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Role of social networks in building household livelihood resilience under payments for ecosystem services programs in a poor rural community in China

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ABSTRACT

Payments for ecosystem services (PES) programs may bring unintended consequences to the coupled socio-ecological system (SES) and incur unexpected feedbacks between social and ecological systems. This paper explores how the SES responds to PES intervention and investigates the role played by social networks in building resilience in a traditionally poverty-stricken area of China. The structure of social networks is measured through the social network analysis with degree and betweenness. Then, we develop an agent-based model to examine how social networks function to affect household livelihood resilience. The model captures feedbacks between PES intervention, social networks, household livelihood decisions, and environmental changes. Results show that the livelihood resilience of rural households is expected to decline during 2013–2030 within the current PES scheme. Social networks impose significant positive impacts on resilience building. However, their effects decay over time due to the fading structure and function of social networks along with massive rural-to-urban migration. Besides environmental conservation, policy-makers should take measures for socio-cultural conservation and preservation, reinforcing the identity, structure, and function within SESs for rural development in China.

1. Introduction

Rural communities are an integral part of the coupled social-ecological system (SES), within which humans, natural resources, and the environment interact at multiple spatial and temporal scales (Li et al., 2018; Liu et al., 2007; Wilson et al., 2013). Such an SES is inherently dynamic, complex, adaptive, and characterized by nested structures and multiple functions, and is constantly reshaped by both external (e.g., environmental, social, economic, and political changes) and internal factors (e.g., variations in labor availability, the health of human and livestock, and other livelihood capital) (Adger, 2006; Rockenbauch and Sakdapolrak, 2017), which pose a great challenge for sustainable management of natural resources and present a necessity to build resilience to various stresses. The challenge particularly applies to rural communities in contiguous poverty-stricken areas (CPSA) of China, where various poverty reduction policies have been implemented. Studies suggest that there is still a large population living in extreme poverty, and the incidences of rural households' falling back to poverty remain common (Zhou et al., 2018). Households in CPSA usually live in remote areas in a harsh environment, extracting scarce

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natural resources (e.g., through over-cultivation, overgrazing, or deforestation). The excessive extraction of natural resources may lead to land degradation, soil erosion, water pollution, and many other environmental problems (Foley et al., 2011; Liu et al., 2001). Meanwhile, the local environmental degradation would, in turn, place greater stress on household livelihood sustainability, creating a poverty trap in CPSA.

Due to the poverty-environment nexus and multiple interactions, policy interventions that intend to "pull" the rural poor out of the poverty trap may fail to achieve the goal or even have unintended ecological and social consequences that may reinforce poverty (Lade et al., 2017). Consequently, the poverty recurrence rate in CPSA is rather high, which erodes the effectiveness of these policies (Liu et al., 2017). For example, Payments for Ecosystem Services (PES) has been widely practiced as a policy tool in natural resources-dependent communities to address the poverty-environment nexus worldwide. By providing economic incentives to rural households, PES reduces their reliance on natural resources to enhance the provision of desired ecosystem services (Jack et al., 2008). However, PES may bring unintended disturbances to the SES (Li and Zander, 2019), and generate feedback effects on social and natural systems (Chen et al., 2019). Thus, there is an urgent need to unpack the complexity of the rural SES and understand how the SES responds to PES interventions.

In recent decades, resilience research has grown significantly and developed a set of concepts and insights, which is collectively known as "resilience thinking" and has emerged as an insightful framework for understanding and managing the SES (Folke et al., 2010; Lade et al., 2017; Li, 2020). Resilience is currently defined in the literature as the ability of an SES to absorb disturbance and reorganize to retain essential functions, structures, identities, and feedbacks (Walker et al., 2004). The literature on resilience has generally concentrated on the responses of SES to climate change (Forsyth, 2018; Tanner et al., 2015), natural hazards (Adger et al., 2005; Galarza-Villamar et al., 2018) or socioeconomic crisis (Kumar et al., 2020; Scheffran et al., 2012), and implications for policies to build resilience (Adger et al., 2011). Specifically, there is a growing number of studies on livelihood resilience in the rural context. Linking livelihood approaches to resilience thinking can enhance understanding of livelihood dynamics and how households maintain and enhance their livelihoods in the face of change, including stresses and shocks (Ifejika Speranza et al., 2014). Much of the current literature on livelihood resilience has centered on the measurement or assessment of livelihood resilience (Quandt, 2018; Sarker et al., 2020; Sina et al., 2019), determinants of livelihood resilience (Alam et al., 2018; Li et al., 2016), the linkages between asset endowment and resilience (Daniel et al., 2019; Goulden et al., 2013; Tebboth et al., 2019), and the strategies to build livelihoods resilience (Huang et al., 2018b; Huck et al., 2020; Li and Zander, 2019; Marschke and Berkes, 2006). However, less attention has been paid to how policy interventions alter dynamics in SESs and in turn affect the long-term livelihood resilience of rural households through influencing socio-cultural conservation and preservation.

Similar to resilience, social networks have attracted great interest in recent years (Kossinets, 2006). Social networks refer to both formal (e.g., membership in organizations or associations) and informal (e.g., relations to kin, friends, and neighbors) connections developed among community members through exchanges in information, labor, money, and materials (Cassidy and Barnes, 2012; Dapilah et al., 2019; Halkos and Jones, 2012). Most recent research has outlined the crucial role of social networks as a source of resilience in SES. It may help define system identity with key components, relationships, and continuity (Cumming et al., 2005; Cumming and Collier, 2005; Wiggins, 1967), delineate system structure through actors, institutions, interactions, and infrastructure (Wieczorek and Hekkert, 2012), and analyze system functions and feedbacks to identify drivers and barriers while developing collaborative efforts and local practices for innovations and fundamental changes (Li, 2020; Milkoreit, 2016; Pereira et al., 2019). In particular, social networks enable information and resource exchanges that facilitate social supports (Beaman and Dillon, 2018; Cassidy and Barnes, 2012), and can be transferred to other forms of capitals (such as financial, human, physical, and natural capitals) that promotes livelihood security (Claasen and Lemke, 2019), and enhance adaptive capacity through livelihood diversification and new farming technology (Dapilah et al., 2019; Johny et al., 2017; Mekonnen et al., 2018). Previous studies have recognized the important roles of kinship/clan, friendships, and neighborhood ties in building household adaptive capacity and facilitating reciprocal resource and labor sharing as a means of managing and diffusing risk to maintain resilience (Koczberski et al., 2018). However, the actual role that different types of social networks play in natural resource-dependent communities (such as CPSA) faced with variations in SES induced by PES has not yet been explored (Rockenbauch and Sakdapolrak, 2017).

