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Integrating Top-Down and Bottom-Up Approaches Improves Practicality and Efficiency of Large-Scale Ecological Restoration Planning: Insights from a Social–Ecological System

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ABSTRACT

Ecological restoration policies and their implementation are influenced by ecological and socioeconomic drivers. Top-down approach-based spatial planning, emphasizing hierarchical control within government structures, and without a comprehensive consideration of social–ecological interactions may result in implementation failure and low efficiency. Although many researchers have indicated the necessity to engage social–ecological interactions between stakeholders in effective planning processes, socioeconomic drivers of ecological restoration on a large scale are difficult to quantify because of data scarcity and knowledge limitations. Here, we established a new ecological restoration planning approach linking a social–ecological system framework to large-scale ecological restoration planning. The new spatial planning approach integrates bottom-up approaches targeting stakeholder interests and provides social considerations for stakeholder behavior analysis. Based on this approach, a meta-analysis is introduced to recognize key socioeconomic and social–ecological factors influencing large-scale ecological restoration implementation, and a stochastic model is constructed to analyze the impact of socioeconomic drivers on the behavior of authorities and participants on a large scale. We used the Yangtze River Basin-based Conversion of Cropland to Forest Program (CCFP), one of the largest payments for ecosystem service programs worldwide, to quantify the socioeconomic impacts of large-scale ecological restoration programs. Current CCFP planning without socioeconomic considerations failed to achieve large-scale program goals and showed low investment efficiency, with 19.71% of the implemented area reconverting to cropland after contract expiry. In contrast, spatial matching between planned and actual restoration increased from 61.55% to 81.86% when socioeconomic drivers were included. In addition, compared to that with the current CCFP implementation, the cost effectiveness of spatial planning with social considerations improved by 46.94%. Thus, spatial optimization planning that integrates both top-down and bottom-up approaches can result in more practical and effective ecological restoration than top-down approaches alone. Our new approach incorporates socioeconomic factors into large-scale ecological restoration planning with high practicality and efficiency.

1. Introduction

Macro-scale ecological restoration programs have been implemented worldwide to restore ecosystem services by paying participants compensation to alter their land management practices to benefit the environment. Land conversion is implemented in interacting social–ecological systems (SESs) coupled across scales where humans are a part of nature. Thus, the successful implementation and cost effectiveness of these programs depend on the interactions between humans and natural systems [1].

Currently, top-down approaches originating from hierarchical government structures [2] have created widespread and immediate conservation mandates and are thus widely applied in

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large-scale ecological restoration programs [3]. Specifically, a higher-level government ("buyer"), like the central government, sets nationwide ecological restoration goals based on the biophysical processes of land conversion. The lower-level government or local-scale organizations, such as local governments, are tasked with achieving these goals through negotiations with the participants ("seller"), like landowners, to achieve certain conservation mandates [4–6]. However, spatial mismatches in implementation often occur on a broad scale, where decisions are based on coarse scale information and the local scale, and the implementation of on-the-ground restoration is impacted by resource limitations and social complexity [7–9]. This mismatch often results in the failure of large-scale restoration planning due to a failure to characterize social–ecological interactions affecting stakeholder behavior during the implementation processes and thus, fails to achieve the desired goals [10,11]. To minimize implementation conflicts, large-scale restoration planning should incorporate a comprehensive analysis of social–ecological interactions, including socioeconomic constraints, participant willingness [12,13], and decision-maker preferences [11].

To better understand the complex social–ecological interactions involved in ecological restoration implementation, an SESs framework, assuming that ecological and social systems are linked to each other, should be coupled with large-scale ecological restoration planning to achieve the desired outcomes. The SESs framework clarifies the relationships between the ecological process of land use conversion in biophysical systems, the socioeconomic processes among stakeholders (i.e., decision-makers and participants) in social systems, and ecological restoration implementation [14]. Thus, the spatial planning of ecological restoration based on the SESs framework can reduce implementation conflicts and realize practical and effective goals with full consideration of local cultural, socioeconomic, and ecological contexts [15]. Based on the SESs framework, the socioeconomic process of stakeholder consensus can be incorporated into large-scale ecological restoration planning. Stakeholder behavior analysis can be conducted through bottom-up approaches by engaging stakeholders in a local area to address problems of local interest. With the integration of top-down and bottom-up approaches, land conversion spatial planning can easily create collaborative and inclusive governance and collective action for large-scale implementation and fulfill the needs of stakeholders at multiple levels (such as higher-level government, local decision makers, and landowners) [2,3].

Although bottom-up approach-based stakeholder behavior analysis has been explored with regard to local vegetation restoration practices, quantitative analysis of the complex social–ecological interactions that influence large-scale stakeholder behavior is challenging [16,17]. Both ecological and socioeconomic heterogeneity make it difficult to identify key variables influencing stakeholder behavior, and traditional data collection methods (e.g., household surveys) are often impractical for investigating overall stakeholder needs. As such, new approaches are required to incorporate quantitative analyses of social–ecological interactions into large-scale spatial restoration planning.

Previous studies using household survey data (e.g., household characteristics, government incentives, and local economic development) have provided information on the effects of socioeconomic factors on stakeholder behavior in different regions [18,19]. Meta-analysis can identify commonalities across different case studies and determine which variables result in behaviors of interest [20]. The collation of decentralized and scattered datasets from discrete locations can be used to identify key social–ecological variables that influence stakeholder behavior at large scales. Such an analysis provides a practical way of overcoming data limitations and cognitive deficiencies to estimate the effects of socioeconomic interactions on the implementation of large-scale ecological restoration programs.

