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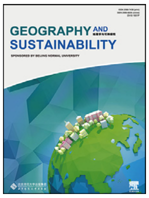

A review of spatial targeting methods of payment for ecosystem services

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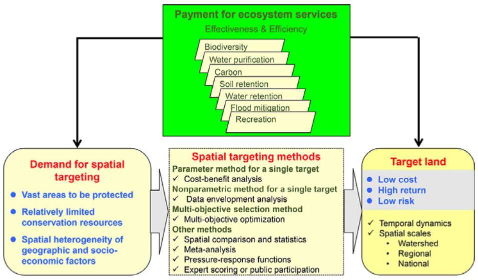
HIGHLIGHTS

- Spatial targeting methods of Payment for Ecosystem Services (PES) were reviewed.
- Cost-benefit analysis is the most widely applied method at different spatial scales.
- Multi-objective optimization and data envelope analysis are also commonly used.
- Advantages, limitations, and application conditions of these methods were compared.
- Combined application of different methods needs to be considered in future research.

GRAPHICAL ABSTRACT



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ABSTRACT

Payments for Ecosystem Services (PES) have been studied extensively over the past decade as an important policy tool for coordinating ecological protection and regional socioeconomic development. One of the greatest challenges of PES implementation is to understand where to pay, i.e., spatial targeting, which can directly impact PES effectiveness and efficiency. In this study, we conducted a systematic review of spatial targeting methods based on literature analysis using Citespace. Firstly, peer-reviewed articles related to spatial targeting of PES were selected from the Web of Science database based on keywords. Cases applying PES spatial targeting methods were then chosen and analyzed after all articles were read. In total, 70% of the chosen cases focused on improving the compensation efficiency of biodiversity or another single environmental objective, whereas the remaining cases focused on coordinating trade-offs between equity and efficiency or multiple environmental objectives. The main PES spatial targeting approaches included cost-benefit analysis, multi-objective optimization, data envelope analysis and other methods aimed at specific issues. Of these, cost-benefit analysis has been most widely applied at different scales, including county, regional and watershed scales. Significant differences among the different PES spatial targeting methods were found, including in PES spatial targeting dimensions, efficiency optimization approaches and method application conditions. The practice of PES spatial targeting requires the selection of appropriate methods based on contextual biophysical and socioeconomic conditions as well as relevant environmental issues. The combined application of PES spatial targeting methods, compensation willingness of stakeholders and dynamic implementation of PES spatial targeting should be considered in future research.

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1. Introduction

Payments for Ecosystem Services (PES) have been recognized over the past decade as an important way to coordinate environmental protection and regional socioeconomic development. Spatial targeting of PES can directly impact the effectiveness and efficiency of related policies. This positioning technology aims to select the most suitable areas for specific policy objectives among all potential ecosystem service providers to be compensated based on regional or individual information (Wunder et al., 2008; Engel et al., 2008; Zhen et al., 2014). Accurate targeting of PES not only reduces costs but can also improve policy effectiveness. For example, the Conservation Reserve Program in the US adopted a cost minimization goal and preferentially selected land with the lowest productivity before 1992, and then gradually turned these areas into “optimal cost-benefit ratio” land (Babcock et al., 1996). Spatial targeting of PES involves understanding of how to allocate compensation funds within a limited budget (Wunder, 2007; Wünschera et al., 2008), and it directly affects compensation effectiveness and efficiency (Alix-Garcia and Wolff, 2014; O’Sullivan et al., 2017).

PES targeting seeks to achieve the following: low costs (Ekroos et al., 2014), high returns (Boyd et al., 2015) and low risk (Börner et al., 2017). In practice, however, many challenges remain including: 1) PES objectives are diverse and trade-offs exist among different targets, which are difficult to coordinate (Wunder, 2007); 2) quantification of the spatial heterogeneity of conservation costs and environmental benefits is difficult (Dai et al., 2009; Duke et al., 2013); 3) potential risks remain uncertain or unclear, i.e., those arising from ecological degradation and climate change, which makes determining conservation costs and environmental benefits increasingly difficult (Duke et al., 2014); and 4) diverse types and contexts of PES require different spatial targeting approaches (Claassen et al., 2008).

Many studies of PES spatial targeting have been conducted due to: 1) the vast number of areas to be protected; 2) limited human, material and financial resources; and 3) spatial heterogeneity of geographic and socioeconomic factors (Engel et al., 2008; Dai et al., 2009). Because of this complexity, various PES spatial targeting methods have been developed using: a range of models from univariate and multidisciplinary (Schroter et al., 2014; Hughes et al., 2018; Mokondoko et al., 2018); cost-benefit analysis (Becker et al., 2018; Lundberg et al., 2018; Rosa Da Conceição et al., 2018); data envelopment analysis (Ferraro, 2004); and multi-objective optimization (Pennington et al., 2017; Wu and Yu, 2017). These methods have been used to identify the spatial heterogeneity of conservation costs and environmental benefits and to enhance the efficiency of PES at diverse spatial scales, including national, regional and watershed (Pynegar et al., 2018; Star et al., 2018; Alix-Garcia et al., 2019; Kroeger et al., 2019).

