E+07	J	1.57E+06	(Odum, 1996)
Forest				
Fruit	3.30E+09	J	4.17E+04	(Odum, 1996)
Pasture				
Beef	2.09E+10	J	3.15E+06	(Odum, 1996)
Lamb	1.41E+10	J	1.57E+06	(Odum, 1996)
Poultry	1.75E+10	J	1.35E+06	(Odum, 1996)
Milk	2.90E+09	J	1.70E+06	(Brandt-Williams, 2001)
Goat milk	2.09E+06	J	1.70E+06	(Brandt-Williams, 2001)
Goat wool	2.09E+06	J	3.46E+06	(Odum, 1996)
Sheep wool	2.09E+06	J	3.46E+06	(Odum, 1996)
Watershed				
Aquatic products	5.50E+09	J	1.57E+06	(Odum, 1996)
Fossil fuel				
Raw coal	2.93E+10	J	5.09E+04	(Lou and Ulgiati, 2013)
Crude	4.71E+10	J	6.88E+04	(Odum, 1996)
Gasoline	4.61E+10	J	8.41E+04	(Odum, 1996)
Coke	2.85E+10	J	5.09E+04	(Odum, 1996)
Kerosene	4.31E+10	J	4.02E+04	(Odum et al., 2000)
Fuel oil	5.02E+10	J	4.02E+04	(Odum et al., 2000)
Natural gas	3.89E+07	J	7.47E+04	(Odum et al., 2000)
Diesel	4.19E+10	J	1.41E+05	(Geng et al., 2010)
Built-up area				
Electricity	3.6E+06	J	2.31E+05	(Campbell and Brown, 2012)
Heat	2.93E+10	J	6.72E+04	(Lou and Ulgiati, 2013)

Note: a means all the transformities refer to the 12E+24seJ/yr GEB (Brown et al., 2016).

Appendix 3

Time series are defined as:

$$x^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \cdots\ x^{(0)}(n)\right\} \tag{9}$$

where n is the number of observations.

We define the series $x^{(1)}$ as:

$$x^{(1)} = \left\{x^{(1)}(1), x^{(1)}(2), \cdots\ x^{(1)}(n)\right\} \tag{10}$$

where:

$$x^{(1)}(1) = x^{(0)}(1) \tag{11}$$

$$x^{(1)}(t) = \sum_{m=1}^{t} x^{(0)}(m), (t = 2, 3, \cdots, n) \tag{12}$$

The GM (1, 1) model is defined by a first order differential equation:

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b \tag{13}$$

The solution can be obtained using the least-squares method:

$$[a, b]^T = \left(B^T B\right)^{-1} B^T X_n \tag{14}$$

where:

$$\mathrm{B} = \begin{bmatrix} -\frac{1}{2}\left[x^{(1)}(1) + x^{(1)}(2)\right] & 1 \\ -\frac{1}{2}\left[x^{(1)}(2) + x^{(1)}(3)\right] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left[x^{(1)}(t-1) + x^{(1)}(t)\right] & 1 \end{bmatrix}, (t = 2, 3, \cdots, n) \tag{15}$$

$$X_n = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \tag{16}$$

The discrete solution of the differential equation is expressed as:

$$\widehat{x}^{(1)}(t+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-at} + \frac{b}{a} \tag{17}$$

Then, the predicted series is calculated following the formula:

$$\widehat{x}^{(0)}(t+1) = \widehat{x}^{(1)}(t+1) - \widehat{x}^{(1)}(t) \quad (t = 1, 2, 3, \cdots, n) \tag{18}$$

Instead, observed time series are described by the following equation:

$$x^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right\} \tag{19}$$

We define the modeled time series as:

$$\widehat{x}^{(0)} = \left\{\widehat{x}^{(0)}(1), \widehat{x}^{(0)}(2), \cdots, \widehat{x}^{(0)}(n)\right\} \tag{20}$$