In the current study, based on the SESs framework, we integrated top-down and bottom-up approaches to incorporate social–ecological drivers into large-scale ecological restoration planning. We selected the Yangtze River Basin-based Conversion of Cropland to Forest Program (CCFP), one of the largest payments for ecosystem service (PES) programs in the world, as a case study. We first evaluated the practicality (spatial match) and cost effectiveness of the current top-down-based CCFP planning. We then used our integrated framework to analyze the social–ecological impact on stakeholders and provided a new CCFP planning outcome, including social–economic drivers. We analyzed and compared the practicality and cost effectiveness of different CCFP plans to determine the importance of socioeconomic impact on the effectiveness of ecological restoration. We aimed to: ① provide a new approach to quantitatively analyze socioeconomic impacts on ecological restoration program implementation at large scales and ② demonstrate the importance of socioeconomic considerations in improving the practicality and effectiveness of PES programs. Finally, we hope that integrating top-down and bottom-up approaches in spatial planning will provide a feasible way to develop effective large-scale ecological restoration policies.

2. Study area and methods

2.1. Yangtze River Basin and CCFP implementation based on top-down approach

The Yangtze River Basin is the largest watershed in China, encompassing nearly 1.8×10^6 km^2 of land, and exhibits enormous ecological and economic heterogeneity (Fig. 1). The basin is the most populous and agriculturally productive economic belt in China and contains over 40% of the nation's population and agricultural output [19]. The terrain gradually flattens from west to east, and soil erosion has become a serious environmental problem, particularly in the upper reaches of the river. In 1998, catastrophic flooding and soil erosion within the basin endured many lives and caused more than 12 billion USD in economic losses [21]. In an attempt to prevent further soil erosion and flooding, the CCFP was implemented in the basin in 1999.

The CCFP, also known as the Grain for Green and Sloping Land Conversion Program, covers a broad geographic span, a large number of participants, and tremendous financial commitments [22]. The program aims to convert sloping croplands into forests to achieve soil erosion control [23]. For cost-effective management and program operability, a top-down approach was adopted for CCFP implementation. In the first round (1999–2013) of CCFP planning under the National Forestry Administration, target plots were defined as cropland patches on slopes > 25°, excluding prime cropland (areas permanently protected against urban development), where productivity was the lowest and erosion was the highest. In 2014, the CCFP was re-launched with extended target areas, croplands on slopes > 15° near water sources, and areas important for water supply. Croplands were designated for conversion into either "ecological forests" or "economic forests," and landholders who agreed to land-management conversion were eligible for compensation either in cash or in-kind (e.g., grain subsidies and seedlings for economic forest plantations) via contracts with the local government [24]. The CCFP payments included a one-time fee of 750 $CNY\cdot ha^{-1}$ (1 ha = 10 000 m^2) for saplings or seeds, an annual living allowance of 300 $CNY\cdot ha^{-1}$, and an annual grain/cash subsidy of 1575 $CNY\cdot ha^{-1}$ [25]. After two rounds of the CCFP, ecological restoration achievements, including improvements in water and soil conservation, timber, carbon sequestration, biodiversity

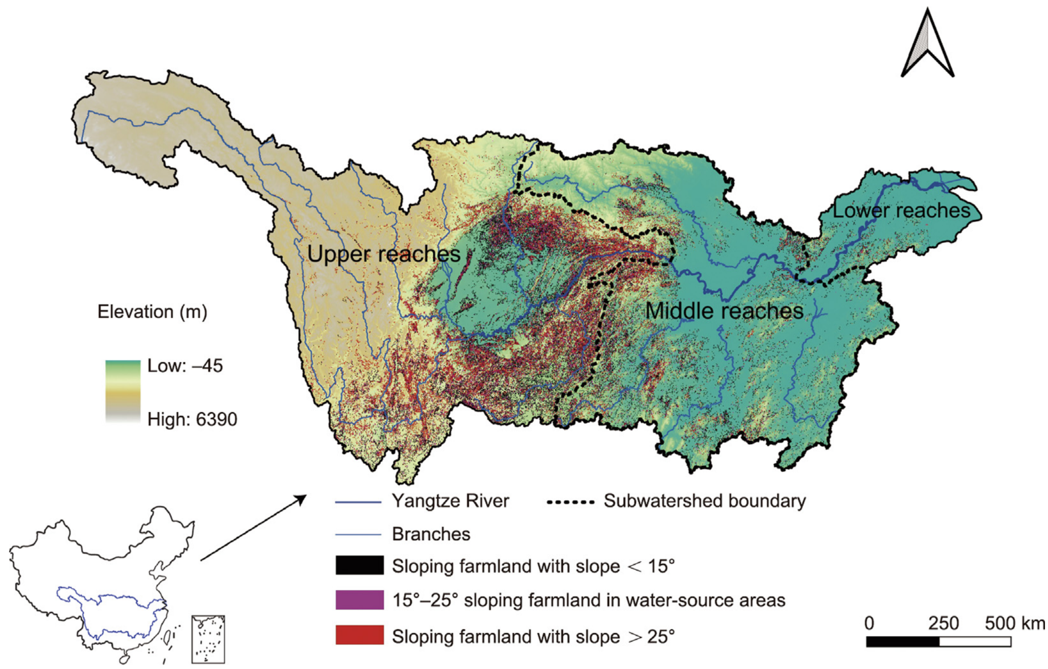

Fig. 1. Location of the Yangtze River Basin, China.

habitat, water quality [26–28], and economic development, including rural livelihood improvement and poverty alleviation, have been widely observed [29].