However, these methods have led to a range of different results with respect to compensation effects and economic efficiency (Mokondoko et al., 2018; Alix-Garcia et al., 2019). Based on bibliometric analysis, we reviewed the major methods of PES spatial targeting, summarized the environmental and socioeconomic targets involved, and expounded the basic principles and application scope of each method. Our specific objectives were to: (1) identify the main types of PES; (2) review the main PES spatial targeting methods and their applications; and (3) clarify the advantages, disadvantages and application conditions of each methodological approach. This systematic review aims to provide a better understanding of PES spatial targeting methods, thereby enabling their more scientific and reasonable application.

2. Methodology

To better understand PES spatial targeting methods and their applications, we conducted a comprehensive search of existing literature for studies related to “payment for ecosystem services”, “spatial targeting” and “land use”. In addition, considering that PES spatial targeting involves investment costs and benefits, we also included “cost-effectiveness” as a search term. The following words were searched in the ISI Web of Science database on 4 November 2019: TS = (payment for ecosystem services * OR environmental compensation * OR PES * OR conservation investment * OR payment for environmental services *) AND TS = (targeting * OR priority * OR tradeoffs * OR spatial * OR Optimizing *) AND TS = (cost * OR benefit * OR cost-benefit * OR cost-effective * OR efficiency * OR effectiveness *) AND TS = (ecosystem services * OR land use * OR landscape * OR land management). The publication timeframe was set from 1976 to 2019. Using the title and abstract, we selected 104 papers related to PES spatial targeting. We then read the full text of each article and 60 PES spatial targeting cases were selected according to the research purposes and methods.

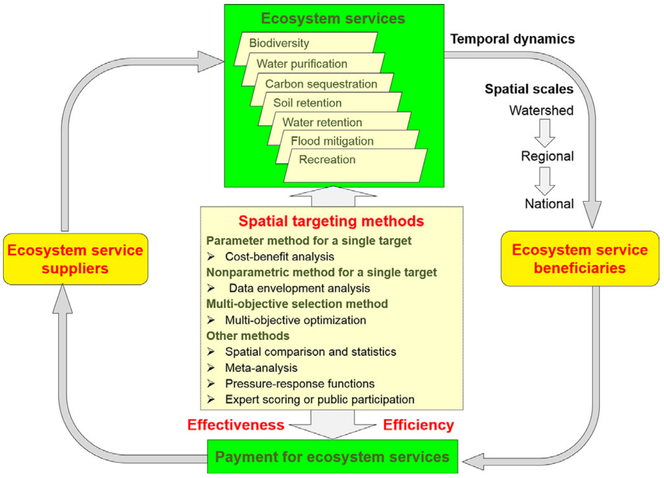

Fig. 1. Application of spatial targeting methods in PES framework.

First, we used Citespace software to analyze the keywords of each chosen article, focusing on high-frequency keywords. Second, in each case, we recorded the: 1) types of ecosystem services involved in PES and their scales; 2) types of PES targets and whether they were single or multiple compensation targets; 3) basic methods used for PES spatial targeting as well as their basic principles and variables; and 4) application cases and effectiveness of these methods. Finally, we summarized and analyzed the collected information and results.

3. Results

3.1. Development of spatial targeting methods

Ecosystems such as forests, grasslands and wetlands provide important services (e.g., water purification, carbon sequestration, soil retention, water retention, flood mitigation and recreation) to beneficiaries at different scales, though can be delivered dynamically due to the impacts of climate change and human activity (Zheng et al., 2019). To maintain their stability, ecosystem services are generally paid for by beneficiaries. To implement PES and achieve high returns with low costs specific areas should be targeted. Various PES spatial targeting methods have been developed to help find cost-beneficial areas for high effectiveness and efficiency as shown in Fig. 1.

PES spatial targeting methods can be classified into four types: parameter methods for a single target (e.g., cost-benefit analysis); nonparametric methods for a single target (e.g., data envelopment analysis); multi-objective optimization methods (e.g., production possibility frontier); and other methods aimed at specific issues (e.g., spatial comparison and statistics) as shown in Fig. 1. Among these methods, cost-benefit analysis was first used in PES spatial targeting (Babcock et al., 1996), followed by data envelopment analysis (Ferraro, 2004). In the face of increasing challenges to coordinate the tradeoffs of multiple PES targets, such as biodiversity conservation, ecosystem services and