Given the complexity of the SES, we develop an agent-based model (ABM) that explicitly addresses the interactions between rural households and the local environment affected by PES. Several major advantages of ABM have made it powerful in studying SES. First, it is a bottom-up method that directly represents the decision-making processes of individual agents and their interactions with the social and natural environment (An et al., 2020; Dou et al., 2020), which can be used to explore responses of social systems to environmental or policy changes in SES and vice versa (Parker et al., 2003; Smajgl et al., 2011; Sun and Müller, 2013). Second, ABM is capable of addressing issues that make traditional approaches studying SES difficult, such as spatial and temporal complexity, non-linearity, feedback loops, and uncertainties (An, 2012; An et al., 2014). Third, ABM has the flexibility to integrate social and ecological processes, relationships in social networks, institutional factors, and other spatial data within GIS platforms (Heppenstall et al., 2021), which enable the establishment of spatial linkage between social and ecological systems, and explore their interactions in a spatially explicit way (An, 2012; Schouten et al., 2013). So far, however, ABM has not been widely applied to explore poverty and livelihood dynamics through the lens of resilience (Dou et al., 2020), let alone the integration with social networks.

This study investigates how a rural SES responds to two nationwide PES programs in China based on resilience thinking and agent-based modeling. The two PES programs are the Ecological Welfare Forest Program (EWFP) and the Conversion of Cropland to Forest Program (CCFP), and the study area is in one of the 14 CPSA of China. We examine the effects of social networks on household livelihood resilience of the rural SES. Both CCFP and EWFP have dual goals of environmental conservation and poverty alleviation (China State Council, 2002; State Forestry Administration, 1999, 2001). Empirical knowledge and data from a household survey in Dabieshan CPSA are used to develop and parametrize the ABM. The study asks the following questions: (1) What processes affect the livelihood resilience of rural households in the CPSA following the implementation of PES programs? (2) How do the rural SES responds and adapts to PES programs and the changes in socio-cultural structure and natural environment? (3) What is the role of social networks in the livelihood resilience building of rural households in CPSA?

2. Theoretical background and analytical framework

2.1. Social networks in China

The social network is also called *Guanxi* in China, which is formed through cultural and social interactions involving repeated favor exchanges and trust among group members (Chang et al., 2017). The social networks of the Chinese rural societies have been widely acknowledged to be highly heterogeneous in structure, with a unique feature that was named the 'differential mode of association' (*Chaxugeju*) by the prominent Chinese sociologist Xiaotong Fei (1992). According to Fei's theory, the social network of a typical Chinese person in rural societies can be analogized as the circles appear on the surface of a lake when a rock is thrown into it. It presents a nested concentric pattern with the Ego in the center, and layers of concentric circles extending from the center represent different categories of relations to the Ego in a descending order of intimacy (Chan, 2009). The networks of the Chinese rural societies also have the characteristics of small-world networks, which are 'acquaintance societies', where the interpersonal relationships are based on ties of blood (i.e., kinship ties) and neighborhood relationships (Xiong and Payne, 2017). Such social networks are based on people's understanding of who they are, their role in the system, and their relation and feeling of belonging to the group. In certain local contexts and cultural environments, social networks connect and include people into nature and societies, composing a specific system identity and structure of SES (Li, 2020).

The *kinship ties* between households are represented by the ties between the household heads, which can be identified from the family trees of a clan (Xiong and Payne, 2017). Clans are typical social organizations in rural China, formed naturally under a centralized bureaucratic state system thousands of years ago (Huang et al., 2018a). Clan members usually share similar social capital and natural resources and form basically unanimous interest groups. The orders and rules followed by the clans are one of the most important informal systems in rural China (Huang et al., 2018a). Although clans are experiencing great changes with the transition of Chinese society (Wang et al., 2021a), most rural villages in China still keep clan halls and family trees (Fig. 1). In the Chinese kinship system, clan members that are beyond five generations are not considered relatives anymore. Before the 1980s, Chinese males used generation names, which means males of the same generation in a clan have the same generation and family names, with only the given names being different (Li and Lawson, 2013).

The *neighborhood tie* is another important social relationship in Chinese rural communities. Rural households can sometimes get even more social support from their neighbors than from their relatives due to their proximity (Xiong and Payne, 2017). Rural homesteads and croplands are the most important livelihood assets for rural households, and also the major spaces for them to live and make a living. Thus, neighborhood relationships can be further divided into *house neighborhood ties* and land *plot neighborhood ties* (Beaman and Dillon, 2018).

The social network of a household is a union of all social relations discussed above, including kinship ties, house neighborhood ties, and plot neighborhood ties. The kinship ties and house neighborhood ties may overlap as the new houses are usually allocated based on extended family; thus house neighbors are often relatives. Additionally, house neighbors are basically from the same resident group (RG). In contrast, plot neighbors may not, as cropland plots extend far away from the RG center, which may border the land of neighboring RGs.

2.2. Livelihood resilience

Resilience was initially used in physics and engineering to depict the ability of systems to bounce back to normality (focusing on recovery and constancy) (Doorn et al., 2018). It was first introduced to ecological science by Holling (1973) to measure the ability to absorb change and disturbance and still maintain the same relationships that control a system's behavior (focus on persistence and robustness). Recently, the concept of resilience has also been increasingly used to understand the dynamics of SES, but emphasize more on adaptive capacity, transformability, social learning, and innovation of SES (Folke, 2006). Specifically, the farm household is the basic unit of livelihood decisions in rural areas (Umezaki and Ohtsuka, 2003). Their livelihoods are a connector between social and natural systems via the management of resource use (Li et al., 2018; Rathi, 2020), thus resilience analysis from the perspective of household livelihoods has gained much attention. Livelihood resilience refers to the ability of households to sustain and improve their livelihoods to cope with and recover from environmental,

