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Driving Forces and Their Effects on Water Conservation Services in Forest Ecosystems in China

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Abstract: Identifying the driving forces that cause changes in forest ecosystem services related to water conservation is essential for the design of interventions that could enhance positive impacts as well as minimizing negative impacts. In this study, we propose an assessment concept framework model for indirect-direct-ecosystem service (IN-DI-ESS) driving forces within this context and method for index construction that considers the selection of a robust and parsimonious variable set. Factor analysis was integrated into two-stage data envelopment analysis (TS-DEA) to determine the driving forces and their effects on water conservation services in forest ecosystems at the provincial scale in China. The results showed the following. 1) Ten indicators with factor scores more than 0.8 were selected as the minimum data set. Four indicators comprising population density, per capita gross domestic product, irrigation efficiency, and per capita food consumption were the indirect driving factors, and six indicators comprising precipitation, farmland into forestry or pasture, forest cover, habitat area, water footprint, and wood extraction were the direct driving forces. 2) Spearman's rank correlation test was performed to compare the overall effectiveness in two periods: stage 1 and stage 2. The calculated coefficients were 0.245, 0.136, and 0.579, respectively, whereas the tabulated value was 0.562. This indicates that the driving forces obviously differed in terms of their contribution to the overall effectiveness and they caused changes in water conservation services in different stages. In terms of the variations in different driving force effects in the years 2000 and 2010, the overall, stage 1, and stage 2 variances were 0.020, 0.065, and 0.079 in 2000, respectively, and 0.018, 0.063, and 0.071 in 2010. This also indicates that heterogeneous driving force effects were obvious in the process during the same period. Identifying the driving forces that affect service changes and evaluating their efficiency have significant policy implications for the management of forest ecosystem services. Advanced effectiveness measures for weak regions could be improved in an appropriate manner. In this study, we showed that factor analysis coupled with TS-DEA based on the IN-DI-ESS framework can increase the parsimony of driving force indicators, as well as interpreting the interactions among indirect and direct driving forces with forest ecosystem water conservation services, and reducing the uncertainty related to the internal consistency during data selection.

Keywords: driving effectiveness; driving force; factor analysis; forest ecosystem; two-stage data envelopment analysis; water conservation service

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1 Introduction

Since the publication of the United Nations Millennium Ecosystem Services Assessment (UNEP, 2005a; 2005b; 2005c; 2005d; 2005e), ecosystem services science has become a hot topic in ecology research in the twenty-first century (Villa, 2012). Forest water conservation function is an important ecosystem service (Notter,

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2012) and an essential component of forest ecological function evaluations. Forests are considered as the most important ecosystems on land due to their conservation of soil water, groundwater recharge, and their runoff regulation effect (Krishnaswamy, 2013). Studies of forest ecosystem water conservation have considered the hydrological process of water conservation (Jetten, 1996; Asdak, 1998; Crockford, 2000; Nunez, 2006; Maes, 2009; Vose, 2011), estimating the conservation quantity and its spatiotemporal variation (Bosch, 1982; Brown, 2005; Farley, 2005; Sun, 2006; Mashayekhi, 2010), as well as the mechanisms related to the water conservation service function.

Human beings are among the primary causes of decreases in ecosystem service, but the factors that drive degradation remain largely unclear. Various hypotheses have produced rich arguments and several studies of the drivers of ecosystem service change were initiated in the late 1960s and early 1970s. Originally, some studies focused on simple causal analysis, such as religion (White, 1967), common property institutions (McCay and Jentoft, 1998), and capitalism and colonialism (O'Connor, 1988). However, ecosystem service change is not influenced by a single factor, but instead it is determined by multiple physical and biological drivers. Therefore, the focus on the mechanisms of ecosystem service change has gradually shifted from simple driver models to multiple driver couplings. The impacts-population-affluence-technology (IPAT) model is a representative multi-factor model that considers more than single causes (i.e., Impacts = Population × Affluence × Technology), which emphasizes that there are multiple and interacting human drivers of environmental change, and their impacts are multiplicative rather than additive (Dietz, 1994). The IPAT model was first proposed to formalize the relationship between population, human welfare, and environmental impacts. For example, Waggoner and Ausubel (2002), and Chertow (2000) conducted empirical analyses based on its analytical elements. Palloni (1994) noted that population size can determine impacts but it is sometimes less important than other factors, while Stern (1998) focused on the effects of affluence on the environmental influence. Thus, the influences of multiple factors on the changes in ecosystem services and the mechanisms that underlie their interactions have been discussed in previous studies.

The ecosystem service assessment approach has been refined further by including factors such as specific sociopolitical, biophysical, and cultural drivers. The drivers of biodiversity loss in the empirical field as well as those of land use and cover changes have been tracked as main drivers of ecosystem service changes (Forester and Machlis, 1996; Geist and Lambin, 2002; Spangenberg, 2007; Jabbour, 2014). Similar to the variety of drivers considered in different studies, various frameworks are available for investigating driving forces, e.g., the driver-pressure-state-impact-response (DPSIR) scheme developed by the Organization for Economic Co-operation and Development. Many assessments have employed this approach, e.g., Kelble *et al*. (2013) proposed a conceptual model that merges the widely applied DPSIR conceptual model with ecosystem services, thereby obtaining a driver, pressure, state, ecosystem service, and response (DPSER) conceptual model, which replaced the 'impact' in DPSIR with 'ecosystem services'. Unlike the DPSIR model, which focuses on negative anthropomorphic impacts on ecosystems, the DPSER model incorporates both negative and positive changes in the ecosystems; thus, it represents the clear hierarchy of drivers by encompassing cause and effect.