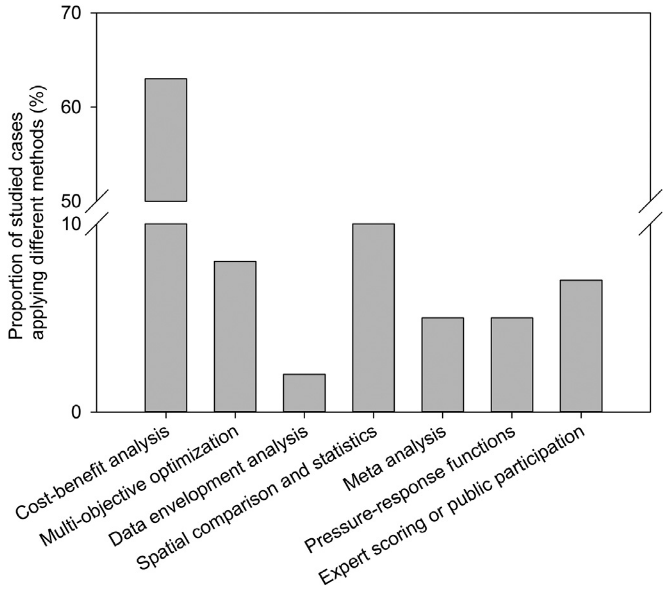

Fig. 2. Proportion of studied cases applying different PES spatial targeting methods.

poverty alleviation, multi-objective optimization was introduced for PES spatial targeting (Gauvin et al., 2010). Recently other methods aimed at specific issues for a given area have been developed (McBride et al., 2007; Howe et al., 2014; Reed et al., 2014; Sheng and Qiu, 2018) (Fig. 1).

Of the PES spatial targeting methods, cost-benefit analysis was used by more than 60% of the studies examined, followed by multi-objective optimization and data envelope analysis. The application of other methods aimed at specific issues accounted for 27% of the cases in our analysis. These methods can be classified into: spatial comparison and statistics; meta-analysis; pressure-response functions; and expert scoring or public participation and were usually aimed at specific issues (e.g., protection willingness) in a given region as shown in Fig. 2.

3.2. *Target types of PES*

The general goal of PES is to protect and improve ecosystem and environmental services. PES targets are often varied due to diverse spatial information including: as physiographic characteristics; environmental issues; and socioeconomic conditions. PES targets can be divided into two groups: single environmental targets, such as biodiversity protection and water purification (Kroeger et al., 2019; Maslo et al., 2019), and multiple targets, e.g., bridging conflicts between ecosystem service conservation and poverty reduction (Jindal et al., 2013; Pennington et al., 2017).

3.2.1. *Single target*

Due to the externalities of ecological protection, relevant individuals or groups are often not sufficiently incentivized to provide additional ecosystem services (Heal, 2000). The main goal of PES is to increase the amount of ecosystem services generated per unit of investment (Sutton and Armsworth, 2014). In the cases we selected, 70% of PES spatial targeting were focused on biodiversity (Didier et al., 2009; Firn et al., 2015; Maslo et al., 2019) or single environmental services including: water purification (Ferraro, 2004; van Grieken et al., 2013; Kroeger et al., 2019); carbon sequestration (Skidmore et al., 2014; Wang and Swallow, 2016; Kim and Cho, 2019); soil retention (Wang et al., 2016; Jones et al., 2017; Jack and Jayachandran, 2019); water retention (Dai and Zhao, 2010; Jia et al., 2012; Song et al., 2012); flood mitigation (Kousky et al., 2013); and recreation services (Paltriguera et al., 2018) as illustrated in Fig. 3a.

We found that PES spatial targeting research has primarily focused on regional and watershed scales, with regional, watershed and national scale cases accounting for 45%, 36% and 17% of cases, respectively. Among the different research scales, biodiversity had the highest frequency (Wendland et al., 2010; Hughes et al., 2018; Alix-Garcia et al., 2019), followed by water purification, carbon sequestration services, soil retention and water retention.

3.2.2. *Multiple targets*

From the perspective of externalities, PES as an incentive mechanism, should give priority to efficiency and ensuring the supply of ecosystem services (Xu et al., 2015). However, from the perspective of providing public goods, PES is often endowed with coordinating the interests of diverse stakeholders. Thus achieving equity and improving efficiency are dual goals of PES (McDonald et al., 2018). Instead of being simply satisfied with the goal of improving a single environmental service, studies have begun to focus on how to achieve win-win outcomes by achieving both environmental benefits and economic development (Wunder et al., 2018).

Excluding the trade-offs between efficiency and equity, it is rare in practice for any measurement to achieve optimal outcomes for all multiple ecosystem services within a certain timeframe due to the inconsistencies of different types of ecological products across spatial and temporal distributions (Tulloch et al., 2015; Wang et al., 2016). Thus some key issues remain for PES, including: balancing various ecosystem services while maximizing total environmental benefits; and reducing the damage caused by trade-offs (Adams et al., 2019; Andeltova et al., 2019).