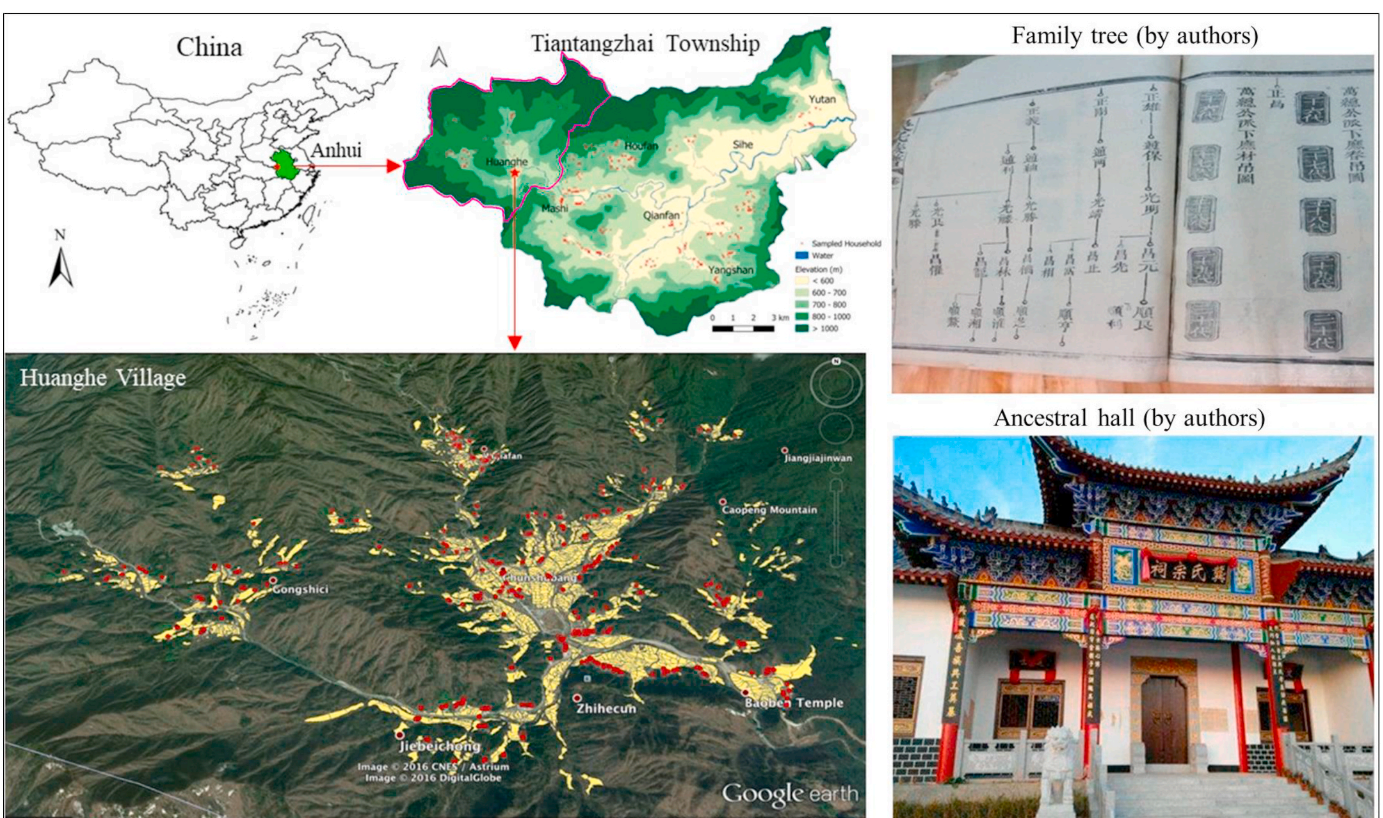

Fig. 1. Huanghe Village (Study area) with locations of rural households, their cropland parcels in Tiantangzhai Township, Anhui, China, and photos of ancestral hall and family tree in rural China.

economic, social, and political disturbances (Li et al., 2016; Tanner et al., 2015), and is recognized as a key component of sustainable livelihoods (Thulstrup, 2015). There have been attempts to address livelihood resilience of households in relation to disasters (Adger et al., 2005; Burton, 2014), climate change (Alam et al., 2018; Forsyth, 2018), market fluctuations (Schouten et al., 2013), migration (Porst and Sakdapolrak, 2018; Rathi, 2020), resettlement (Liu et al., 2020), food insecurity (Atara et al., 2020), and policy interventions (Huang et al., 2018b; Thulstrup, 2015).

Different frameworks and methods have been developed to evaluate the livelihood resilience of households quantitatively, which can be divided into five main categories: capital-based, network-based, definition-based, decomposition-based, and other proxies-based methods. The capital-based approach has its root in the sustainable livelihoods theory (DFID, 1999; Ellis, 2000) and uses human, financial, physical, social, and natural capitals to measure household resilience (Cassidy and Barnes, 2012; Quandt, 2018; Thulstrup, 2015). The approach has proven useful for assessing the ability of households to withstand adverse and undesirable situations, as capitals are necessary to buffer stresses and shocks (Daniel et al., 2019). The network-based approach evaluates resilience from the network perspective and using network metrics such as centrality or connectivity to measure the information and resource flows through social networks (Janssen et al., 2006; Schouten et al., 2013), as these are vital inputs to resilience, providing informal insurance and support in the event of disturbances (Li et al., 2016; Tanner et al., 2015). By integrating scenario analysis, they impose different disturbance regimes and simulate responses of social actors using these network metrics to understand the mechanism underlying resilience.

Either the capital-based or the network-based approach assesses livelihood resilience focusing on households' adaptive capacity or social learning, suggesting that more livelihood capitals and larger connectivity in social networks contribute to higher resilience to cope with disturbances (Dapilah et al., 2019). However, the ability of a household livelihood to function and persist after disturbances is determined by not only adaptive capacity, but also the extent of exposure and its resistance or sensitivity to disturbances (Adger et al., 2005; Walker et al., 2004). A livelihood is resilient if it is less exposed to disturbances, has higher resistance or lower sensitivity to disturbances for maintaining its key functions (food, health, and income, etc.), and has higher adaptive capacity to recover from the disturbance without causing major declines in production and wellbeing (Ifejika Speranza et al., 2014). Thus, the capital-based or network-based approach to a limited extent addresses the issues of exposure, sensitivity, and adaptive capacity to disturbances, which may not be able to provide a thorough understanding of resilience.

In contrast, the definition-based approach quantifies resilience based on its concept and definition (Alam et al., 2018; Ifejika Speranza et al., 2014; Li and Zander, 2019). For example, Li and Zander (2019) constructed a composite Livelihood Resilience Index (LRI) from three broad categories of factors, including disturbance, sensitivity, and adaptability, and applied it to assess the resilience of rural households to PES intervention. This approach can capture the heterogeneity in capacity and sensitivity of rural households to persist and adapt to different extent of disturbances. Given that resilience is an evolving concept, scholars and researchers have developed different assessment frameworks based on their specific understanding of livelihood resilience. Alam et al. (2018) referred to resilience as a function of sensitivity and adaptive capacity and used these two components to represent resilience. Sarker et al. (2020) proposed a framework for assessing livelihood resilience based on adaptive, absorptive, and transformative capacity. Ifejika Speranza et al. (2014) described resilience as a buffering mechanism, self-organization, and the capacity to learn from experience; thus resilience is estimated based on these three components. The lack of a generally accepted definition of livelihood resilience makes cross-case comparison difficult.

Since resilience has the property of multidimensionality, some studies adopt the decomposition-based method to disaggregate resilience into different dimensions, such as social resilience, economic resilience, institutional resilience, infrastructure/engineering resilience, and ecological/environmental resilience (Burton, 2014; Dressler et al., 2019; Huang et al., 2018b); then they select indicators for each dimension and aggregate a host of indicators to form a composite index to measure resilience. This approach enables the identification of the "short plank" among various dimensions of resilience, but it provides less information on the mechanism underlying resilience.

In 2016, FAO (2016) proposed a more comprehensive framework called Resilience Index Measurement and Analysis (RIMA), which evaluate resilience from five perspectives, including access to basic services (e.g., schools, health centers, water, electricity, and nearby markets), assets (productive and non-productive), social safety nets (formal and informal), sensitivity (exposure to risk as well as to persistence or resistance to shocks), and adaptive capacity. This framework is a combination of various frameworks and methods, taking into account capital assets (capital-based) and social networks (network-based), addressing sensitivity and adaptive capacity (definition-based), and using a composite indicator-based method to estimate resilience. This framework has been applied in most recent studies and proved to be effective for evaluating household resilience in developing countries (Atara et al., 2020; Sarker et al., 2020).

In essence, all these frameworks and methods mentioned here aiming to quantify livelihood resilience can be summarized as the process of identification and measurement of resilience surrogates/proxies, as resilience itself is unobservable and cannot be directly measured (Bennett et al., 2005; Carpenter et al., 2005). In addition, many other indices are also widely adopted as proxies of resilience in the literature, such as livelihood diversity (Goulden et al., 2013), food security (Koczberski et al., 2018), well-being (Marschke and Berkes, 2006), etc.