2.2. Analytical framework in SESs

Large-scale ecological restoration programs, such as the CCFP, are typical SESs. Linking the SESs framework to large-scale ecological restoration planning helps to better understand comprehensive social–ecological interactions in program implementation [17]. Based on the SESs framework, the integration of top-down and bottom-up approaches provides a quantitative way to analyze the socioeconomic impacts on program implementation and guide spatial planning.

In this study, we created a general framework for ecological restoration planning in SESs by integrating the top-down and bottom-up approaches. We used the CCFP in the Yangtze River Basin as an example and put it into the SESs framework (Fig. 2(a)). In this framework, the CCFP can be divided into three sub-systems: a resource system and resource system unit (e.g., slope and grain yield), governors (e.g., local government), and actors (e.g., farmers). The outcomes (practicality and efficiency) of CCFP planning are controlled by social–ecological interactions among these three subsystems.

Based on the SESs framework, we analyzed the complex social–ecological interactions involved in CCFP implementation. For the current CCFP policy with a top-down approach, the implementation rules developed at the central government level are based on the ecological characteristics related to land use conversion in the resource subsystems [30,31]. The central government distributed land enrollment quotas followed by subsequent distribution through counties, townships, and finally to participating villages. The million decentralized volunteer farmers were core agents of the program. Although the CCFP standards were set by the central government, the actual implementation was still locally variable and, in many ways, flexible in different places and regions, especially at the county level, the main implementation unit of the policy. Local (village and township) governments, serving as key mediators between the central government and farmers, have the right to decide which plots are enrolled in the CCFP [32]. Farmers also have the right to decide whether to participate in the CCFP. CCFP implementation mismatch or failure occurred when the local government chose target plots that did not coincide with the CCFP standards, or the farmers were unwilling to participate in the CCFP after the contract ended and reconverted the plot to cropland. Thus, the behaviors, attitudes, and preferences in both the governance subsystem (local governments) and actor subsystem (farmers) influenced by local political settings (such as trust between government and farmers), social norms, and economic conditions (such as gross domestic product (GDP) and household income) heavily affect CCFP implementation [18].

To reduce the spatial mismatch and improve program efficiency in large-scale ecological restoration implementation, it is necessary to quantify the social–ecological impacts on the behavior of stakeholders (local government and farmers). In this study, we integrated fine-scale bottom-up approaches into large-scale spatial planning. The integrated approaches allow quantitative analysis of the impacts of stakeholder behaviors on CCFP implementation by ① identifying key social–ecological variables using meta-analysis, ② establishing stakeholder behavior modeling, and ③ predicting the probability of successful implementation (Fig. 2(b)). We tested the practicality and cost effectiveness of spatial planning using top-down and bottom-up integrated approaches to determine the impact of socioeconomic processes on CCFP implementation.

2.3. Identification of social–ecological variables influencing decision-maker preference and participant willingness based on a bottom-up approach

Socioeconomic impacts on program implementation can be reflected in decision-maker preferences and participant willingness. The CCFP is a government-led PES, yet the local government, which decides the CCFP implementation plots, and landowners who participate in the CCFP and receive compensation, are considered core agents of the program. We used meta-analysis to identify key social–ecological factors affecting CCFP implementation and constructed a stochastic model to estimate the probability of CCFP

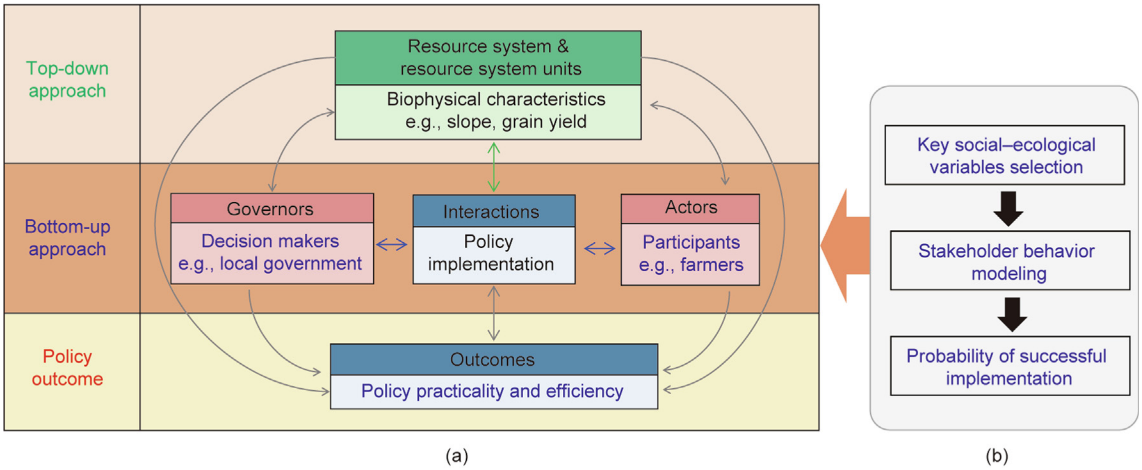

Fig. 2. Integrated framework for top-down and bottom-up approaches within social–ecological systems based on a large-scale ecological restoration program. (a) An analytical framework was established to integrate top-down (focusing on ecological characteristics) and bottom-up (considering behaviors of stakeholders) approaches to increase practicality and efficiency of large-scale ecological restoration programs. (b) A three-step bottom-up approach to integrate impacts of stakeholder behaviors from previous fine-scale research into large-scale ecological programs.

implementation in cropland plots based on social–ecological process analysis. The selection of social–ecological variables may be restricted by local government land enrollment strategies and farmers' willingness to participate [33].