For the trade-offs mentioned above, PES spatial targets aim to: 1) minimize the trade-offs between biodiversity and ecosystem services; 2) maximize the multiple ecosystem services (Claassen et al., 2008; Wünscher et al., 2008; Larsen et al., 2011); and 3) coordinate the conflicts between biodiversity/ecosystem services and economic development (Gauvin et al., 2010; Schneider et al., 2011; Howe et al., 2014). Of the 60 cases in this study, 30% involved multiple targets. A high frequency (50%) of these studies focused on coordinating trade-offs between biodiversity conservation and ecosystem service improvement (Larsen et al., 2011; Gilroy et al., 2014) or on the maximization of multiple ecosystem services (11%), such as simultaneously improving carbon sequestration and water purification services (Claassen et al., 2008; Mokondoko et al., 2018), water quality and product supply services (Pennington et al., 2017) as shown in Fig. 3b. Other case studies (approximately 39%) involved coordination between biodiversity/ecosystem services and economic development (e.g., poverty alleviation) (Turner et al., 2012; Jindal et al., 2013; Wu and Yu, 2017).

3.3. *PES spatial targeting methods*

Among the PES spatial targeting methods, cost-benefit analysis is the most widely used approach. Multi-objective optimization and data envelope analysis also have broad application. Under different application circumstances, various other methods have been introduced or developed to examine or solve specific issues.

3.3.1. *Cost-benefit analysis*

3.3.1.1. Method overview. Cost-benefit analysis is used to calculate the ratio between compensation costs and environmental benefits in a given PES area (Carwardine et al., 2008; Austin et al., 2015; Campanhão and Ranieri, 2019). This method can help to select PES targets with low costs and high benefits (Duke et al., 2014; Wang et al., 2017). Common cost-benefit analyses include ranking (Drechsler et al., 2016; Campos et al., 2017) and optimal planning methods (Babcock et al., 1996; Robillard and Kerr, 2017; Alix-Garcia et al., 2019). Both are based on the accurate measurement of environmental benefits and conservation costs. The former is usually based on the ratio of benefits to costs, directly sorted under a certain budget, followed by selection of

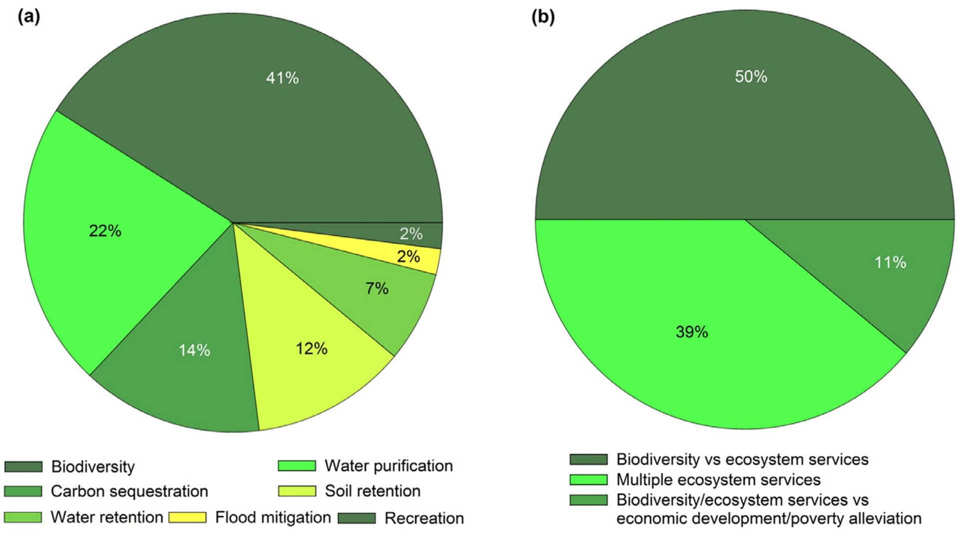

Fig. 3. Compositions of (a) single and (b) multiple targets of PES.

the highest-ranked choices until the budget is exhausted. The latter is usually achieved by establishing a planning function to maximize benefits under certain costs as per the formula below (Babcock et al., 1996):

$$\text{MAX} \sum_{i=1}^{l} x_i e_i \,, \tag{1}$$

$$\text{s.t.} \ \sum_{i=1}^{l} x_i b_i \le B, \tag{2}$$

where:

B is the total budget;

x_i is the ith area to be protected; and

e_i is the environmental benefit of the ith area.

This model is built to optimize total environmental benefits – $x_i e_i$ – under the constraint of total budget B.

3.3.1.2. Method application. Cost-benefit analysis focuses on accounting and mapping of environmental benefits and conservation costs. Environmental benefits include biophysical attributes and the amount or valuate of an ecosystem service. For example, Storms et al. (2005) considered the connection between ocean and land and selected the valuation of juvenile fish per unit area, degree of soil erosion reduction and frequency of sea-land-related species as income variables. There are two main methods of accounting for the additional environmental benefits brought by compensation: one is to calculate the amount of ecosystem services based on biophysical information (Chen et al., 2010; Bateman et al., 2015; Maslo et al., 2019); and the second is to calculate market value directly or indirectly (Liang et al., 2017; Hermoso et al., 2018; Geussens et al., 2019). Expert scoring is a widely accepted method in the calculation of market value (Didier et al., 2009). In addition, proxies such as species number, richness and density can be directly used as environmental benefits (Carwardine et al., 2008; Cattarino et al., 2015; Firn et al., 2015) as well as environmental indices generated by weight assignment (Martin et al., 2018).