2.3. Analytical framework

The analytical framework of this study is described in Fig. 2. The overall structure of this framework can be understood as an SES involving complex interactions under environmental policy interventions, i.e., PES programs for forest conservation and restoration. The implementation of PES programs (i.e., CCFP and EWFP) directly and/or indirectly leads to forest recovery, yet accompanied by feedback effects of crop raiding by wildlife. Increased crop raiding reduces returns from crop production and hence undermines farmers' intention to retain land cultivation, leading to subsequent abandonment of cropland, facilitating forest recovery in the long term. In the meantime, rural households can allocate extra labor (due to cropland abandonment) from farming to other agricultural activities, such as animal husbandry and collecting forest products (e.g., *Gastrodia Elata*, GE[1]), taking advantage of the improved forest condition under PES programs. Social networks play vital roles in the process for households adopting new livelihood strategies after implementation of PES programs, such as sharing information, experiences, and technology, and improved households' access to resources such as labor, land, and capital. Other livelihood alternatives include local off-farm work and migration to work in cities, which are assumed to be positively influenced by social networks (Zhang et al., 2019). For example, earlier employees and migrants can provide social supports to the newcomers, such as job opportunities and shelter. Thus, social connections developed in villages

[1] Gastrodia Elata (GE) is a type of fungus in East Asia that grows on certain species of freshly cut trees in a semi-shaded environment below ground, which can be used as a valuable ingredient in traditional Chinese medicine and is sold at a high price. GE can yield higher incomes than crop production, but also higher risk due to requirement of specific skills, strict habitat and relatively high initial cost to purchase seeds.

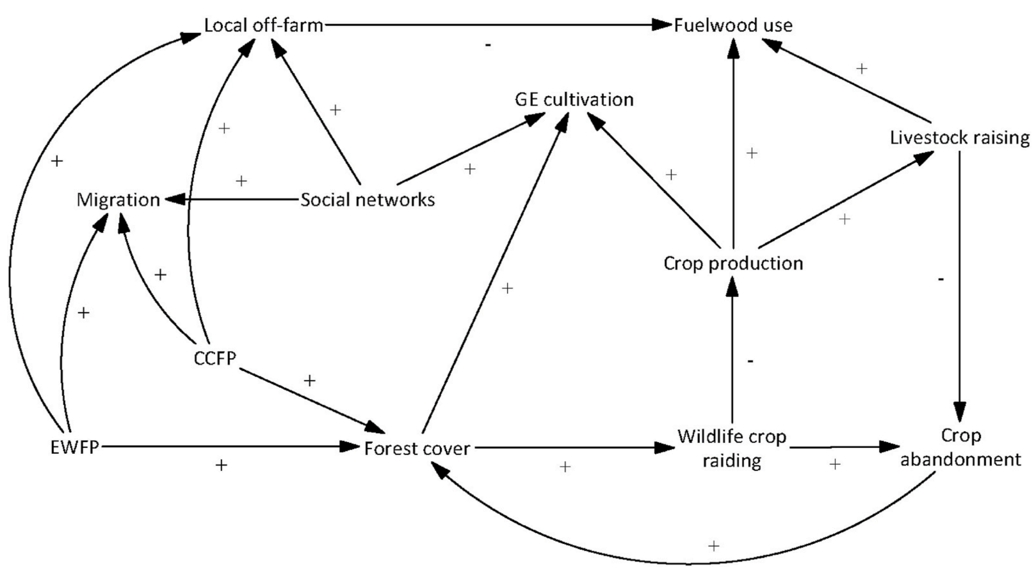

Fig. 2. Conceptual framework for dynamics of the coupled socio-ecological systems with interrelationships among PES intervention, household's social networks, household livelihood decisions, and environmental changes.

among households play an important role in livelihood development and enhancement of a household's resilience to withstand unexpected shocks. In this study, we assume that social networks affect household livelihood decisions, including GE cultivation that needs special technique, local off-farm work, and out-migration. Households with more social connections have more social resources to draw upon for information about and access to broader livelihood opportunities. In addition, PES programs may also affect household local off-farm work and out-migration decisions (Wang et al., 2020b; Zhang et al., 2020). These connections reflect the complex interplays in an SES under PES disturbance that would be explored in this study are shown in Fig. 2.

3. Materials and methods

3.1. Study area and data collection

3.1.1. Study area

Our study area is Tiantangzhai township in the western corner of Anhui Province, China (115°39′-115°53′E, 31°9′-31°17′N, Fig. 1). It is a mountainous region located in Dabieshan CPSA, delineated under the Rural Poverty Alleviation and Development Program (2011–2020) (China State Council, 2011). The livelihoods of residents in these areas are primarily based on natural resources, which may cause environmental degradation that exacerbates poverty. To alleviate poverty and reduce household's dependence on natural resources, two national PES programs have been implemented in the study area. The CCFP was initiated in Tiantangzhai township in 2002, with 17.5% of household participants. The CCFP subsidy for households in Tiantangzhai was 230 yuan/mu/year (mu is an area unit used in rural China, 1 mu = 1/15 ha) during the first eight-year contract period starting from 2002. It was reduced to 125 yuan/mu/year when the policy was renewed for an additional eight years in 2007. The mean subsidy received by CCFP participants was 173 yuan/year. The EWFP has been implemented in Tiantangzhai since 2001. Almost all households in the township have some natural forests and are automatically enrolled in the EWFP program. Under EWFP contracts, each household is responsible for managing its forest to prevent illegal logging. The EWFP subsidy for households is 8.75 yuan/mu/year.

To characterize the social connections among all households, we confine our study site to a small village named Huanghe village that lies on the north-western corner of Tiantangzhai township (Fig. 1). It consists of 548 households residing in 24 resident groups (RGs) and comprising a population of around 1,900. The village is relatively remote from the township center and the provincial capital of Hefei. The most common primary occupations are agricultural work (such as crop production, animal husbandry, and *Gastrodiae Elata* (GE) cultivation), local off-farm work (local business and hired work), and migratory work (Wang et al., 2020b). In the study area, wild boars, birds, and voles are blamed for crop damage, especially on fields growing corn, GE, and sweet potato. Strategies to deal with human-wildlife conflicts are rather limited, and most households take no measures.

3.1.2. Data collection and processing

We first conducted a household survey in Tiantangzhai township in the summer of 2014 using a detailed structured questionnaire designed for information on PES participation and payments, household demographics, cropland use, agricultural inputs, and outputs from agricultural production activities and other livelihood activities. This survey eventually collected 481 complete household data. In 2015, another household survey of 513 households, representing 94% of all households in Huanghe village, was conducted to collect basic demographic and livelihood data. Furthermore, we recorded the geographic locations of all 548 households and delineated the boundary of 2,225 paddy and dryland parcels managed by households in the village (Fig. 1). Since all households and cropland parcels are geo-located, the connections between human and land systems are established spatially explicitly.