Socio–ecological factors influencing decision-maker preferences. Based on previous fine-scale studies, we found that local governments prefer to enroll high-slope, low-quality, and contiguous land near roads [23,34,35]. Therefore, we selected social–ecological variables, including biophysical (slope and average grain yield from 2010 to 2015) and socioeconomic factors (distance of croplands to roads and distance of croplands to households), as key factors influencing decision-maker preferences.

Social–ecological factors influencing participant willingness. To understand participant willingness on a large scale, social–ecological variables were collected based on the SESs framework, and a meta-analysis was used for key social–ecological variable selection.

First, five categories (i.e., land features (resource units and resource system), government characteristics (government system), household characteristics (actors), socioeconomic and political settings (social, economic, and political settings), and socioeconomic interactions between the decision maker and participants (interactions)) were set to classify the social–ecological variables based on the first-level core subsystem of the SESs framework (Fig. 2) [14]. The key social–ecological variables were obtained from a meta-analysis of small-scale case studies [15]. We used "Sloping Land Conversion/Grain for Green Project," "Conversion of Cropland to Forest Program," "householder," "farmer," and "participation" as keywords to collect case studies from the peer-reviewed scientific literature ("Web of Science," "ScienceDirect," and China National Knowledge Infrastructure ("CNKI")). The inclusion criteria were that the study had to provide sufficient evidence to assess social–ecological impacts on CCFP participant willingness and quantitatively analyze the relationship between social–ecological factors and participation rates. In total, 47 case studies were selected for which the relevant social–ecological factors influencing participant willingness could be traced (Table S1 in Appendix A).

Second, key social–ecological variables influencing participant willingness were selected based on two standards: a significant correlation with participant willingness documented more than ten times based on meta-analysis and data availability. Seven social–ecological indices were chosen to reflect the key social-ecological factors influencing participant willingness. The two biophysical indices were slope and grain yield, which reflect the impact of slope and opportunity costs, respectively. The five socioeconomic indices were education level, off-farm labor allocation (labor allocation toward non-farm activities), household labor endowments (the available labor for households), age, and household income level, reflected by the average illiteracy rate at the county level, distance to the metropolis, population, average percentage of people aged above 65 at the county level, and GDP (Table S2 in Appendix A).

2.4. Probability simulation of CCFP implementation in cropland plots

Based on the key social–ecological variables selected, we used the MaxEnt model, a fuzzy classification algorithm based on the principle of maximum entropy [35], to quantify the social–ecological impacts on stakeholder behavior and simulate the probability of successful CCFP implementation in sloping cropland plots, that is, an enrolled plot will not be reconverted after the contract ends. In this study, we used implemented CCFP plots from 2000 to 2010 as sample data, as the first phase of the CFFP ended in 2013. Successfully implemented CCFP plots from 2000 to 2015 were obtained from the CCFP plots from 2000 to 2015, extracting the reconverted plots from 2010 to 2015. Land use data for 2000, 2010, and 2015 and slope data were obtained from national land survey data. We used the Dismo package[†] in R for correlation analysis to select variables for the MaxEnt simulation. If the correlation between two variables was above 0.95, only one of the variables was selected for the simulation [36]. We found that GDP was significantly correlated with the average village population, distance to cities, and distance to roads, while the slope was highly related to average grain yield and distance to roads.

Thus, we excluded the average grain yield, distance to road, and average village population from key social–ecological variables and selected GDP and slope as independent variables for regression analysis. Finally, six social–ecological indices, including slope, GDP, distance from cropland to household, illiteracy, age, and distance from household to metropolis, were chosen and used to estimate CCFP implementation probability.

Two-thirds of the sample plots were selected to calibrate the fuzzy classification algorithm and one-third were used to validate the output probability map. Cross-validation was maintained in the replicate run, and the number of iterations was fixed at 500.

[†] https://CRAN.R-project.org/package=dismo.

We used 0.1 as the regularization number to avoid overfitting the test data [37]. The area under the receiver operating characteristic (ROC) curve was used to measure model accuracy, ranging from 0.5 (random prediction) to 1 (perfect discrimination) [38].

In this study, the ROC score demonstrated high accuracy in CCFP implementation prediction (ROC score = 0.803). Based on the modeling results, the contributions of social–ecological factors and their impact on MaxEnt prediction were analyzed using the Jackknife test (Table S3 in Appendix A). Response curve analysis was also performed to explain the social–ecological impact on decision-maker preferences.

2.5. Embedding a bottom-up approach into CCFP planning

Based on the probability map of successful CCFP implementation in sloping cropland plots, we adopted the multi-objective spatial optimization method to select target plots for spatial planning with socioeconomic dimensions. Target plots were selected based on three objectives: ① target plot probability above 0.5, ② plots with the highest implementation probability prioritized, and ③ overall plot area not larger than that of current CCFP target plots, solely based on biophysical characteristics.