Research into drivers has employed the full repertoire of methods, including quantitative (e.g., statistical model and simulation) and qualitative approaches, and the volume of studies is growing in terms of both size and sophistication (Rudel *et al*., 1996; Lambin *et al*., 2001). Based on 152 cases reported at the sub-national level and by analyzing the frequency of proximate causes and the underlying driving forces of deforestation, Geist and Lambin (2001; 2002) concluded that tropical deforestation is driven by causal factor synergies, including economic factors, institutions, and national policies at local and regional scales. Structural equation modeling has been used to analyze the relationship between biodiversity loss based on socioeconomic and ecological factors (Forest, 1996).

In previous studies, different qualitative conceptual frameworks have been presented for drivers of ecosystem change. and analyses have considered the driving forces that underlie changes in ecosystem services, as well as developing indicators. Most studies have considered bioscience aspects, especially the driving forces of deforestation and biodiversity. Clearly, previous studies have three main weaknesses in terms of the diversity of the driving forces considered and the effectiveness of these drivers. Firstly, few studies have investigated the social and economic driving forces, and there has been a lack of research into the main drivers of forest ecosystem water conservation service change. Secondly, few investigations have attempted to quantitatively identify and evaluate the effectiveness of the main drivers of change in forest ecosystem water conservation services. For example, due to the lack of any theoretical justification for weighting each component differently, the components are usually weighted equally in additive models. Thirdly, there have been no attempts to discuss or distinguish the effectiveness of the indirect, direct, and overall driving forces that affect change in forest ecosystem water conservation services.

In the following sections, factor analysis (FA) and two-stage data envelopment analysis (TS-DEA) models are first reviewed briefly, with a graphical illustration of their coupling. Next, we describe the models for identifying the driving forces of forest ecosystem service change, before calculating the overall and individual stage effectiveness of drivers of forest ecosystem service in China during 2000 and 2010. Finally, we give some conclusions based on our discussion of these results.

2 Methods and Materials

2.1 Study area

In this study, we focused on the dynamics of the effectiveness of forest water conservation and its driving forces in China during 2000 and 2010. The overall area considered was approximately 9 600 000 km^2. The landscape of China varies significantly across its vast width, where the diverse landscape types and different hydrothermal conditions in the latitudinal, longitudinal, and vertical terrains have formed a complex natural and geographical environment. China has an abundance of forest resources with a great variety of biological species and vegetation types, which provide humans with a wealth of eco-products, wood products, and eco-cultural services. In China, the total forest area is 208 million ha and forest covers 21.67% of the total land area. The forest stock volume is 1.51×10^{10} m^3. The research units include 22 provinces, 5 autonomous regions, and 4 municipalities according to the administrative boundaries. Hong Kong, Macao, and Taiwan were excluded from this study because appropriate data were not available. Thus, 31 provincial administrative regions were analyzed as decision-making units (DMUs) for data envelopment analysis (DEA) in the study.

2.2 FA as a major tool for identifying driver indicators

This study comprised two processes: screening indicators and estimating the effectiveness of driving forces (Fig. 1).

A driver is any natural or human-induced factor that directly or indirectly causes a change in an ecosystem. Two processes were used to screen for indicators in order to estimate forest ecosystem water conservation services (Fig. 1). The procedures used for selecting indicators generally comprised qualitative and quantitative methods. The former approach involved selecting the variables according to ecosystem theory and ecosystem service changes. The latter was based on a statistical procedure, such as FA. This step related a large number of variables to an outcome measure in order to identify statistically significant factors.

The general indicator set was determined by collecting relevant studies and by consulting ecologists. The candidate indicators were then subtracted from the general indicators using availability and scalability criteria, and divided into two groups of factors. The first group comprised indirect driving forces, i.e., fundamental social processes such as human population dynamics or economic growth, which underpin the proximate causes and that operate either at the local level or that have an indirect impact on forest ecosystem water conservation at the national or global level. An indirect driver influences the decision-making process and operates more diffusely, often by altering one or more direct drivers, where its influence was established by understanding its effects on direct drivers. The other group comprised the direct driving forces, i.e., human activities or immediate actions at the local level, such as infrastructural extension, agricultural expansion, and ecological restoration. These drivers originated from intended land use and directly impacted forest cover. A direct driver directly affects ecosystem conditions and services, thereby unequivocally influencing ecosystem processes, and thus they could be identified and measured with differing degrees of accuracy. For example, to explain the distinction between indirect and direct driving forces, inappropriate economic growth may increase greenhouse gas