Once the household survey data were collected, the social relations between households within Tiantangzhai village can be identified. For *kinship ties*, since most of the household heads in our study area were born before the 1980s and are males, we can identify the kinship ties between households by matching their generation and family names. We collected a census data in 2012 with records of all members in each household, including their full name, birth year, gender, and relationship to the household head. Therefore, kinship ties can be established. Regarding *house neighborhood ties*, we had collected the location of each household using GPS receivers during our field survey; thus the house neighboring relationships between households can be identified. Due to the rough terrain, households in this mountainous area are distributed relatively sparsely. In this study, two houses that are less than 180 m apart are considered as house neighbors. In the sensitivity analysis, we also set the value as 90 m and 360 m to test its impact on our variables of interest (see section 3.4.2 and Fig. S3). We extract the *plot neighborhood relationship* based on the map of the confirmation and registration of the contracted cropland right conducted in 2015. The neighboring plots of a household are well documented in the confirmation map that the household signed with the village committee. We can establish plot neighborhood ties based on the map of the plot ownership for the village.

3.2. Social network analysis

Social networks can facilitate knowledge, information, and technology spread as interactions between network members influence individual behavior and encourage social learning. However, the extent of knowledge, information, and technology spillovers depends on the structure of the network as it determines who interacts with whom (Koczberski et al., 2018). Social network analysis has been widely used to measure and analyze the complex structural characteristics of networks (El-Sayed et al., 2012). First, the social networks of households can be abstracted into simple undirected networks and visualized as node-link graphs, denoted as $G = \{N, E\}$, in which $N = \{n_1, n_2, ..., n_N\}$ is the set of nodes (here refers to households), and $E = \{e_{ij} | i, j \in N\}$ is the set of edges, where e_{ij} denotes a link from node i to node j. We treat our social network data as undirected, thus $e_{ij} = e_{ji}$. All links form an adjacency matrix whose value in ijth cell is equal to 1 if household i has a link to household j ($e_{ij} = 1$), and 0 otherwise; the diagonal of the matrix is 0, indicating that a household is not a link to itself (Johny et al., 2017). Then various network metrics can be used to quantitatively describe the structure of social networks. In our analysis, we use two important network metrics of *degree* and *betweenness* to measure each household's social connectivity.

Degree refers to the number of direct links a node has with other nodes in a network, which measures the number of nodes to which the node is connected, as shown below:

$$D_i = \sum_{j=1}^{n} e_{ij} \tag{1}$$

whereD_i is the degree of node i. A household with a large degree is deemed an important node for mobilizing the network. Thus, it is expected to have a large impact on other households connected to it and possibly the entire network (Bourne et al., 2017; Johny et al., 2017). A high degree can enhance livelihood resilience by facilitating access to new information and social learning (Cassidy and Barnes, 2012).

Betweenness is a measure of the share of shortest paths from all pairs of nodes in the network that are connected to that node and is one measure of how influential a node is within the network (Wang et al., 2018):

$$B_i = \sum_{j,h \in N,\ j \neq h} \frac{\sigma_{jh}(i)}{\sigma_{jh}} \tag{2}$$

whereB_i is the betweenness of node i, σ_{jh} is the total number of links connecting j and h in the network, and $\sigma_{jh}(i)$ is the number of these links that pass through node i. Specifically, $j \neq h \neq i$. A household with high betweenness would be one that connects two otherwise unconnected cliques (known as a bridge). Thus, betweenness measures the indirect connectivity of each household and captures a household's role in facilitating information communication in the network (Beaman and Dillon, 2018). High betweenness across social networks can facilitate social learning in the community. However, the removal of nodes with high betweenness may make a system highly vulnerable as this significantly reduces the connectivity of subgroups in the network (Cassidy and Barnes, 2012).

3.3. Resilience evaluation

In this study, we adopted a definition-based resilience framework developed by Li and Zander (2019) to measure the livelihood resilience of rural households, which referred to resilience as a function of disturbance, sensitivity, and adaptability. The livelihood resilience evaluation involves two steps: first select indicators for each of the three components, and then aggregate them to form a composite index to measure resilience.

3.3.1. Selection of composite indicators

The selection of indicators to measure the livelihood resilience of rural households is based on an intensive review of the literature and the place-specific information obtained from our household survey and fieldwork. Table 1 shows the three components (disturbance, sensitivity, and adaptability) and the composite indicators.

Disturbance represents the stress or unintended effects of the PES intervention on the SES that puts pressure on households and affects their livelihoods. PES programs would affect household livelihoods through their accumulated effects on the local environment. Following the implementation of the PES programs, croplands on steep slopes or

Table 1
An assessment for household livelihood resilience and descriptive statistics of indicators.

Component	Indicator	Description	Unit	Mean	SD
Disturbance	Proximity to forest	Inverse of Euclidean distance of the house location to nearest forest edge		0.027	0.035
	Wildlife crop raiding	Share of remaining cropland parcels raided by wildlife	%	21.67	8.41
Sensitivity	Dependency ratio	Share of the population under 16 and over 65 years of age to the population between 16 and 65 years of age	%	61.64	95.39
	Cropland abandonment	Share of remaining cropland parcels abandoned by households	%	14.88	11.88
	Fuelwood consumption	Amount of fuelwood consumed by a household for cooking and heating	1000 kg	11.23	2.14
Adaptability	Highest education	Highest year of education received by household members	Year	8.33	2.24
	Agricultural diversity	Number of agricultural livelihood activities: 1–3 (crop production, livestock husbandry, *Gastrodia elata* cultivation)		2.18	0.59
	Local off-farm work	Number of household members engaged in local off-farm work	Person	0.44	0.52
	Out-migration	Number of household members out-migrate to work in cities	Person	1.17	0.39
	Dominant income source	Dominant income source for a household: 0 = agriculture, 1 = non-agriculture	0/1	0.37	0.22

ecologically sensitive areas have been converted into forests. Due to the improvement of forest conditions, crop raiding by wildlife has been increasing in many places in China (Chen et al., 2019). These changes in the coupled SES have substantial impacts on agricultural production activities. Specifically, the closer the proximity to the forest, the higher likelihood of crop raiding by wildlife, the larger the disturbance of policy intervention on household livelihoods. Thus, these two factors, i.e., *proximity to forest* and *wildlife crop raiding* are selected to represent the disturbances of PES programs on household livelihood resilience.

Sensitivity refers to the ease or difficulty a household experienced in maintaining normal livelihood after the introduction of disturbance from PES intervention (Tian et al., 2015). Households with lower sensitivity will be less likely to be affected by the disturbance and more likely to maintain their proper functioning. We used three indicators to measure the sensitivity. The sensitivity of household livelihoods to disturbances is often measured by the consumer-to-labor dependency ratio among the family members (Alam et al., 2018; Hahn et al., 2009; Robinson et al., 2015). Thus, the first indicator is the *dependency ratio*, which denotes the proportion of household members whose livelihoods depend on income-earning members. The second sensitivity indicator is *fuelwood consumption,* representing a household's reliance on natural resources for energy needs. Higher fuelwood consumption would make a household more sensitive to the health condition of household members who collect fuelwood, climate change-induced natural disaster, and other disturbances to the household, all of which affect its resilience to fuelwood disruption (Alam et al., 2018). The third indicator is *cropland abandonment*, reflecting how a household adjusts its farming scale to respond to changes in the local environment. In addition to crop raiding, the large-scale afforestation and forest conservation programs also affected water availability for cropland irrigation because of increased evapotranspiration from improved forest conditions, both of which could lead to cropland abandonment.