Conservation costs are typically divided into three categories: opportunity, implementation, and transaction costs (Liu et al., 2016). These costs can exist at the same time, or opportunity and implementation costs can be considered alone, an approach recognized and applied in previous studies (Wunder, 2007; Wunder et al., 2018; Yang et al., 2019). Recently, the impact of farmers' willingness to consider compensation efficiency has attracted broad attention. Related methods such as auction and willingness-to-pay surveys, e.g., investigating farmer willingness to pay and determining the opportunity costs of protection, have also been applied in practice (Jindal et al., 2013; Cheng and Liu, 2015; Alix-Garcia et al., 2019).

In addition, some factors, such as the level of ecological degradation, can be added to the variable settings of cost-benefit analysis to reduce the risks brought by PES practice. These risks include: (1) the area after PES implementation cannot effectively achieve or maintain the expected environmental benefits over the long-term due to the physical geographic constraints; and (2) some areas to be protected may have a higher probability of ecological degradation or damage due to complex natural and socioeconomic factors (Wünschera et al., 2008; Ezzine-de-Blas et al., 2016; Wunder et al., 2018). By introducing variables, such as ecological degradation, to cost-benefit analysis, and by comparing the possible impact that risk considerations may have on PES spatial targeting, PES implementation efficiency can be improved significantly. Several selected case studies showed that consideration of ecological degradation risks helped to improve PES efficiency, e.g., Mexican Ecological Compensation Project (Ezzine-de-Blas et al., 2016) and Gannan Prefecture Grazing and Grazing Compensation Project (Dai, 2010).

Cost-benefit analysis is the most widely used method in the selection of PES targets (Hily et al., 2015; Mokondoko et al., 2018), including forests, grasslands, farmlands, wetlands and other ecosystem types at the country, watershed and regional scales (Jia et al., 2012; Duarte et al., 2016; Drechsler et al., 2016). The method allows for the successful achievement of single objectives under budget constraints (Dai et al., 2009). For example, in the Lake Eyre Basin (Australia), selecting PES targets based on cost-benefit analysis and spatial information boosted biodiversity conservation efficiency by 20% while only raising costs by 0.01% (Firn et al., 2015). In the Colorado River (US), identification of PES targets through cost-benefit analysis reduced protection costs by 50%–80% compared with the existing policy (Jones et al., 2017). Similar studies have also been conducted in the Amazon Basin (Newton et al., 2012) and Gannan Tibetan Autonomous Prefecture of northwestern China (Dai and Zhao, 2010), among other locations, to improve PES efficiency by mapping the spatial heterogeneity of conservation costs and environmental benefits.

With improvements in comprehensive accounting of conservation benefits and costs, the socio-economic factors influencing PES efficiency (preferences of ecosystem service providers) can be integrated into cost-benefit analysis to improve PES spatial targeting accuracy (Alix-Garcia et al., 2019). Software packages such as InVEST and Maxran are commonly used tools for scenario setting, land use simulation and accounting in cost-benefit analysis (Robillard and Kerr, 2017).

3.3.2. Multi-objective optimization

3.3.2.1. Method overview. In PES policy, multiple objectives usually include trade-offs between efficiency and equity, as well as Pareto optimality of multiple ecosystem services. In this approach, it is necessary to build a multi-target production frontier based on clarification of the spatial patterns of conservation benefits and costs (Zheng et al., 2019). Production possibility frontiers are often used to achieve multi-objective optimization.

Taking the goal of optimizing PES benefits and improving the equity of impoverished participants in PES as an example, we can construct the following equations:

$$\text{MAX} \sum_{i=1}^{n} B_i,\ B_i \in B,\ i = 1, 2, \ldots\ldots n, \tag{3}$$

$$\text{s.t.} \sum_{i=1}^{n} C_i \le C_0,\ C_i \in C,\ i = 1, 2, \ldots\ldots n\ , \tag{4}$$

$$\sum_{i=1}^{n} P_i \ge P_0,\ P_i \in P,\ i = 1, 2, \ldots\ldots n\ , \tag{5}$$

where:

B_i is the conservation benefits obtained by the ith compensated area;

C_i is the costs required by the ith compensated area;

P_i is the impoverished population covered by the ith compensated area;

B is a collection of environmental benefits corresponding to the compensation area;

C is a collection of corresponding protection costs for each compensated area;

P is the number of impoverished people in a given area;

C_0 is a certain budget; and

P_0 is the coverage of the impoverished population.