2.6. Practicality and efficiency of CCFP planning integrating top-down and bottom-up approaches

To estimate the cost effectiveness of CCFP spatial planning with embedded social considerations, we tested the cost effectiveness of three CCFP spatial targeting scenarios: ① current CCFP targeting plan, ② targeting plan embedded with socioeconomic drivers, and ③ actual CCFP implementation from 2015 to 2017.

We used the actual CCFP implementation from 2015 to 2017 to evaluate the practicality and efficiency of different spatial planning approaches.

(1) Current CCFP spatial planning based on a top-down approach. For current CCFP planning based on ecological analysis alone, target plots were croplands, excluding prime croplands (obtained from land survey data), with slopes > 15° in water-source areas or > 25° in non-water-source areas [24]. Water source areas were obtained from a list of the most important water sources in China published by the Chinese Ministry of Water Resources.

(2) CCFP spatial planning integrating top-down and bottom-up approaches. The target cropland plots for spatial planning with an embedded bottom-up approach, which also excluded prime croplands, were selected based on the method mentioned in the previous steps.

(3) Actual CCFP implementation from 2015 to 2017. The actual sloping cropland converted to forest from 2015 to 2017 was obtained via land survey data analysis.

Practicality. We analyzed the degree of spatial matching between CCFP spatial planning and actual implementation to reflect planning practicality. We created a 1 km × 1 km fishnet across the study area as grid cells. Grid cells containing actual CCFP plots were selected as implementation cells, and cells containing both actual and candidate CCFP plots were selected as matched cells. Although this only provides an approximation because not all cells are under the CCFP, it is a common approach applied in pixel-based imagery classification [39]. The matching degree is the percentage of matched cells in the actual implementation cells.

Efficiency. We also analyzed the efficiency of different CCFP spatial plans based on the proxy indicator of benefit (soil retention, the main goal of CCFP) and payment from CCFP. As there was no specific CCFP spatial planning from 2015 to 2017, we used the target area from the CCFP task report [40] as the selection rule and randomly selected candidate CCFP plans 30 times. The average cost effectiveness of the selected CCFP plans was used to compare the efficiency of different CCFP spatial plans. The efficiency of CCFP implementation was computed using the following equations:

$$E = B/C \tag{1}$$

$$C = p \cdot P_{\mathrm{s}} + (1 - p) \cdot P_{\mathrm{f}} \tag{2}$$

where E is the CCFP implementation efficiency, soil retained under CCFP payments per hectare (kg·CNY^{-1}); B is the benefit of soil retention increment (kg·(ha·a)$^{-1}$) after CCFP implementation (calculated by Kong's method [41]); C is the CCFP investment per hectare; p is the probability of target plots being successfully transitioned through land-management conversion; P_{s} is the payment (CNY·(ha·a)$^{-1}$) for successful implementation of CCFP; and P_{f} is the payment (CNY·(ha·a)$^{-1}$) for failed implementation of CCFP (five times the current payment, the average payment value based on a previous participant willingness survey [35,42]).

3. Results

3.1. Practicality of first-round CCFP planning based on a top-down approach

Based on the State Forestry Administration criteria, target croplands for the first round of the CCFP and croplands on slopes > 25°, excluding prime croplands (Fig. 3), were primarily distributed in decentralized and mountainous areas. However, only 59.30% of the CCFP plots enrolled between 2000 and 2010 fell within the above target areas, indicating that 40.70% of the plots did not follow the CCFP policy rules and were implemented on slopes < 25°. Moreover, 19.71% of CCFP plots were reconverted to cropland after contract expiry, indicating the low practicality of current slope-based only CCFP planning and top-down approaches.

3.2. Impacts of socioeconomic factors on practicality of CCFP planning based on a bottom-up approach

In SESs, both the CCFP land enrollment preferences of local governments and farmers' willingness to participate were significantly influenced by social–ecological factors. The former was significantly influenced by distance to road and opportunity costs of land, whereas the latter was significantly influenced by slope, opportunity costs of land, education level, off-farm labor allocation, household labor endowments, and household income level (Fig. 4(a), Table S1). After exclusion of strongly correlated variables, CCFP implementation was influenced by GDP (45.6%), distance from households to cropland (13.8%), illiteracy (13.6%), and slope (13.4%) (Fig. 4(b), Table S3). Taking these socioeconomic factors into account in the bottom-up approach increased the accuracy of the CCFP implementation prediction (ROC score = 0.803) (Fig. 4(c)).

3.3. Practicality and efficiency of adjusted CCFP pattern integrating top-down and bottom-up approaches

Compared to that with candidate CCFP croplands without socioeconomic considerations (Fig. 5(a)), the spatial matching rate of candidate croplands with socioeconomic factors to actual CCFP croplands registered between 2015 and 2017 increased from 61.55% to 81.86% (Fig. 5(b)). These results suggest that incorporating bottom-up approaches could significantly improve the practicality of CCFP spatial planning implementation.