Adaptability represents the ability of households to adapt their production activities and resource management strategies to deal with the disturbance. First, the *education* of household members is considered an indicator because it is linked to the capacity to cope with disturbance and learn new knowledge (Li et al., 2019; Sina et al., 2019). Here, we use the highest year of education received by household members to represent a household's education level. Second, households may adopt diversification of agricultural activities and off-farm employment as adaptive strategies to combine and transform their livelihood assets to be resilient to the PES disturbance (Li et al., 2016). A household may diversify the farming system, such as raising livestock and cultivating GE, in addition to traditional grain farming. Agricultural diversification provides insurance against potential crop failures due to undesirable climatic changes or livestock diseases (Lin, 2011), and makes the best use of surplus labor. In addition, allocating labor for non-farming employments, such as local off-farm hired work and small businesses, or out-migration to work in cities, are other adaptive strategies to cope with PES disturbance on household livelihoods. Furthermore, we also select the *dominant income source* (i.e., agricultural or non-agricultural) to measure adaptability as it is a key indicator of livelihood reliability. The income from non-agricultural employment (e.g., local business, locally hired work, migratory work in cities) is often more reliable and perhaps much higher than agricultural activities that require a lot of investment with thin profit margins and subject to uncertainties (e.g., flood, drought, and crop raiding, etc.). Therefore, five indicators – the *highest education*, *agricultural diversity*, *local off-farm*, *out-migration*, and *dominant income source* – are selected as measures of adaptability.

3.3.2. Estimation of livelihood resilience

As described above, the livelihood resilience of rural households is measured from three components, i.e., disturbance, sensitivity, and adaptability. Each of the components is represented by several indicators. We integrate all indicators to form a composite index to estimate the livelihood resilience for each household (Table 1). Because each indicator is measured on a different scale, we adopt Eq. (2) to standardize each indicator as an index, respectively:

$$index_{ij} = \frac{S_{ij} - S_{j,\ min}}{S_{j,max} - S_{j,min}} \tag{3}$$

where S_{ij} and $index_{ij}$ are the original and standardized value of indicator j for household i, respectively. $S_{j,min}$ and $S_{j,max}$ are the minimum and maximum values of indicator j, respectively. Using Eq. (3), all indicators are scaled from 0 to 1.

After each indicator is standardized, we use a balanced weighted average approach where each indicator contributes equally to its corresponding component to calculate the value of each major component k for household i using Eq. (4):

$$M_{ik} = \frac{\sum_{i=1}^{n_k} index_{ij}}{n_k} \tag{4}$$

where M_{ik} denotes one of the three major components of resilience for household i. Specifically, M_{i1}, M_{i2}, and M_{i3} represent for the values of major components for adaptability, disturbance, and sensitivity, for household i, respectively; n_k is the number of indicators in each major component k ($n_1 = 2$, $n_2 = 3$, and $n_3 = 5$).

Finally, the three major components derived from Eq. (4) are aggregated to estimate resilience for each household with a reduced form of the multidimensional resilience equations based on Li and Zander (2019):

$$R_i = M_{i1} - M_{i2} \times M_{i3} \tag{5}$$

where R_i is the composite index of livelihood resilience for household i.

3.4. The agent-based model

3.4.1. Model development

This study integrates social network analysis within an ABM to explore the extent of household livelihood resilience to PES disturbances. The conceptual framework is implemented in the following sequence (Fig. 3). In this part, we introduce the main structure and key modules of the ABM, while a detailed description of the model following the ODD (Overview, Design concepts, and Details) protocol (Grimm et al., 2006, 2010) is given in Supplementary Materials (Section S1). The simulation started at 2013 when the household survey data was collected. Each simulation proceeds in an annual time step and runs for 18 time steps. Thus the model can be used to predict social-ecological changes during 2013–2030.

Fig. 3 shows the flowchart of the structure of the ABM. The modeling process can be divided into three phases: initialization, simulation, and output. The main steps at the initialization phase include (1) importing GIS files of individuals, households, and cropland parcels into the model; (2) setting up initial states for individual and households; (3) importing environment layers; (4) initializing household social networks; and (5) defining PES program context.

In the simulaiton phase, the following modules are repeated in each time step. First, the Wildlife Crop Raiding module, a parcel-level module, is called to predict the probability of crop raiding for each cropland parcel based on a host of factors. As shown in Table S1, parcels used for upland crops (such as corn and sweet potato), located in higher elevations, closer to the forest edge and further away from houses, are more likely to be raided by wild animals.

After that, the simulation moves to the Cropland Abandonment module. It is a parcel-level module predicting the probability of cropland abandonment. For each parcel, a random coefficients logistic regression model is used to examine both fixed effects of the parcel and household characteristics and random effects among households on cropland abandonment. The dependent variable of the model is whether the land parcel had been abandoned (=1) or was still under cultivation (=0). The

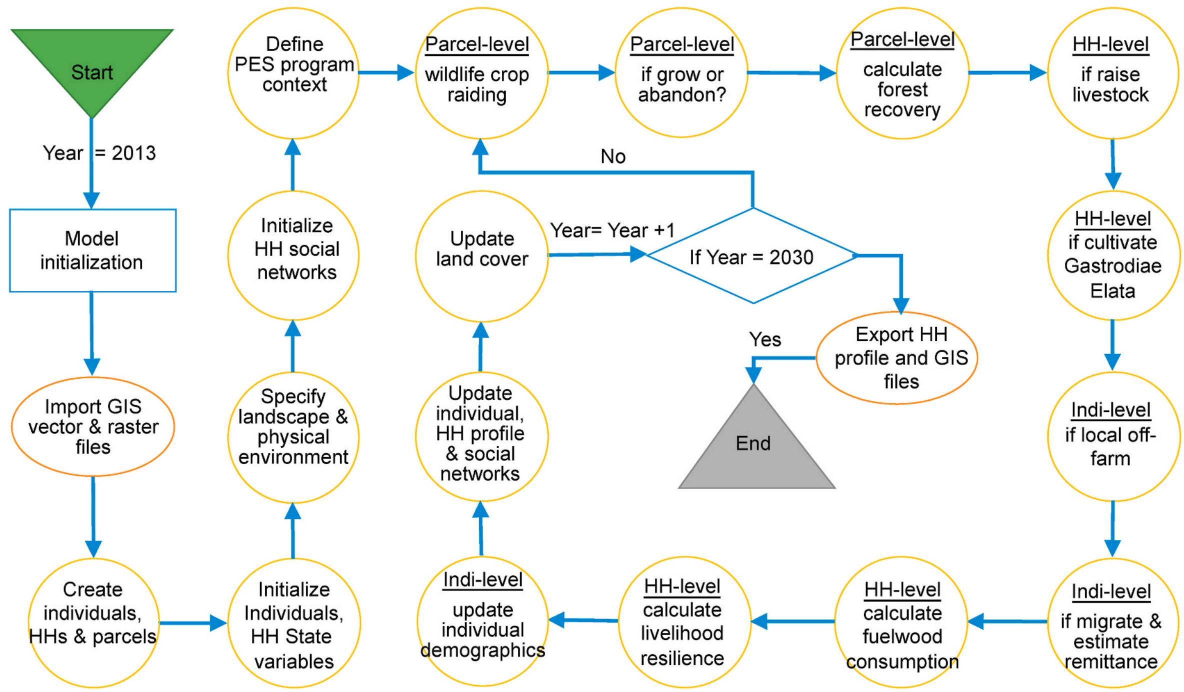

Fig. 3. A flowchart of process overview of the agent-based model. Note: indi-level indicates individual-level, and HH-level household-level.

independent variables include biophysical characteristics of the land parcels and socioeconomic characteristics of the households (Zhang et al., 2018b).