Then, the residual series is:

$$\begin{aligned} \varepsilon^{(0)} &= \{\varepsilon(1), \varepsilon(2), \cdots, \varepsilon(n)\} \\ &= \left\{x^{(0)}(1) - \widehat{x}^{(0)}(1), x^{(0)}(2) - \widehat{x}^{(0)}(2), \cdots, x^{(0)}(n) - \widehat{x}^{(0)}(n)\right\} \end{aligned} \tag{19}$$

The mean and variance of $x^{(0)}$ are, respectively, $\overline{x}$ and s_1^2. They are defined as:

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x^{(0)}(t) \tag{21}$$

$$s_1^2 = \frac{1}{n}\sum_{i=1}^{n}\left[x^{(0)}(t) - x\right]^2 \tag{22}$$

The mean and variance of the residuals are $\overline{\varepsilon}$ and s_2^2 respectively:

$$\overline{\varepsilon} = \frac{1}{n}\sum_{i=1}^{n}\varepsilon(t) \tag{23}$$

$$s_2^2 = \frac{1}{n}\sum_{i=1}^{n}[\varepsilon(t) - \overline{\varepsilon}] \tag{24}$$

The accuracy of GM (1, 1) is measured by the mean square deviation ratio (C) and small error probability (P). The formulas of C and P are as follows:

$$C = s_2/s_1 \tag{25}$$

$$P = P\{|\varepsilon(k) - \overline{\varepsilon}| < 0.6475 s_1\} \tag{26}$$

The smaller the C and the larger the P, the more accurate the model. In general, the accuracy level of the model is classified into four levels as shown in Table A3.

Table A3
Accuracy level of the emergy-grey forecast model GM (1, 1) according to the small error probability (P) and the mean square deviation ratio (C).

Level	Small error probability (P)	Mean square deviation ratio (C)
Good	$0.95 \le P \le 1$	$0 < C \le 0.35$
Qualified	$0.8 \le P < 0.95$	$0.35 < C \le 0.5$
Unconvincing	$0.7 \le P < 0.8$	$0.5 < C \le 0.65$
Substandard	P<0.7	C>0.65

Appendix 4

Beijing is selected as an example to detail the calculation process.

Step 1: the *eec* and *eef* calculation (see Table A4–A6);

Table A4
The emergy-ecological capacity and footprint of Beijing in 2015.