By solving the above equations, we can draw a curve of conservation benefits and production possibilities for impoverished people under certain budget constraints. This curve can be regarded as a frontier boundary representing the optimal combination of efficiency and equity at various levels. Raising the budget and reducing compensation costs can shift the efficiency-equity curve as a whole. Each point on the curve indicates the level of efficiency or equity corresponding to that particular point. If the budget is not changed, it is not possible to improve efficiency or equity without reducing the other (i.e., Pareto optimality has been reached).

3.3.2.2 Method application. Before the creation of the production possibility curves, the selection of PES targets was conducted by measuring the environmental benefits and costs of multiple targets, using correlation analysis to reveal the cooperative trade-off relationships among the various targets, then selecting compensation targets (Wang et al., 2016; Mokondoko et al., 2018; Dybala et al., 2019), and finally using weight assignment methods to combine multiple targets represented by indices into a comprehensive indicator (Turner et al., 2012). The key task of this approach is to construct a production frontier curve to analyze the contemporaneous correlations among multiple targets under a certain budget in order to reach Pareto optimality (Pennington et al., 2017; Wu and Yu, 2017). In addition, if the goal is to optimize the relationship between economic development (reducing poverty) and environmental protection, it is necessary to consider the specific meanings of the variables used for poverty or equity (as these general terms can have different definitions depending on context), such as fair access and distribution (Geussens et al., 2019).

Multi-objective optimization based on production possibility frontiers and curves has been successfully applied in weighing various ecosystem services and coordinating the relationships between biodiversity/ecosystem service protection and economic development. Many studies have been conducted at the county, regional and watershed scales (Pennington et al., 2017; Wu and Yu, 2017; Kim and Cho, 2019).

Using the SWAT model and production frontier curves a case study in Minnesota (Pennington et al., 2017). found that spatial targeting achieved a 20% reduction in phosphorus output and an 18% reduction in sediment without affecting agricultural production. Wu and Yu (2017) constructed an efficiency-equity frontier curve designed to balance compensation efficiency and equity and applied it to the US Fallow Land Project and found that the project achieved 91% compensation efficiency, but performed poorly on equity. Using the curve, however, the compensation scheme can achieve 18%–23% improvement in equity with an efficiency loss of only about 9%. It is also possible to perform multi-objective optimization on existing PES spatial targeting schemes. However, the spatial targeting results often do not achieve maximum cost-benefit of all single objectives and not all cases can be successfully constructed using multi-objective programming equations (Kim and Cho, 2019). Software packages such as Matlab, Mathematica and Linear Interactive Discrete Optimizer (LINDO) are the most widely used tools for solving multi-objective programming equations.

3.3.3. Data envelopment analysis

3.3.3.1. Method overview. Data Envelopment Analysis (DEA) is a non-parametric method. It refers to linear programming that uses multiple input and output indicators to evaluate the relative effectiveness of comparable units (Wang and Wu, 2011). In practice, the input distance function can be defined as follows:

$$\begin{aligned} D_1\ (x,\ y) &= \max\{\rho : (x/\rho, y) \in S\}, \\ &= (\min\{\rho : (\rho x, y) \in S\})^{-1} \end{aligned} \tag{6}$$

where:

S is land trait technology, which describes the transformation of contract inputs into ideal biophysical traits, such as $S = \{(x, y)$: x can produce $y\}$, which is a joint-production technology assumed to be a closed, convex set with arbitrary inputs and outputs;

vector x is the parcel input;

vector y is the parcel output; and

distance measure ρ is the factor by which all input quantities can be reduced while still remaining within the feasible input set for the given output level. The distance measure is 1) greater than or equal to one, 2) equal to one only if a parcel belongs to the frontier, or 3) non decreasing in x and increasing in y.

The distance function defined by the above formulas can be estimated using a mathematical methods. For example a linear faceted cone is established by observing the input and output of the parcel. Parcels are sorted according to a contract cost that can be reduced based on the trait vector and target of the given parcel. The distance function in DEA usually needs to be calculated with DEA Frontier or another auxiliary software.

3.3.3.2. Method application. To solve PES targeting, the DEA method considers various environmental inputs and outputs from the perspective of efficiency and skips the intermediate link of how each biophysical property generates environmental benefits. There are two important factors that influence the effectiveness of this method: 1) whether the target ecosystem services can be characterized by several biophysical indicators, i.e., reflect the characteristics of the ecosystem effectively and be as comprehensive as possible to improve calculation accuracy (Ferraro and Pattanayak, 2006); and 2) the existence of certain limitations in the number of selected variables and total number of samples and the inability to use number of species (i.e., biodiversity) as an indicator of environmental benefits using this method.