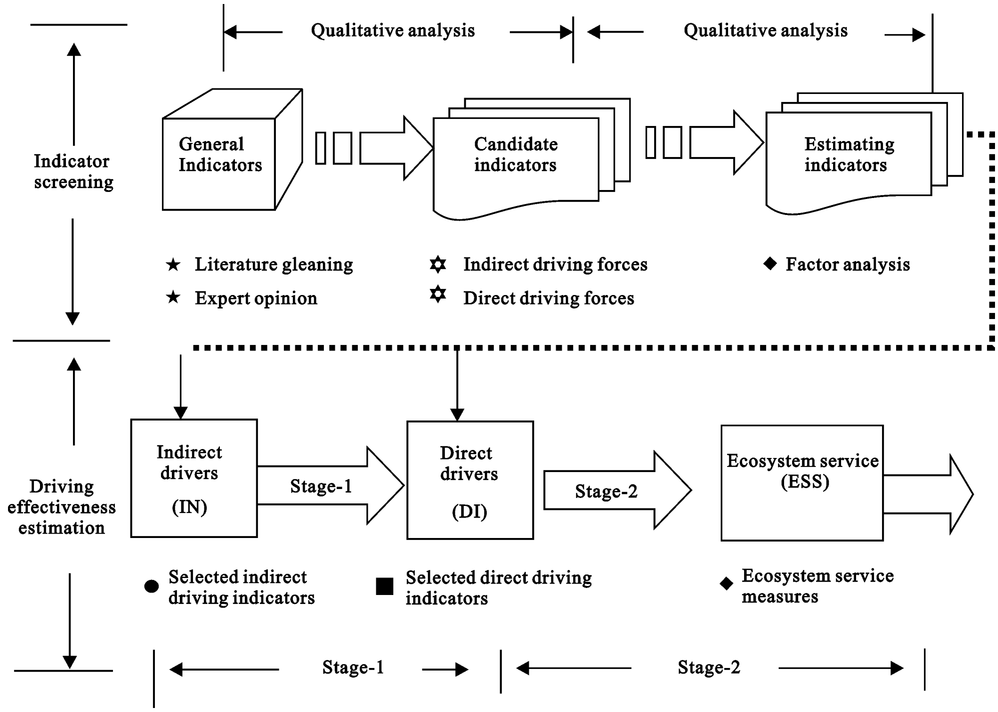

Fig. 1 Procedures for identifying indicators and estimating effectiveness of drivers. IN: indirect drivers; DI: direct drivers; ESS: ecosystem service

emissions, which are linked to climate change with predicted warmer temperatures and changes in precipitation. If climate change continues, extreme weather events will be more frequent, such as heat waves, floods, and droughts, as well as associated fires and pest outbreaks.

Indirect and direct driving forces were used to summarize the driving forces that underlie the variations in forest ecosystem water conservation services, which are defined as the capacity of ecosystems to hold part of the water input from precipitation at certain spatiotemporal scales. The interacting driving forces coupled with ecosystem services comprise an indirect-direct-ecosystem service (IN-DI-ESS) framework.

During the estimation of candidate indicators, it was necessary to reduce the number of indicators in order to satisfy the criteria for the number of DMUs vs. the numbers of inputs and outputs, i.e., the number of DMUS should be at least 2–3 times the combined number of inputs and outputs (Banker *et al*., 1989; Golany and Roll, 1989). We used 31 provincial administrative regions to estimate the effectiveness of driving force units, so we abstracted 10 or less variables for DEA.

FA can reduce the number of indicators, characterize the main information, and ensure the parsimony of the model. FA was used to identify the underlying structures and to minimize the number of indicators estimated in the final subset. A reduced number of variables were used to examine the socio-ecological and biophysical factors that contribute to forest ecosystem services.

2.3 TS-DEA analysis for estimating effectiveness of drivers

Suppose that a driving process comprises a series of two sub-processes, as depicted in Fig. 2.

The whole process uses m inputs X_{1k}, i=1, …, m to produce s outputs Y_{rk}, i=1, …, s, where the driving process is divided into two sub-processes with q intermediate products Z_{pk}, p=1, …, q, which differs from the conventional single stage driving process. Based on the constant return to scale DEA model (Charnes *et al*., 1978), the effectiveness scores for the two-stage process

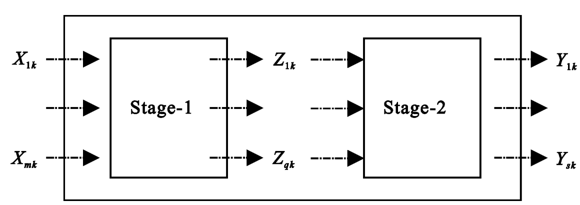

Fig. 2 Tandem driving force process with inputs X, outputs Y, and intermediate products Z

and the two individual stages can be expressed as:

$$E_k = \max \sum_{r=1}^{s} u_r Y_{rk}$$

$$\text{Subject to} \sum_{i=1}^{m} v_i X_{ik} = 1$$

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \le 0, \quad j = 1, \ldots, n \tag{1}$$

$$\sum_{p=1}^{q} w_p Z_{pj} - \sum_{i=1}^{m} v_i X_{ij} \le 0, \quad j = 1, \ldots, n$$

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{p=1}^{q} w_p Z_{pj} \le 0, \quad j = 1, \ldots, n$$

$$u_r \ge \varepsilon\ ,\ v_i \ge \varepsilon\ ,\ w_p \ge \varepsilon\ ,\ r = 1, \ldots, s\ ,\ i = 1, \ldots, m\ ,\ p = 1, \ldots, q\ ,$$

where X_{ij} (i=1, …, m) and Y_{rj} (r=1, …, s) are the ith input and rth output of DMU_j (j=1, …, n), respectively, and we denote Z_{pj} (p=1, …, q) as the pth intermediate product. We denote u_r, v_i and w_p as the multipliers of overall effectiveness E_k and the sub-process effectiveness E_k^1 and E_k^2. The first stage effectiveness E_k^1 can be solved while maintaining the overall efficiency score at E_k based on Equation (1). This idea can be formulated as follows.

$$E_k^1 = \max \sum_{p=1}^{q} w_p Z_{pk}$$

$$\text{Subject to} \sum_{i=1}^{m} v_i X_{ik} = 1$$

$$\sum_{r=1}^{s} u_r Y_{rk} - E_k \sum_{i=1}^{m} v_i X_{ik} = 0$$

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \le 0, \quad j = 1, \cdots, n \tag{2}$$

$$\sum_{p=1}^{q} w_p Z_{pj} - \sum_{i=1}^{m} v_i X_{ij} \le 0, \quad j = 1, \ldots, n$$