Items	Raw data	unit	UEVs (sej/unit)	Reference	Emergy (sej)
Renewable resources					
Sunlight	6.15E+19	J	1	(Brown and Ulgiati, 2016)	6.15E+19
Earth cycle, heat flow	3.56E+17	J	4.90E+03	(Brown and Ulgiati, 2016)	1.74E+21
Wind	7.11E+15	J	8.00E+02	(Brown and Ulgiati, 2016)	5.69E+18
Rain, chemical potential	2.91E+13	J	1.28E+04	(Brown and Ulgiati, 2016)	3.72E+17
Rain, geopotential	1.92E+15	J	2.13E+04	(Brown and Ulgiati, 2016)	4.10E+19
Production or consumption					
Cropland					
Rice	2.28E+13	J	6.53E+04	(Odum, 1996)	1.49E+18
Wheat	1.74E+15	J	5.35E+04	(Odum, 1996)	9.31E+19
Corn	8.16E+15	J	9.72E+05	(Brandt-Williams, 2001)	7.93E+21
Sorghum	1.37E+16	J	6.53E+04	(Odum, 1996)	8.92E+20
Potatoes	1.40E+14	J	1.63E+03	(Odum, 1996)	2.27E+17
Cotton	8.41E+11	J	1.79E+06	(Brandt-Williams, 2001)	1.51E+18
Soybeans	1.35E+14	J	4.83E+05	(Brandt-Williams, 2001)	6.52E+19
Oil crops	1.44E+14	J	6.99E+04	(Odum, 1996)	1.01E+19
Vegetables	5.13E+15	J	2.12E+04	(Odum, 1996)	1.09E+20
Beet or sugar cane	3.25E+13	J	6.68E+04	(Odum, 1996)	2.17E+18
Tobacco	7.79E+14	J	3.56E+04	(Zhong, 2013)	2.77E+19
Pork	4.50E+15	J	1.34E+06	(Odum, 1996)	6.01E+21
Egg	1.08E+15	J	5.33E+06	(Brandt-Williams, 2001)	5.74E+21
Honey	2.19E+10	J	1.57E+06	(Odum, 1996)	3.44E+16
Subtotal					2.09E+22
Forest					
Fruit	2.23E+15	J	4.17E+04	(Odum, 1996)	9.28E+19
Subtotal					9.28E+19
Pasture					
Beef	3.24E+14	J	3.15E+06	(Odum, 1996)	1.02E+21
Lamb	1.69E+14	J	1.57E+06	(Odum, 1996)	2.66E+20
Poultry	1.96E+15	J	1.35E+06	(Odum, 1996)	2.63E+21
Milk	1.66E+15	J	1.70E+06	(Brandt-Williams, 2001)	2.82E+21
Goat milk	1.08E+10	J	1.70E+06	(Brandt-Williams, 2001)	1.84E+16
Sheep wool	3.16E+10	J	3.46E+06	(Odum, 1996)	1.09E+17
Subtotal					6.74E+21
Watershed					
Aquatic products	4.54E+14	J	1.57E+06	(Odum, 1996)	7.14E+20
Subtotal					7.14E+20
Fossil fuel					
Raw coal	3.38E+17	J	5.09E+04	(Lou and Ulgiati, 2013)	1.72E+22
Crude	4.67E+17	J	6.88E+04	(Odum, 1996)	3.21E+22
Gasoline	2.13E+17	J	8.41E+04	(Odum, 1996)	1.80E+22
Coke	1.25E+14	J	5.09E+04	(Odum, 1996)	6.38E+18
Kerosene	2.35E+17	J	4.02E+04	(Odum et al., 2000)	9.43E+21
Fuel oil	2.46E+15	J	4.02E+04	(Odum et al., 2000)	9.90E+19
Natural gas	4.06E+14	J	7.47E+04	(Odum et al., 2000)	3.03E+19
Diesel	7.64E+16	J	1.41E+05	(Geng et al., 2010)	1.08E+22
Cleaned coal	2.30E+15	J	5.31E+04[a]	(Lou and Ulgiati, 2013)	1.22E+20
Other washed coal	3.96E+12	J	5.31E+04 [a]	(Lou and Ulgiati, 2013)	2.10E+17
Briquette coal	3.00E+15	J	5.31E+04 [a]	(Lou and Ulgiati, 2013)	1.59E+20
Liquefied petroleum gas	2.57E+16	J	5.31E+04 [a]	(Lou and Ulgiati, 2013)	1.36E+21
Refinery Gas	3.52E+16	J	5.31E+04 [a]	(Lou and Ulgiati, 2013)	1.87E+21
Naphtha	5.50E+16	J	5.31E+04 [a]	(Lou and Ulgiati, 2013)	2.92E+21
Lubricating oil	3.41E+14	J	5.31E+04 [a]	(Lou and Ulgiati, 2013)	1.81E+19
Paraffin	8.09E+13	J	5.31E+04 [a]	(Lou and Ulgiati, 2013)	4.29E+18
Solvent oil	3.16E+13	J	5.31E+04 [a]	(Lou and Ulgiati, 2013)	1.68E+18
Asphalt	5.27E+15	J	5.31E+04 [a]	(Lou and Ulgiati, 2013)	2.80E+20
petrol coke	6.86E+15	J	5.31E+04 [a]	(Lou and Ulgiati, 2013)	3.64E+20
Liquefied natural gas	5.62E+15	J	5.31E+04 [a]	(Lou and Ulgiati, 2013)	2.98E+20
Other petroleum products	1.16E+17	J	5.31E+04 [a]	(Lou and Ulgiati, 2013)	6.16E+21
Other energy	3.24E+16	J	5.31E+04 [a]	(Lou and Ulgiati, 2013)	1.72E+21
Subtotal					1.03E+23
Built-up area					
Electricity	9.51E+10	J	2.31E+05	(Campbell and Brown, 2012)	2.20E+16
Heat	6.60E+17	J	6.72E+04	(Lou and Ulgiati, 2013)	3.50E+22
Subtotal					3.50E+22
Total					1.66E+23

Note: a means that the unit of this item is transformed into standard coal, therefore the transformity of this term is replaced with the transformity of coal. According to this calculation, the emergy of all the renewable resources and production or consumption can be calculated in from 2006 to 2014 in the other provinces. After these calculation, according to equation (1)–(4), the *eec* and *eef* calculation table (Table A3 and A4) is as below.