At present, research using this method has only been conducted at the watershed scale. Ferraro (2004) selected five biophysical variables (acreage, distance to intake, priority area, stream length and hydrologically sensitive areas) as output variables and used contract cost as the input variable at the watershed scale. Although DEA can obtain optimal characteristics at the lowest cost, it exhibits an efficiency loss of ∼33%

compared with cost-benefit analysis. Guo (2018) applied this method to croplands in a forest conversion program in Yunnan Province, China and found results similar to that of Ferraro (2004).

The DEA method itself is often used for ecological efficiency measurements rather than for PES spatial targeting. It is still a significant challenge to precisely reflect changes in the returns from target ecosystems under PES policies. However by refining the selection of input variables, it may be possible to improve DEA accuracy (Dai et al., 2009).

3.3.4. Other PES spatial targeting methods

In addition to the three methods previously discussed, less common PES spatial targeting methods exist: spatial comparison and statistics (Claassen et al., 2008; Mokondoko et al., 2018; Dybala et al., 2019; Maslo et al., 2019); meta-analysis (Howe et al., 2014); pressure-response functions (Reed et al., 2014; Sheng and Qiu, 2018); and expert scoring or public participation (Didier et al., 2009; Larsen et al., 2011; Jindal et al., 2013; Paltriguera et al., 2018). Turner et al. (2012) analyzed the spatial relationship between priority areas for biodiversity protection and poverty-stricken areas globally and found that it may be possible to simultaneously increase biodiversity and reduce poverty. In meta-analysis, statistical methods are often used to collect, collate and analyze empirical studies on a certain topic (e.g., trade-offs among stakeholders) and to find the relationships among variables of concern (Howe et al., 2014). Finally, stress-response and hybrid dynamic models, as well as various forms of public participation, have been applied to focus on protection willingness and stakeholder responses, respectively (Reed et al., 2014; Sheng and Qiu, 2018).

The above-mentioned methods are not universal and cannot guarantee optimization and efficiency. For example, meta-analyses are limited due to the lack of data from large-scale field surveys and calculation accuracy cannot be guaranteed and may be hard to customize for particular areas (Howe et al., 2014). However, the above approaches still have advantages in circumventing restrictions on data collection and model construction when compared to other PES spatial targeting methods. They also have specific application advantages when fully considering farmers' (and other stakeholders') willingness to participate, which may significantly impact PES efficiency (Reed et al., 2014).

4. Discussion

With increasing demand for the sustainable management of socio-ecological systems, PES spatial targeting methods have improved and become more diversified. These methods not only explicitly quantify conservation benefits and costs, but also attempt to integrate social-economic criteria (e.g., conservation willingness, economic development level) into PES spatial targeting. As has been demonstrated in numerous case studies, these methods quantify the spatial heterogeneity of conservation benefits and costs to maximize benefits or minimize costs under given budget and geographic constraints, including spatial optimization of nature reserves (e.g., Wu et al., 2002; Wang, 2011; Jones et al., 2017).

PES spatial targeting methods have been used at the national, watershed and regional scales (Robillard and Kerr, 2017; Jack and Jayachandran, 2019). Compared with one-size-fits-all spatial targeting, current targeting methods can effectively improve PES efficiency and better use limited conservation funds (Bryan et al., 2016; Campos et al., 2017; Jones et al., 2017). Among the methods reviewed in this paper, cost-benefit analysis was most frequently used, constituting not only the mainstream PES spatial targeting method, but also the one most applicable in improving compensation efficiency over expanding scales (Boyd et al., 2015; Abell et al., 2018; Pynegar et al., 2018). However, each method has specific advantages as shown in Table 1. These advantages include:

i) achieving the optimal solution under a certain budget. Cost-benefit analysis can maximize the conservation benefits within a certain budget through optimum programming (Dai, 2010) for a single target. The production of possibility frontiers can achieve simultaneous multi-objective optimization (Calvet-Mir et al., 2015), as well as optimization of existing compensation spatial targeting schemes (Wu and Yu, 2017);
ii) integrating biophysical and socioeconomic information. Factors such as risk and willingness-to-pay can be integrated into PES through geographic models and travel cost methods (TCM) to improve calculation accuracy of conservation benefits and costs (Ezzine-de-Blas et al., 2016; Kim and Cho, 2019);
iii) avoiding the subjectivity of parameter settings. The DEA method does not need to monetize compensation proxies or benefits and has low data requirements as well as intuitive results, as multiple ecosystem services cannot easily be reduced to a single dimension (Ferraro., 2004).

However, as described above, there are also various limitations for existing spatial targeting methods (Hermoso et al., 2018) including the following:

i) limitations and details abstracted from the real world make it difficult to fully integrate relevant knowledge from ecology, economics, geography, sociology, and other disciplines, which may be key to various important practicable concerns, such as the accurate assessment of preferences (Wunder et al., 2018).
ii) the lack of universally accepted method. Methods cannot be applied at all spatial scales, which makes the choice of method sensitive to environmental and socioeconomic contexts, as well as the overall policy goal of a given PES (Ren et al., 2018).
iii) the lack of interactive analysis for examining the socioeconomic impacts of compensation. Considering that PES calls for the coordination of economic development and biodiversity/ecosystem service protection, the interactive analysis of existing research methods on the socioeconomic impacts of compensation is limited. In particular, there has been insufficient focus on temporal dynamics in the existing literature.