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{p=1}^{q} w_p Z_{pj} \le 0, \quad j = 1, \ldots, n$$

$$u_r \ge \varepsilon, v_i \ge \varepsilon, w_p \ge \varepsilon,\ r = 1, \ldots, s,$$
$$i = 1, \ldots, m,\ p = 1, \ldots, q$$

After calculating E_k^1 using the model above, the effectiveness of the second stage is obtained from the calculation as follows:

$$E_k^2 = E_k / E_k^1$$

3 Identification of Driving Force Indicators and Estimating Effectiveness of Drivers

3.1 Identification of driving force indicators

3.1.1 Constructing general indicator set

In the first step, a literature review was performed to obtain a list of 53 variables considered in this study (Fig. 3). The general indicators were specified according to three criteria. The first was that the variables should be justifiable according to previous studies. The second was that the variables were available from national data sources, and the last was that variables should be scalable at different scales. Figure 3 presents an overview of the indicator systems taken from different sources. Four broad clusters of indirect causes were identified: demographic factors, economic factors, science and technology, and cultural and policy, where each category was further subdivided. Direct driving forces were categorized into five broad clusters: climate change, land use and cover, biodiversity, water use, and energy and resource extraction, where each was also subdivided into specific factors (Geist and Lambin, 2002; Spangenberg, 2007). Water use was considered in the water conservation index because we shifted the forest ecosystem water yield from supply to demand. Despite scientific and technological advances, as argued by Spangenberg (2014), the provision of ecosystem services is determined by human agencies and not ecosystem functions.

3.1.2 Constructing candidate indicator set

Table 1 shows the general indicator set comprising 30 variables from the 53 variables in the list (Fig. 3), which operationalized some of the more general concepts of ecosystem service change drivers. These variables were considered suitable for estimating the effects of driving forces according to the three conditions mentioned above. The list of 30 variables formed the candidate set used for further FA. In order to distinguish the mechanisms driving ecosystem service change, they were grouped into indirect drivers of 12 variables and direct drivers of 18 variables.

The indirect driving forces were obtained from the Statistical Yearbook of China (NBSC, 2001; 2011) and China Water Resources Bulletin (CMWR, 2001; 2011). The direct driving forces comprised climate change and variability, land use and cover, biodiversity, energy and

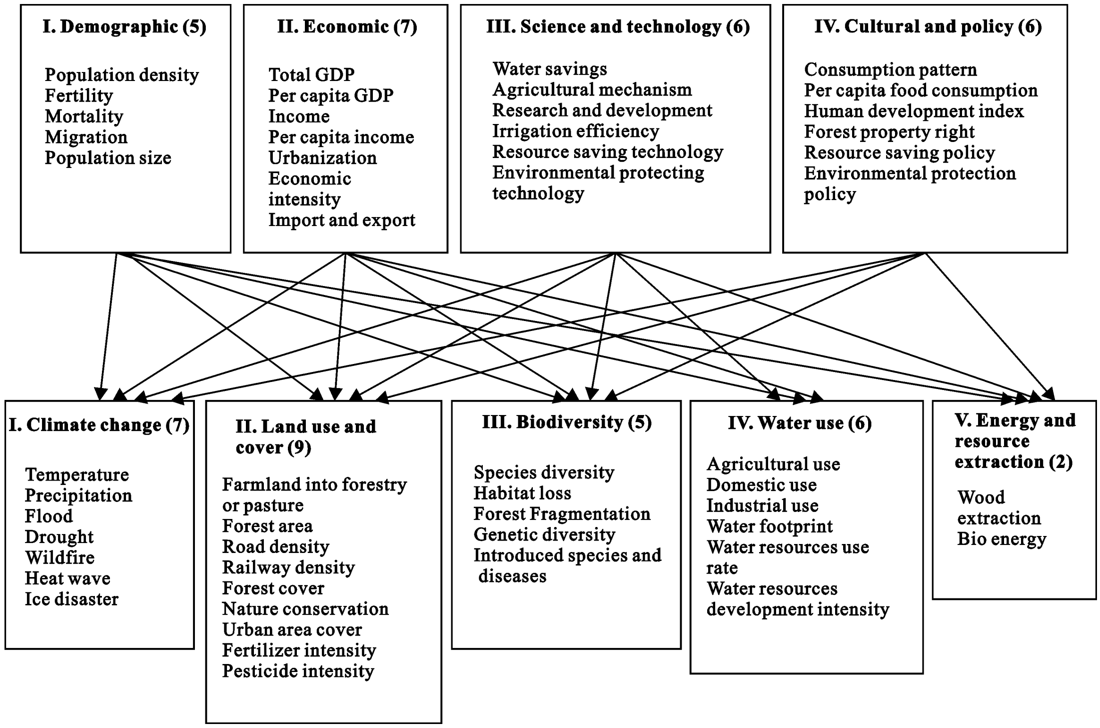

Fig. 3 Indirect and direct driving forces for forest water regulation services

resource extraction, and water use. The climate change variables considered as independent comprised the mean minimum temperature, mean maximum temperature, mean temperature, and precipitation. All of these variables were extracted from the digital climatic atlas of China with a pixel size of 500 m × 500 m (http://www.resdc.cn/) and the water-related disaster data were taken from the Bulletin of Flood and Drought Disaster in China (OSFCDRH, 2001; 2011). Land use and cover change data for China in 2000 and 2010 were obtained from the Resource and Environment Data Center of the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences. We used habitat areas and forest fragmentation to quantity the system diversity. Habitat areas and ecosystem service values were taken from the Research Report of Ecosystem Service and its Change during 2000 and 2010 in China, edited by the Research Center for Eco-Environmental Sciences, Chinese Academy of Sciences. Forest fragmentation selectively impedes the reproductive capacities of species that require a larger habitat, thereby shifting the balance of species and the state of the system. Considering both habitat areas and fragmentation indicates that the total area and its specific allocation are important. Introducing fragmentation and location as biodiversity specific policy criteria was a direct innovation. The reduction procedure is discussed in the following section.