The successful implementation rate from spatial planning integrating the bottom-up approach increased from 52.82% to 77.53% with socioeconomic impacts (Fig. 6(a)). Furthermore, based on

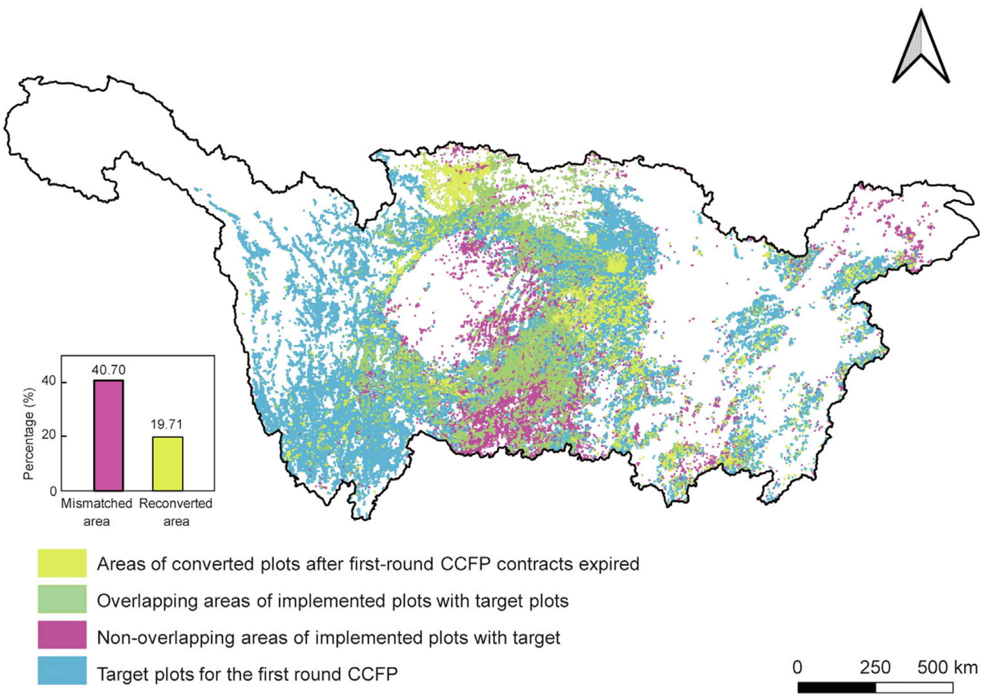

Fig. 3. Distribution patterns of CCFP candidate and actual croplands between 2000 and 2010 and reconverted croplands after the first-round CCFP.

the average decrease in soil erosion under payment for each hectare, the cost effectiveness of CCFP planning based solely on biophysical attributes, 10.38 kg·CNY^{-1} was the lowest, and that of the spatial planning integrating the bottom-up approach improved by 46.95% (Fig. 6(b)), compared to that with the actual CCFP implementation. The results indicate the importance of a bottom-up approach with socioeconomic integration to improve spatial planning efficiency.

4. Discussion

For large-scale ecological restoration programs implemented in SESs, a better understanding of social–ecological interactions is essential to a successful implementation. Top-down approaches based on biophysical characteristics can provide policymakers with a better understanding of the ecological processes involved in restoration [43]. However, spatial planning that relies solely on the biophysical processes of ecological restoration may fail despite considerable investment in time and effort [17]. In this study, we examined the success of top-down prioritization of plots for the CCFP policy based solely on biophysical attributes (i.e., slope). The results show that in the first round of the CCFP (2000–2010), over 40% of the actually implemented plots in the Yangtze River Basin (Fig. 3) failed to comply with policy rules regarding specific minimum slopes, resulting in a failure to maximize outcomes for ecological restoration. In addition, over 19% of the implemented CCFP plots were reconverted to cropland after contract expiry. These results are similar to previous observations in other CCFP case studies [33,44,45]. The mismatch and failure of implementation highlights the low efficiency of spatial planning based on ecological process analysis alone.

Effective program implementation requires information on the effects of socioeconomic factors on stakeholder behavior, such as preferences (e.g., maximizing income and minimizing investment) and background experiences (e.g., socioeconomic norms) [46,47]. Bottom-up approaches are essential for obtaining information on stakeholder needs and reducing implementation conflicts. Most agent-based models focusing on stakeholder behavior quantification at the local scale cannot be applied on a large scale because of data limitations and limited knowledge of complex socioeconomic interactions [48,49]. Traditional data collection methods, such as household surveys, are impractical for collecting data on overall social–ecological factors for scientific modeling. Consequently, the main challenge for quantifying large-scale ecological restoration processes is to identify the indicators of key social–ecological factors influencing agent behavior. In this study, we provide a new method to collect data on stakeholder behavior and model large-scale ecological restoration processes by using meta-analysis and regression modeling and integrating top-down and bottom-up approaches based on the SESs framework.

Compared to previous analytical frameworks in SESs [50,51], our method provides a quantitative analysis of the social–ecological impact of large-scale ecological restoration implementation and spatial information on large-scale ecological restoration planning. Based on this approach, we find that the CCFP planning we propose here shows an improvement in the spatial matching rate (from 61.55% to 81.86%) (Fig. 5) as well as the cost effectiveness (Fig. 6). The results emphasize the contribution of socioeconomic impacts to large-scale PES program implementation. Based on our regression model results, we find that social–ecologica factors, such as household income level (GDP), distance to household, education level, slope, and age (average percentage of people aged above 65), significantly affect the implementation of CCFP in the Yangtze River Basin by influencing local government preferences, the willingness of residents to participate, and long-term adherence to the program. In general, the CCFP was more likely to fail in areas with low household income and education, high age, long distances from settlements, and low slopes (Fig. 4(b)).