Table A5
The emergy-ecological capacity calculation in Beijing during 2006–2015.

Year	Renewable resources (sej)	Renewable resources per capita (*e*) (sej/cap)	National emergy density (NED) (sej/ha)	Emergy-ecological capacity (*eec*) (ha)
2006	1.82E+21	1.15E+14	1.43E+15	0.07
2007	1.82E+21	1.09E+14	1.46E+15	0.07
2008	1.82E+21	1.03E+14	1.47E+15	0.06
2009	1.82E+21	9.80E+13	1.43E+15	0.06
2010	1.82E+21	9.30E+13	1.48E+15	0.06
2011	1.82E+21	9.08E+13	1.43E+15	0.06
2012	1.82E+21	8.86E+13	1.48E+15	0.05
2013	1.82E+21	8.64E+13	1.47E+15	0.05
2014	1.82E+21	8.47E+13	1.47E+15	0.05
2015	1.82E+21	8.42E+13	1.46E+15	0.05

Table A6
The emergy-ecological footprint (*eef*) calculation in Beijing during 2006–2015.

Year	Emergy of production and consumption (*U*) (sej)	U Per capita (sej/cap)	Emergy-ecological footprint (*eef*) (ha)
2006	1.86E+23	1.18E+16	0.64
2007	1.93E+23	1.15E+16	0.60
2008	1.97E+23	1.11E+16	0.54
2009	2.01E+23	1.08E+16	0.51
2010	2.00E+23	1.02E+16	0.45
2011	1.96E+23	9.70E+15	0.39
2012	1.91E+23	9.23E+15	0.36
2013	1.74E+23	8.21E+15	0.30
2014	1.78E+23	8.30E+15	0.30
2015	1.66E+23	7.66E+15	0.28

Step 2: the evaluation indicators of ecological security (see Table A7);

Table A7
The evaluation indicators of ecological security of Beijing.

Year	Ecological deficit per capita (*ed*)	Ecological footprint intensity (EFI)	Ecological security state (ESS)	Ecological footprint diversity index (H)	Ecological and economic coordination index (EECI)
2006	−0.57	9.12	Sub-security	1.00	1.103
2007	−0.53	9.13	Sub-security	0.97	1.103
2008	−0.48	8.79	Sub-security	0.99	1.107
2009	−0.45	8.47	Sub-security	1.00	1.110
2010	−0.39	8.05	Sub-security	1.00	1.116
2011	−0.34	7.03	Sub-security	1.03	1.131
2012	−0.30	6.77	Sub-security	1.03	1.135
2013	−0.25	5.86	Sub-security	1.05	1.154
2014	−0.25	5.97	Sub-security	1.01	1.151
2015	−0.23	5.47	Sub-security	1.04	1.163

Step 3: the ESS projection of Beijing.
According to session 2.2.3, the observed time series is:

$$x^{(0)} = \{0.07, 0.07, 0.06, 0.06, 0.06, 0.06, 0.05, 0.05, 0.05, 0.05\} \tag{27}$$

The series $x^{(1)}$ is:

$$x^{(1)} = \{0.07, 0.14, 0.20, 0.26, 0.31, 0.37, 0.42, 0.47, 0.52, 0.58\} \tag{28}$$

Therefore, the matrix B is:

$$B = \begin{bmatrix} -0.10 & 1 \\ -0.17 & 1 \\ -0.23 & 1 \\ -0.29 & 1 \\ -0.34 & 1 \\ -0.40 & 1 \\ -0.45 & 1 \\ -0.50 & 1 \\ -0.55 & 1 \end{bmatrix} \tag{29}$$