3.1.3 Constructing estimation indicator set

FA and reliability analysis are often used in a complementary manner to explore whether the different dimensions of indexes are well-balanced (Nardo *et al.*, 2005; 2008). The reliability of the factor data was tested using Cronbach's alpha (Cronbach, 1951). The FA results (and reliability analysis) are presented in Table 1. Based on the results of principal components analysis, five factors were retained according to the Kaiser criterion (eigenvalue > 1) and varimax rotation. Varimax rotation minimizes the number of variables that load highly on a single factor, which increases the percentage of variation between each factor. These five factors captured about 86% of the total variance in the 30 variables.

Factors with Cronbach's alpha values larger than 0.6 are considered reliable (Cronbach, 1951). Variables are usually identified in a factor if their loading on that factor is more than 0.7, which ensures that the factor extracts sufficient variance from the variable. We selected a factor loading of 0.7 as a cutoff point because the factor loading represents the correlation coefficient, and

Table 1 Indirect and direct driving force indicators for forest ecosystem water conservation services

	Component	Indicator	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Indirect driving forces (12)	I. Demographic factor	**Population density**	**0.8914**	0.5965	0.5670	0.3651	0.1733
		Population size	0.7725	0.4988	0.2237	0.5623	0.1466
	II. Economic factor	Total GDP	0.35890	0.5171	0.5858	0.5590	0.1029
		Per capita GDP	**0.9522**	**0.8848**	0.3022	0.1738	0.4869
		Per capita income	0.5654	0.5943	0.3679	0.3552	0.1216
		Urbanization	0.6159	0.6023	0.7543	0.1353	0.0286
		Economic intensity	0.5671	0.2294	0.6815	0.3069	0.0304
	III. Scientific and technical factor	Water savings	0.3862	0.2984	0.4855	0.2019	0.4675
		Agricultural mechanism	0.7028	0.7943	0.5545	0.4926	0.3647
		Irrigation efficiency	0.6332	**0.8749**	0.3532	0.1109	0.2853
	IV. Cultural and sociopolitical factor	**Per capita food consumption**	0.6083	0.6556	0.0795	**0.8807**	0.5556
		Human development index	0.2560	0.4033	0.5151	0.7536	0.7278
Direct driving forces (18)	I. Climate change and variability	Temperature	0.7060	0.6054	0.1848	0.6992	0.5499
		Precipitation	**0.8660**	**0.9502**	0.5939	0.0606	0.7039
		Flood	0.7670	0.2662	0.5026	0.4893	0.7033
		Drought	0.6687	0.6480	0.5092	0.5891	0.4957
		Wildfire	0.6334	0.2485	0.6559	0.6137	0.0762
	II. Land use and cover	**Farmland into forestry or pasture**	0.7834	**0.9312**	**0.8768**	0.2223	0.1442
		Forest area	0.7752	0.1942	0.5002	0.3122	0.2701
		Road density	0.3943	0.3870	0.1434	0.0966	0.1352
		Railway density	0.5801	0.2528	0.3916	0.4648	0.1718
		Forest cover	0.3578	0.3112	0.7669	0.0940	**0.9590**
		Nature conservation	0.5690	0.6812	0.7489	0.5086	0.6957
	III. Biodiversity	Species diversity	0.2577	0.4131	0.4838	0.7863	0.2482
		Habitat area	0.6472	0.7386	0.1909	**0.8203**	**0.9385**
		Forest fragmentation	0.2683	0.3641	0.7299	0.7562	0.3169
	IV. Water use	**Water footprint**	0.4740	0.1387	0.5065	**0.8503**	0.4579
		Water resources use rate	0.2109	0.3327	0.5979	0.3206	0.2217
		Water resources development intensity	0.1839	0.5574	0.4948	0.3739	0.2377
	V. Energy and resource extraction	**Wood extraction**	0.7510	0.3844	0.7000	**0.9880**	0.6143
Variance (%)			17.68	19.76	15.87	15.64	17.86
Cumulative variance (%)			17.68	37.44	53.31	68.95	86.81
Cronbach's alpha			0.826	0.745	0.762	0.746	0.856

Note: Factor loadings greater than 0.8 are shown in boldface type and selected indicators are also in boldface letters

thus at least 49% of the variance in the variable must be explained by the factor to which it belongs (Verma, 2013). According to variable number constraints when solving the DEA model on a per component basis, this was accomplished by selecting all factor scores ≥ 0.8 and ≤ –0.8. The factors that did not satisfy these two threshold levels were considered orphans and listed in the respective tables but excluded from further analyses. Based on the loadings of individual variables in each factor, four variables (population density, per capita gross domestic product (GDP), irrigation efficiency, and per capita food consumption) and six variables (precipitation, farmland into forestry or pasture, forest cover, habitat area, water footprint, and wood extraction) were retained in the final solution, which were used as inputs in the subsequent two-stage DEA analysis.