The empirical evidence from field surveys supports our findings. In our study, distance to the household was highly related to the local government's preference for target plot selection. Similar studies have shown that most village and township government decision-makers prefer the easier-to-implement method of simply

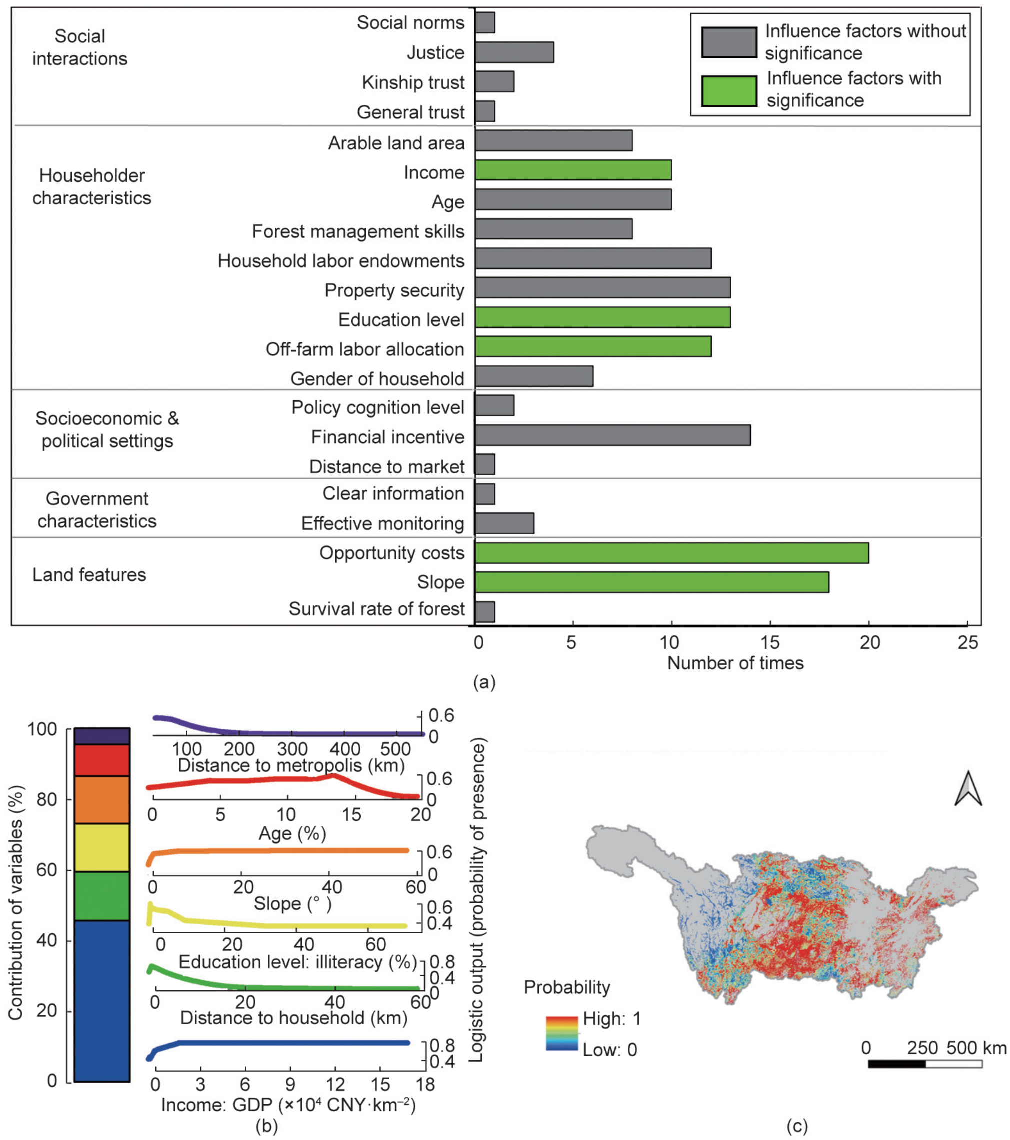

Fig. 4. Social–ecological impact on CCFP implementation based on the bottom-up approach. (a) Based on meta-analysis, landowner participation willingness was strongly influenced by social–ecological factors. Based on (b) the probability-response curves of key social–ecological factors, (c) these social–ecological factors were integrated in CCFP implementation modeling through the predicted probability (from MaxEnt modeling) of successful CCFP implementation in sloping cropland plots.

targeting all steep croplands in a densely populated area rather than targeting enrollments based on conditions across the entire catchment [34]. Therefore, the target plots far from households might increase the opportunity costs for CCFP management and thus were less likely to be chosen as CCFP plots, even if they met the current CCFP standard. Household income, education level, age, and slope also showed a high correlation with farmers' willingness to participate in the CCFP. Many studies found that if post-conversion lands combined with non-agricultural benefits did not provide farmers with enough food and income, they were likely to revert forests back to cropland [23,48,52]. Therefore, social factors related to household income, such as GDP, have a strong impact on CCFP implementation [25]. Other social–ecological factors, such as education level, age, and slope, are related to the opportunity costs of land conversion, affect non-agricultural benefits for farmers, and thus indirectly influence CCFP implementation [32,53]. Our modeling results provide evidence of the importance of social–ecological analysis for large-scale ecological restoration implementation and provide robust scientific information on complex SES dynamics for ecological management.