In practice, these PES spatial targeting methods are not used independently. Due to the various disadvantages, improving spatial targeting needs to combine different methods, including, but not limited to, the targeting methods discussed above. The combination of different methods could help overcome the limitations of a single approach. For example, integrating cost-benefit analysis and multi-objective optimization could help achieve maximum overall benefits of multiple objectives (Cattarino et al., 2015). The Land Change Modeler tool, which assesses and predicts Land Use and Land Cover (LULC) changes and the Water Assessment Tool model, which assesses target watershed interventions for sediment reduction, were combined with the cost-benefit analysis to improve the efficiency of watershed management in Brazil (Kroeger et al., 2019). In addition, we offer the following recommendations as a way to improve the accuracy and applicability of PES spatial targeting methods.

Understand the spatial characteristics of biophysical and socioeconomic conditions in the PES area. The main research topics should include: the effects of spatial dependence, spatial transfers and spatial distribution of conservation benefits and costs (Babcock et al., 1996; Wu et al., 2002); differences between potential environmental benefits and actual environmental benefits and their measurement methods (Bryan et al., 2016); spatial assessment methods of conservation costs (Liu et al., 2016); and input-output thresholds for environmental benefits and conservation costs (Wu et al., 2002).

Integrate farmers' willingness-to-pay for PES with measurement of conservation benefits and costs. Willingness-to-pay methods have been widely applied in PES research, with an increasingly robust theoretical foundation and accrued practical successes (Kim and Cho, 2019). Several factors should be considered to quantify PES willingness-to-pay accurately, including age, education level and attitudes to existing PES policies by relevant stakeholders. These can then be integrated into assessment

Table 1
Comparison of PES spatial targeting methods.

Method	Principle	Advantages	Limitations	Method application condition
Cost-benefit analysis	Calculate ratio of conservation costs to benefits or maximize benefits within certain budget	• Achieve maximum compensation benefits for a single target under a defined budget (Veloz et al., 2015; Kroeger et al., 2019) • Integrate risk and willingness to improve accuracy (Tulloch et al., 2015; Ezzine-de-Blas et al., 2016)	• Narrow focus on single targets regardless of trade-offs or multiple targets (Hily et al., 2015; Wang et al., 2016)	• Single target • Spatial conservation benefits costs can be calculated
Multi-objective optimization	Build multi-objective function, using simulated annealing	• Analyze trade-offs and synergies between multiple objectives (Pennington et al., 2017; Gilroy et al., 2014) • Optimize PES spatial targeting scheme and achieve multi-objective Pareto optimality (Wu and Yu, 2017);	• Optimal cost-benefit ratios cannot maximize all goals (Pennington et al., 2017) • Not all scenarios can be optimized simultaneously (Cattarino et al., 2015)	• Multiple targets • Spatial conservation benefits costs can be calculated • Understanding relationships among different targets
Data development analysis	Construct distance function	• No need to assign values to compensation income parameters or monetize compensation income • Strong operability and intuitive results (Ferraro, 2004)	• Only efficiency ranking can be obtained, as opposed to optimal return ratio (Ferraro and Pattanayak, 2006; Dai et al., 2010)	• Single target • Biophysical characteristics of targeted ecosystem services are accessible

models to quantify willingness-to-pay in the real world which would improve PES spatial targeting.

Dynamic implementation of PES spatial targeting. Regional land use and ecosystem services are always changing. Scenario analysis methods or long-term land use monitoring can be used to analyze changes in ecosystem services and trade-offs between ecological conservation and poverty reduction (Kurttila et al., 2019). They can also aid in the assessment of PES efficiency over time and under different spatial targeting schemes. These analyses could help dynamically identify suitable PES targeting to enhance efficiency at different stages of socioeconomic development.

5. Conclusions

Diverse PES spatial targeting methods have been widely used to select the most suitable areas for implementing PES policies in an effort to improve their effectiveness and efficiency at watershed, regional and national scale. Cost-benefit analysis is the most commonly used method, with more than 60% of studies in our analysis using this method, followed by multi-objective optimization and data envelope analysis. Other methods aimed at specific issues including spatial comparison and statistics, meta-analysis, pressure-response functions and expert scoring or public participation. Among the different PES spatial targeting methods, PES spatial targeting dimensions, efficiency optimization approaches and method application conditions were significant different. The successful practice of PES spatial targeting requires the selection of appropriate methods based on contextual biophysical and socio-economic conditions as well as relevant environmental issues. To improve PES spatial targeting methods the following strategies are recommended: combined application of multiple methods; compensation willingness of stakeholders; and dynamic implementation of PES spatial targeting.

Declaration of Competing Interest

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

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