3.2 Effectiveness of indirect and direct driving forces

A positive directionality was assigned to all factors known to increase effectiveness, whereas a negative directionality was assigned to all factors known to decrease effectiveness. In the latter case, we replaced a component with its inverse, thereby allowing the final dimension to be subtracted from the overall effectiveness index. All the factors were fed into the DEA to obtain relative effectiveness scores. By applying Equations (1) and (2), we calculated the overall effectiveness and those for stage 1 and stage 2 (Table 2).

Table 2 Effectiveness and the ranks of indirect and direct drivers for forest ecosystem water conservation service change in 31 Provincial administrative regions in China

Provincial administrative regions	2000						2010					
	Overall		Stage 1		Stage 2		overall		Stage 1		Stage 2	
	Effectiveness	Rank	Effectiveness	Rank	Effectiveness	Rank	Effectiveness	Rank	Effectiveness	Rank	Effectiveness	Rank
Beijing	0.1265	13	0.2830	14	0.4472	16	0.2196	7	0.2451	22	0.8958	3
Tianjin	0.0491	26	0.1336	27	0.3672	21	0.0748	22	0.6900	5	0.1084	31
Hebei	0.1032	19	0.2655	15	0.3888	19	0.1781	12	0.7723	4	0.2305	18
Shanxi	0.1384	9	0.2955	13	0.4684	15	0.2356	5	0.3305	18	0.7130	6
Inner Mongolia	0.0475	27	0.0481	31	0.9879	2	0.4278	2	0.3640	17	1.0000	1
Liaoning	0.3765	3	0.4410	9	0.8536	5	0.6305	1	0.7900	3	0.7981	4
Jilin	0.0332	28	0.2364	16	0.1403	27	0.0554	24	0.2730	21	0.2029	22
Heilongjiang	0.0187	30	0.1136	28	0.1650	26	0.0312	27	0.1606	27	0.1944	25
Shanghai	0.1017	20	1.0000	1	0.1017	31	0.1754	13	1.0000	1	0.1754	27
Jiangsu	0.1042	18	0.1429	26	0.7296	7	0.1733	14	0.5732	10	0.3023	14
Zhejiang	0.1353	10	0.3111	12	0.4350	18	0.2256	6	0.9594	2	0.2352	16
Anhui	0.1171	14	0.4957	8	0.2362	23	0.0200	30	0.1410	29	0.1419	28
Fujian	0.1283	12	0.2168	20	0.5921	12	0.2148	8	0.4584	12	0.4686	8
Jiangxi	0.1392	8	0.1685	22	0.8260	6	0.2365	4	0.4366	14	0.5418	7
Shandong	0.3134	4	0.7107	5	0.4410	17	0.0559	23	0.3103	19	0.1803	26
Henan	0.2468	5	0.5244	7	0.4706	13	0.0421	26	0.2080	26	0.2024	23
Hubei	0.0850	22	0.2195	19	0.3871	20	0.1422	16	0.6618	6	0.2148	20
Hunan	0.1156	15	0.1627	23	0.7105	8	0.1939	10	0.5797	9	0.3345	13
Guangdong	0.1322	11	0.1972	21	0.6705	9	0.0226	29	0.1034	30	0.2184	19
Guangxi	0.1095	17	0.1095	30	1.0000	1	0.1833	11	0.4284	15	0.4279	11
Hainan	0.1137	16	0.9709	2	0.1171	30	0.2000	9	0.4554	13	0.4392	10
Chongqing	0.0797	23	0.3873	10	0.2057	24	0.1397	17	0.6028	7	0.2318	17
Sichuan	0.4907	2	0.5573	6	0.8804	4	0.0833	21	0.2416	23	0.3448	12
Guizhou	0.0753	24	0.1607	24	0.4687	14	0.1329	18	0.2858	20	0.4649	9
Yunnan	0.6690	1	0.7409	4	0.9030	3	0.1124	19	0.1536	28	0.7320	5
Tibet	0.2190	6	0.3657	11	0.5987	11	0.3690	3	0.3690	16	1.0000	1
Shaanxi	0.0277	29	0.1568	25	0.1769	25	0.0477	25	0.2376	24	0.2008	24
Gansu	0.1444	7	0.2355	17	0.6133	10	0.0246	28	0.2221	25	0.1110	30
Qinghai	0.0149	31	0.1129	29	0.1317	29	0.0003	31	0.0019	31	0.1335	29
Ningxia	0.0578	25	0.2199	18	0.2629	22	0.1050	20	0.4947	11	0.2122	21
Xinjiang	0.1013	21	0.7498	3	0.1351	28	0.1724	15	0.5888	8	0.2927	15
Mean	0.1489		0.3462		0.4810		0.1590		0.4238		0.3790	
Variance	0.0200		0.0650		0.0790		0.0180		0.0630		0.0710	

3.2.1 Overall effectiveness of driving forces and in two stages in 2000

It was notable that none of the 31 provinces, municipalities, and autonomous regions (referred to simply as regions in the following) had adequate effectiveness in all stages during 2000, which was demonstrated by the overall scores for all the regions, where the highest score was 0.6690 for Yunnan, followed by 0.4907 and 0.3765 for Sichuan and Liaoning, respectively. For stage 1, three regions had relatively high effectiveness: Shanghai, Hainan, and Xinjiang. For stage 2, three other regions had high effectiveness: Guangxi, Inner Mongolia, and Yunnan. Most regions had greater effectiveness in stage 2 than stage 1, except for Shanghai, Anhui, Shangdong, Henan, Hainan, Chongqing, and Xinjiang. Wilcoxon's matched-pairs signed-rank test (Daniel, 1978) confirmed that the effectiveness of stage 1 was lower than that of stage 2. Thus, the low effectiveness score of the overall impact process was positively correlated with the low effectiveness score of the indirect dynamic process.