Although our study provides evidence that scientific design and systematic surveys during large-scale ecological restoration planning can help improve practicality and efficiency, several study limitations in model estimation accuracy are worth outlining. First, as social–ecological factor indicators were based on a meta-analysis, our quantification method cannot be applied to large-scale ecological restoration programs without case studies at a finer scale. For newly established restoration programs, the proposed method may not predict stakeholder behavior with high accuracy if there is a lack of available information on socioeconomic interactions at the fine scale. Second, since multiple key social–ecological indicators were chosen as the inputs for implementation estimation of large-scale PES programs in this study, the different spatial resolutions of these indicators may have impacted the accuracy of the model results. Although our simulations showed high accuracy (ROC score = 0.803) in the prediction of CCFP implementation, low-resolution social statistical data (e.g., county-level statistics and raster data) still provide information on the spatial heterogeneity of related variables and increase the uncertainty in estimation accuracy. For future studies, finer

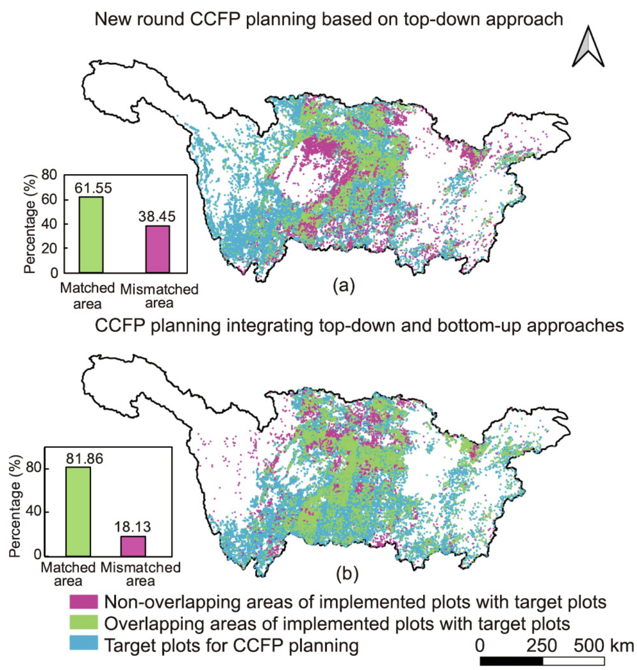

Fig. 5. Distribution of actual and target CCFP cropland enrolled from 2015 to 2017. Spatial matching between actual and target croplands under the new CCFP was only (a) 61.55%, but this increased to (b) 81.86% after socioeconomic integration using the bottom-up approach.

resolution data are required to provide a more accurate estimation for the precise management of large-scale PES programs. Third, our observation data for the implementation of large-scale PES programs comes from discrete time series, which cannot represent the actual situation since its implementation changes year by year. For future studies, with continuous time series added, dynamic changes in PES program implementation can be observed and used to decrease uncertainty in social–ecological interaction analyses.

5. Conclusions

Our method integrates top-down and bottom-up approaches to investigate the complex social–ecological processes of large-scale ecological restoration, providing a solution for spatial planning with socioeconomic considerations. Based on our analysis, the practicality and efficiency of spatial planning could be greatly increased by including socioeconomic considerations. This is an important finding because macro-scale top-down spatial prioritization [54,55] is still the norm for many natural resource management and payments for ecosystem service schemes. Our findings demonstrate the possible inefficiencies of such approaches in the CCFP program in the Yangtze River Basin, where program goals are often not achieved. Our coupled top-down and bottom-up prioritization method provides scientific support for improving the practicality of spatial planning for effective ecological restoration management in China and beyond.

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Compliance with ethical guidelines

Zhaowei Ding, Hua Zheng, Jun Wang, Patrick O'Connor, Cong Li, Xiaodong Chen, Ruonan Li, and Zhiyun Ouyang declare that they have no conflicts of interest or financial conflicts to disclose.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eng.2022.08.008.

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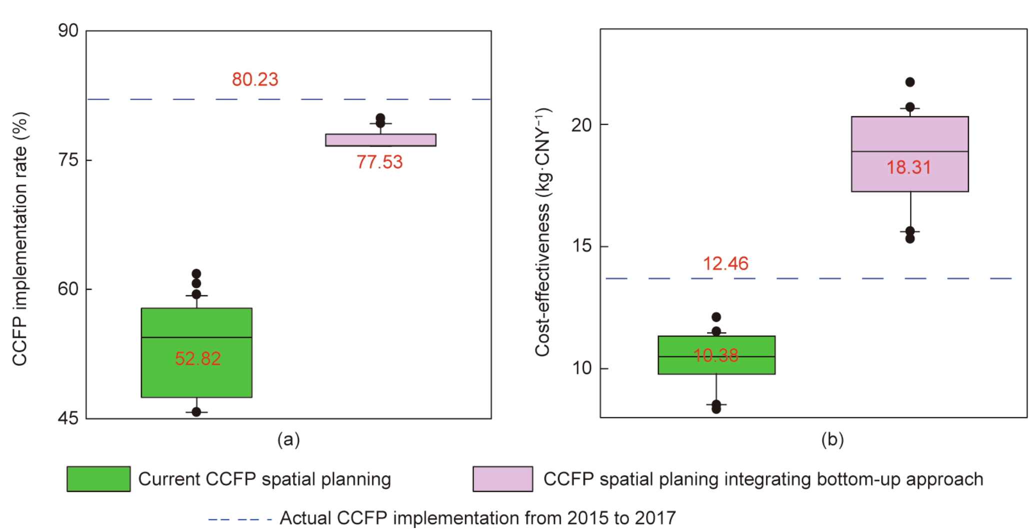

Fig. 6. (a) CCFP implementation rate and (b) cost effectiveness of CCFP implementation from 2015 to 2017 based on current slope-based CCFP spatial planning and CCFP spatial planning integrating the bottom-up approach.

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