The GM (1, 1) model is defined by a first order differential equation:

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b \tag{30}$$

The solution can be obtained using the least-squares method:

$$[a,b]^T = \left(B^T B\right)^{-1} B^T X_n \tag{31}$$

And

$$X_1 = \{0.07,\ 0.06,\ 0.06,\ 0.06,\ 0.06,\ 0.05,\ 0.05,\ 0.05,\ 0.05\} \tag{32}$$

Therefore:

$$[a,b]^T = [0.034, 0.067] \tag{33}$$

The discrete solution of the differential equation is expressed as:

$$\widehat{x}^{(1)}(t+1) = \left[x^{(0)}(1) - 2.00\right] e^{-0.034t} + 2.00 \tag{34}$$

Then the predicted series is:

$$\widehat{x}^{(1)}(1) = \{0.06, 0.06, 0.06, 0.06, 0.06, 0.05, 0.05, 0.05\} \tag{35}$$

Then, the residual series is:

$$\varepsilon^{(0)} = \{0.0000, 0.0015, 0.0000, 0.0004, -0.0023, -0.0002, -0.0012, -0.0003, 0.0002, 0.0019\} \tag{36}$$

Then,

$s_1 = 0.0064$, $s_2 = 0.0012$, $c = 0.1797 < 0.35$, $P = P\{|\varepsilon(k) - \overline{\varepsilon}| < 0.6475 s_1\}$

$$\{|\varepsilon(k) - \overline{\varepsilon}| - 0.6475 s_1\} = \{-0.004, -0.003, -0.004, -0.002, -0.004, -0.003, -0.004, -0.004, -0.004, -0.002\}$$

Therefore, $|\varepsilon(k) - \overline{\varepsilon}| - 0.6475 s_1 < 0$ and. $P = P\{|\varepsilon(k) - \overline{\varepsilon}| < 0.6475 s_1\} = 1$

Therefore, the projection model is accurate and can be used to predict the future ecological security state of Beijing.

Appendix 5

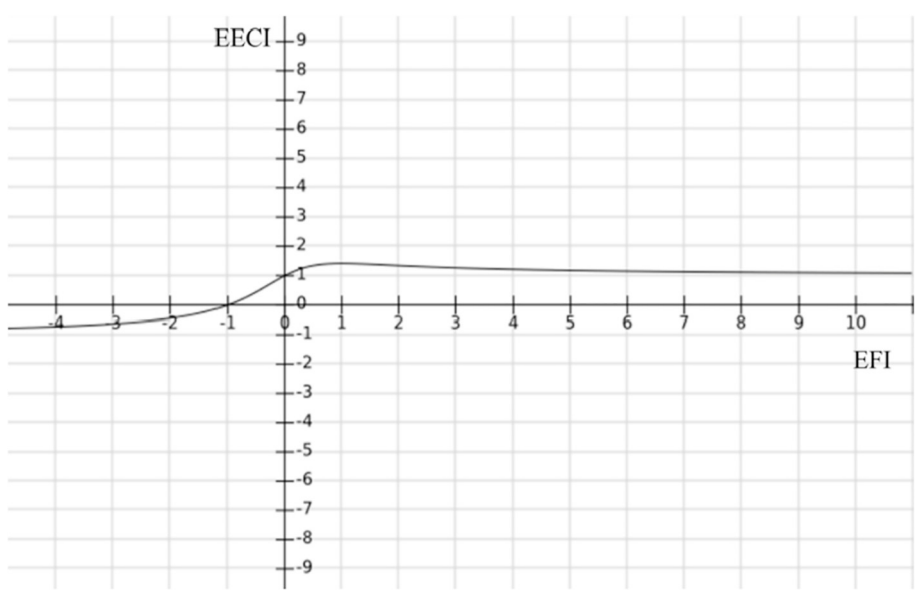

Fig. A2. The function relationship between EFI and EECI. The curve indicates the function relationship between EFI and EECI and the function is EECI $= (EFI + 1)/\sqrt{EFI^2 + 1}$.

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