The overall effectiveness is always less than or equal to the effectiveness of the corresponding stages, so there is little benefit to be obtained from examining the effectiveness scores themselves. By contrast, it is more informative to consider the ranks of the effectiveness scores (Table 2). Most regions had similar ranks in terms of their overall effectiveness and effectiveness in stages 1 and 2, thereby indicating that the overall effectiveness could be attributed equally to the effectiveness of the two sub-processes. However, several regions exhibited large differences in terms of these ranks. A large difference indicated the source of ineffectiveness for the whole process. For example, Inner Mongolia, Jiangsu, Jiangxi, Hunan, and Guangdong had less effectiveness in stage 1 compared with stage 2, whereas Jilin, Shanghai, Shandong, Anhui, Hainan, and Xinjiang had less effectiveness in stage 2 compared with stage 1. Decomposing the overall effectiveness into the product of two components helped to identify the sub-process responsible for the ineffectiveness for a region. Logically, the rank of overall effectiveness for a region should lie either between the ranks of those in stages 1 and 2, or in their neighborhoods, because the effect of the overall process comprises the aggregated effectiveness of the two sub-processes. Among the 31 regions, the overall effectiveness ranks for 15 regions were between their ranks in stages 1 and 2, while the remainder were in the neighborhood of stages 1 and 2, which agreed with our intuitive expectation.

3.2.2 Overall effectiveness of driving forces and in two stages in 2010

Table 2 shows the results for the effectiveness of drivers in 2010. Three regions were effective in the overall driving process: Inner Mongolia, Liaoning, and Tibet. Surprisingly, none of them were effective in both sub-processes, which differed from the rationale of the relational model. Among the three regions, Liaoning had similar effectiveness in both sub-processes, whereas Inner Mongolia and Tibet were more effective in stage 2 than stage 1. In terms of the sub-process of the indirect driving mechanism, Shanghai, Zhejiang, and Liaoning were ranked first, second, and third, respectively. However, for the sub-process of driving ecosystem and service change, Inner Mongolia and Tibet had a maximum effectiveness score of 1, while Beijing also obtained a score of 0.8958, which were significantly higher scores than those for the other regions.

The overall effectiveness is the product of the effectiveness in stages 1 and 2, so the overall scores could not exceed the effectiveness in the corresponding stages. The averages of these three measures validated the formulation (Table 2). We found that the average region had an overall score of 0.159, thereby indicating that this region would be able to produce more than six times as much if it used its inputs efficiently. The average overall driving effectiveness was slightly higher than the score of 0.1489 in 2000, so this also implies the urgent need for Chinese ecosystem management. However, it should be mentioned that the overall effectiveness can only explain the general trend in the driving effect. For specific regions, analyzing the driving effectiveness for individual stages is important for ecosystem management. Table 2 shows that the mean driving effectiveness scores in stage 1and stage 2 were 0.4238 and 0.379, respectively, which indicates that there were minor differences in the relative driving effectiveness in stage 1 compared with stage 2. This result suggests that forest ecosystem service management policy-makers should first focus on improving direct drivers and then proceed to improve the indirect drivers associated with direct drivers.

3.2.3 Changes in the effectiveness of driving forces from 2000 to 2010

By comparing the dynamics of the driving effectiveness from 2000 to 2010, we found that some regions performed effectively in stage 1 (e.g., Shanghai in 2000) or stage 2 (e.g., Inner Mongolia and Tibet in 2010), but their overall efficiency was not ranked highly. Wilcoxon's test showed that there was no significant difference between the overall effectiveness and that in stage 1, as well as between the overall effectiveness and that in stage 2. Nevertheless, the average effectiveness in stage 2 was slightly lower than that in stage 1 during 2010, which was not similar to that in 2000.

To investigate the difference between the overall effectiveness in 2000 and 2010, it was more appropriate to compare the ranks rather than numerical scores because the models for measuring the different periods used two boundaries, which produced different reference sets, i.e., the calculated driving effectiveness scores in 2000 and 2010 were derived from their specific comparative criteria.

The ranks for the total effectiveness were quite similar in 2000 and 2010 (Table 2). The ranks for the total driving effectiveness in some provinces (municipallities and autonomous regions) changed significantly, i.e., the ranks for Inner Mongolia, Shandong, Henan, Sichuan, Yunnan, and Gansu were 27, 4, 5, 2, 1, and 7 in 2000, respectively, and 2, 23, 26, 21, 19, and 28 in 2010.

Spearman's rank correlation test indicated that the overall effectiveness in the two periods was weakly correlated, with a calculated coefficient of 0.245 compared with the tabulated value of 0.562 (n = 31, P = 0.001). By analyzing the same path, we studied the changes in the indirect and direct driving effectiveness.

For the indirect driving effectiveness, the Spearman's rank correlation coefficient was 0.136, which was much lower than the tabulated value of 0.562, thereby indicating a weak correlation. However, there was an opposite trend in the direct driving effectiveness, where the Spearman's rank correlation coefficient of 0.579 was higher than the tabulated value of 0.562, thereby indicating a relatively strong correlation between the ranks of the direct driving effectiveness calculated for the two periods.

The variances in the three processes were also considered. The values for the overall process, stage 1, and stage 2 were 0.020, 0.065, and 0.079, respectively, in 2000, and 0.018, 0.063, and 0.071 in 2010. The variance represents the magnitude of the variation among the scores around the mean value. A higher variance indicates greater heterogeneity, whereas a lower variance represents more homogeneity in the data. The variance results indicated that the heterogeneity of direct driving effectiveness was highest in 2000, followed by indirect drivers, and the heterogeneity of the overall driver effectiveness was lowest. In addition, the ranks of the driving effectiveness variances in the two periods were always similar, e.g., the indirect driving effectiveness was ranked second in 2010, which was the same as that in 2010.