Then the model moves to the Crop Production module to determine whether a household engages in crop production. We calculate cropland planted by subtracting cropland abandoned from the cropland owned. If cropland planted >0, the household engages in farming; otherwise, if cropland planted = 0, the household quits farming. The share of cropland planted can also be computed.

The Forest Recovery module is a parcel-level module predicting forest recovery in the study area. Three Landsat images were acquired in 1992, 2002, and 2013 from the United States Geological Survey (http://glovis.usgs.gov/). From 1992 to 2002, the overall forest area does not change much, while there is 14.0% increase from 2002 to 2013. Deciduous and mixed forests both have substantial increases in the study area. The forest expansion was contributed mainly by afforestation due to PES programs, i.e., CCFP and EWFP. The tree species provided by the government for the PES programs were mainly deciduous forests, which have relatively higher survival rates (Chen et al., 2019; Zhang, 2014). In addition, forests also naturally emerge after the abandonment of croplands (Lugo and Helmer, 2004), as the abandoned croplands are gradually replaced by spontaneous growth of grass, shrubs, and trees via secondary succession (Wang et al., 2016). We use a multivariate logistic regression from a set of spatially distributed variables to simulate the process of secondary succession (Table S2).

The Livestock Raising module is a household-level module predicting the probability of keeping livestock as a livelihood resource (Table S3). Crop production is closely correlated with domestic animals, as households that raise animals have to cultivate more land to produce food for them, especially larger animals, such as cows and pigs (Wang et al., 2019). Other explanatory factors for animal raising include household size, age and education of household head, household elevation, and distance to township center.

The GE Cultivation module is a household-level module predicting the probability of cultivating GE as a source of cash income supporting livelihood (Table S4). Social networks play a crucial role in the diffusion of GE cultivation technique among rural households as they rely on social networks for information and skills for GE cultivation. The role of social networks in the diffusion of agricultural innovation, information, and technologies has been well established in the literature (Bourne et al., 2017; Maertens and Barrett, 2012; Mekonnen et al., 2018). Following this GE activity, theoretically, other activities also rely strongly on the social network, such as migration and local off-farm work. People need some introduction from known relatives and friends to start certain activities. Thus, several social network indexes are selected to predict the likelihood of GE adoption for each household.

The Labor Allocation module is an individual-level module predicting the probability of a household to adopt local off-farm employment or out-migration as livelihood adaptive strategies to reduce risks from agricultural activities. In this module, we assume that each household labor engages in only one of the three types of work during each time step, i.e., on-farm work, local off-farm work, or migratory work. The empirical knowledge gained from household survey data is used to parametrize the module. Here, we use the binary logistic regression to predict the probability for a household to adopt local off-farm or migratory work based on a host of factors, including personal attributes (gender, age, education, and marriage), household characteristics (dependency ratio, distance to center and cropland area), social networks, and the policy context (CCFP and EWFP subsidies) (Table S5 & S6).

The Fuelwood Consumption module is a household-level module predicting the quantity of fuelwood per capita used by each household each year, which can be predicted by a multiple linear regression model. Our fuelwood collection module is adopted from a previous study in the study area (Song et al., 2018). Regression analyses indicate that households with less educated heads, larger household size, have more elderly members, engage in animal raising and GE cultivation, have more EWFP forests, locate in higher elevations, closer to the forest edge but farther away from the main road tend to consume more fuelwood each year (Table S7).

The Individual Demographic module is an individual-level module comprising several submodules, including mortality, education, marriage, fertility, and migration, which simulate an individual's life history at one-year increments (Table S8-11). The demographic module is adopted from previous studies in the study area (Wang et al., 2021b). In-migration (by marriage), return-migration (migrants working in cities return), and out-migration (due to education, marriage, or employment) are simulated in the model.

Then the Update Individual and Household Demographics modules are computed to update an individual's age, education, marriage, employment, and each household's size, labor availability, land use, agricultural production, fuelwood use, labor allocation, social networks, resilience score, etc. The Update Land Use module updates the land use over the landscape at the end of the year, including spatial distributions of EWFP forests, CCFP forests, abandoned croplands, and cultivated croplands.

Finally, after the above sequences are repeated for 18 time-steps, the ABM moves to the output phase and exports results of interests at an annual time step for further analyses.

3.4.2. Model verification and validation

The verification and validation protocol proposed by An et al. (2005) is applied to verify and validate the ABM, which includes model debugging, uncertainty testing, empirical validation, and sensitivity analysis. At the model initialization, we compared the initial value distributions of state variables of human agents generated by the initialization module of the ABM with the descriptive statistics of household survey data. Results show the distributions from the initialization match with the observed distributions well, indicating that the initialization module can represent the human agents of the real world (Fig. S2). A vital characteristic of the ABM is stochasticity, which is reflected by the randomization processes of model initialization for assigning agent attributes, and the processes for decision making during model simulation. For example, descriptive statistics suggest that the natural logarithmic of fuelwood consumption follows a normal distribution (mean = 2.2, SD = 0.733). Thus, the random-normal package with NetLogo is used to randomly generate initiate values for households with missing data on fuelwood consumption. In addition, during the simulation, the probabilistic approach (Entwisle et al., 2016) that integrates empirical knowledge and uncertainty is used to parameterize behavior rules of agents. The approach draws a random number in [0,1] and compares it with the estimated probability of adopting a behavior. If the number is smaller than the portability, then the specific decision would be taken. Given the stochasticity of the ABM, it is not reliable to draw conclusions based on the outputs of a single simulation. In this study, we conducted independent simulations 50 times, and derive the means of the outputs and their standard deviations. This is an effective way to quantify the model outputs and their uncertainty. Finally, sensitivity analysis is conducted to test the robustness of the model to changes in input parameters. Sensitivity can be assessed by perturbing each major parameter and then analyze the changes in model outputs. For example, when defining house neighbors, we assume that two houses that are less than 90, 180 and 360 m apart are considered as house neighbors and test the impact of different distance settings on our variables of interest (Fig. S3).