4 Discussion

Despite advances in understanding causality in complex forest ecosystem water conservation services, determineing the interactions between these drivers remains a major challenge. We investigated the IN-DI-ESS model (feedback loop B, indicated by double lines with an arrow), but to understand the water conservation function in forest ecosystems, it will be necessary to explore the influence of causal chains comprising more than two sub-processes, i.e., the extended IN-DI-ESS model, indirect-direct-ecosystem service-ecosystem impact-human response (IN-DI-ESS-EI-HR) framework (feedback loop A, indicated by dotted lines with an arrow), or its shortcut format indirect-direct-ecosystem-human well-being (IN-DI-ESS-HB) framework (feedback loop C, indicated by solid lines with an arrow) (Amado, 2003). In addition, there are almost always multiple interacting driving forces, so a one-to-one linkage between particular driving forces and particular changes in ecosystems rarely exists. Multiple interacting drivers cause changes in ecosystem services and create a feedback loop involving the drivers of changes in ecosystem services (Fig. 4). Thus, it is important to extend this idea to include situations where the outputs from the second stage can be fed back as inputs into the first stage of the DEA model. The formulation of the two-stage DEA could be extended to systems with multiple stages connected in series, where the effectiveness of the overall process is the product of the effectiveness of individual sub-processes.

Analyzing the direct drivers is the first step toward defining a policy, but not the solution. The indirect driving forces that underlie pressures need to be identified and used to derive priorities for policy action, although directly addressing certain pressures might be

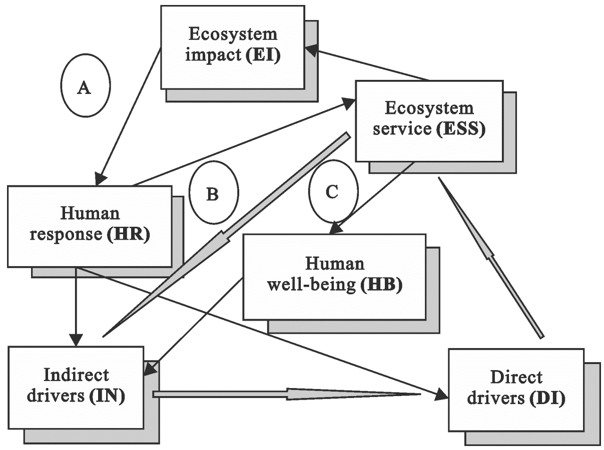

Fig. 4 Causal feedback loop for ecosystem service change

necessary as a type of emergency relief in particularly critical impact situations (Spangenberg, 2007).

Considering the functional interdependencies between and among the indirect and direct drivers of change, the two-stage DEA can also be extended to a complex formulation with feedback because the driving route of ecosystem service change is a process where the outputs from the first stage are intermediate variables that serve as inputs for the second stage (Liang, 2011). There are functional interdependencies between and among the indirect and direct drivers of change, and thus changes in ecological services lead to feedback to the drivers of changes in ecological services. Synergetic driver combinations are very common.

5 Conclusions

Drivers are often defined as natural or human-induced factors that directly or indirectly cause change. The driving factors are complex and varied in forest ecosystem water conservation services. Thus, it is essential to identify the main driving forces of change in forest ecosystem water conservation services and to evaluate their effectiveness. The drivers of water conversation change have been discussed widely in previous studies, but some important issues have not been explored previously. As a research topic, the problem of decomposing the drivers of water conversation services has been investigated rarely. A two-stage process concept has been applied infrequently in some previous studies of the effectiveness of drivers. The approach proposed in the present study allows the black-box comprising the driver measurement process to be assessed, thereby providing a new option for measuring the effectiveness of drivers. The results of this study may help managers to improve the effectiveness of forest water conversation services.

Our findings can be summarized briefly as follows. First, four indirect factors (population density, per capita GDP, irrigation efficiency, and per capita food consumption) and six direct factors (precipitation, farmland into forestry or pasture, forest cover, habitat area, water footprint, and wood extraction) are the most critical driving factors with positive or negative impacts on forest ecosystem water conservation services. Second, 31 provinces, municipalities and autonomous regions had a lower average indirect driving effectiveness compared with the direct driving effectiveness in 2000, whereas the average indirect driving effectiveness was higher than the direct driving effectiveness in 2010. This suggests that managers should have paid more attention to improving the macro-social economic environment of forest ecosystem water conversation services in 2000, whereas specific ecological management measures needed to be prioritized in 2010. Third, the two-stage DEA model was used to estimate the effectiveness of forest ecosystem water conservation services, thereby explicitly defining the physical relationship between the overall causal chain of drivers and the component sub-processes, but this also produced reliable results in terms of the effectiveness measurement. This innovative effectiveness measurement can locate weak regions so appropriate efforts can be made to improve their effectiveness. For example, if the two-stage DEA model shows that inefficiency is linked mainly to stage 1, then a decision maker might improve the indirect drivers by adjusting the demographic and economic policies associated with them.

Future research might use network DEA techniques to examine the effectiveness of drivers of forest water conversation services with internal structures. The internal network structures range from a simple two-stage process to a complex system, where multiple divisions are linked together by intermediate measures. The network DEA approach can help decision makers to understand the system under evaluation by opening the DEA transformation 'black box'. We also hope that the models and methods implemented in this study can facilitate related research in other ecosystem service areas.

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