3.5. Empirical modeling of social network impacts

Based on the simulated outputs of our ABM for the households in the study area during 2013–2030, we develop an empirical model to test the effects of social networks on household livelihood resilience. Eq. (6) below represents this model:

$$\mathrm{R} = \alpha_0 + \alpha_1 \mathrm{Ln(SN)} + \sum_{j=1}^{n} \beta_j \mathrm{X}_j + \varepsilon \tag{6}$$

where R is the composite index of livelihood resilience based on Eq. (5). SN represents social networks. Here, we use degree and betweenness to quantify the structural characteristics of social networks and evaluate their impacts separately by running two regression models shown in Eq. (6). As the degree and betweenness of the social networks are strongly right skewed, the natural logarithmic transformation is used prior to model development to reduce the effects of skewed outlier values. X_j is one of the other factors that might influence livelihood resilience, including labor availability (number of members aged between 16 and 60), household head's age and education, cropland area, distance from house location to the nearest forest edge, CCFP payment, EWFP payment, and RG size (number of households in a resident group). The natural logarithmic transformation are also applied for CCFP payment, and EWFP payment. The parameter, α_0, is the constant coefficient; α_1 is the regression coefficient, measuring the effect of the two social network metrics on livelihood resilience; β_j is the coefficient of X_j; and ε is the error term.

Our goal is to test whether or not a household's livelihood resilience is significantly influenced by its social network (i.e., $\alpha_1 \neq 0$) and how (i.e., the magnitude of α_1 and its signs (positive or negative)), while controlling other confounding factors (i.e., X_j). The regression model is estimated at each time step of the implementation of the ABM.

4. Results

4.1. Descriptive analysis of key variables

4.1.1. Descriptive analysis of resilience indicators

Table 1 presents descriptive statistics of indicators for evaluating household livelihood resilience. The average distance of the house location to the forest edge was 37 m (1/0.027), and wild animals raided 21.7% of the remaining cropland parcels. The cropland abandonment had reached 14.9%, which could attribute to the increase of crop raiding as a result of improvement of forest conditions after the implementation of PES programs (Chen et al., 2019) and the massive rural-to-urban migration (Zhang et al., 2018b).

The average dependency ratio was 0.62, indicating the working age population was a bit larger than dependents. The higher the value, the higher the financial burden for a household. The average amount of fuelwood consumed by households for cooking, heating, and livestock feeding was 11.23 tons, which is rather high, as our previous study shows that almost all households (98%) use fuelwood, and 73% as the primary fuel (Song et al., 2018). The education level in the study area is low, with the mean value of the highest year of education received by household members being about eight years. Households usually engaged in two of the three types of agricultural activities, i.e., crop production, animal raising, and GE cultivation. The dominant income source for households in Huanghe village is still agricultural income, as only 37% of the respondents relied on non-agricultural activities. The average numbers of household members engaged in local off-farm work and out-migratory work in cities were 0.44 and 1.17, respectively.

4.1.2. Descriptive analysis of network metrics

Table 2 presents summary statistics for the degree and the betweenness of the whole social networks and the three distinct types that comprise the networks (i.e., kinship, house neighborhood, and plot neighborhood networks) in Huanghe village and its 24 Resident Groups (RGs). The mean degree of social networks of the full sample was 15.31, indicating that each household in our sample had network links with about fifteen other households. On average, each household had kinship connections with about three households, plot neighborhood associations with seven households, and house neighborhood relations with eleven households. Moving to RGs, households in Guanyan had the least connections with other households (degree = 5.7). In contrast, households in Yewan had the most connections (degree = 28.2), especially for kinship ties degree = 9.7). Households in Xiafan and Yeci had the most plot neighborhood ties. Regarding household neighborhood ties, the Jieshang and Jiexia groups were the most connected. In addition, the mean betweenness in the study area is 139.6, with households from Yewan had the largest betweenness.

Fig. 4 visualizes the kinship ties, house neighborhood ties, plot neighborhood ties, and the social networks for all households and

Table 2
Descriptive statistics of social network metrics of different resident groups (RGs) in the study area.

RG name	RG size	Degree of total social networks		Degree of kinship ties		Degree of plot neighbor ties		Degree of house neighbor ties		Betweenness centrality	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Seping	10	6.44	5.80	2.28	1.82	3.74	2.06	3.97	4.23	32.77	72.04
Sanjian	12	9.19	2.27	0.16	0.36	7.05	2.53	4.96	1.64	40.14	20.71
Gongwan	12	15.20	6.81	0.33	0.49	7.85	1.85	9.60	7.19	129.27	108.91
Jieshang	13	25.18	2.36	0.46	0.52	9.15	3.03	22.06	2.38	307.35	58.01
Laowan	13	10.22	3.75	1.52	2.00	6.46	1.85	4.61	3.69	53.71	44.47
Guanyan	15	5.72	1.93	3.13	2.74	2.83	2.05	3.91	1.72	15.33	10.43
Jiexia	16	23.52	5.87	4.15	3.58	6.46	2.16	22.49	6.77	281.96	140.55
Xiaowan	17	19.87	8.70	1.98	2.29	8.24	2.07	15.27	10.18	223.86	147.23
Pu’an	18	10.52	2.88	3.00	2.05	6.87	2.76	5.86	3.28	53.99	27.55
Yiwan	19	7.50	2.78	1.39	1.31	4.46	2.68	4.38	1.51	28.21	19.84
Hexi	20	9.53	3.80	0.66	0.90	6.53	3.61	4.90	2.58	47.75	31.85
Caowan	21	13.78	9.92	0.57	0.74	6.25	3.51	9.04	9.00	135.03	184.38
Shangli	22	14.13	4.03	1.70	1.38	3.55	2.08	12.80	4.03	100.78	49.47
Yangwan	23	10.92	2.68	1.39	2.06	8.93	3.22	4.99	1.11	57.76	27.66
Yeci	24	13.68	3.93	2.33	2.53	10.19	4.15	8.75	3.74	94.58	50.59
Baochong	25	15.39	4.51	1.35	1.71	7.67	3.71	11.70	5.89	120.72	54.96
Huamiao	25	19.04	6.42	1.25	1.25	9.33	4.55	14.93	5.86	191.74	132.90
Longmen	25	13.46	3.23	2.09	2.16	8.55	3.71	7.81	2.14	89.09	42.61
Dai’ao	27	8.09	2.74	1.71	1.07	2.99	1.83	5.57	2.36	32.41	25.43
Hedong	35	20.40	5.39	6.62	5.96	7.98	3.53	12.89	5.30	212.21	107.31
Xiali	35	19.21	7.62	2.39	2.89	3.46	2.17	18.12	7.78	204.19	111.67
Xiafan	36	16.92	5.36	1.26	1.45	10.65	4.73	11.35	4.57	148.93	91.23
Yewan	38	28.23	4.90	9.74	5.36	8.07	4.59	19.74	4.63	396.43	125.74
Zhihe	47	12.45	4.56	4.64	4.41	5.21	3.28	6.02	3.13	81.93	56.70
Full sample	548	15.31	7.72	2.82	3.83	6.86	4.02	10.70	7.37	139.56	133.34

resident groups in Huanghe village. We visualize the structure of social networks in the study area using Gephi 0.9.2 (Bastian et al., 2009). Fig. 4a shows the whole social network made up of kinship ties, plot neighborhood ties, and house neighborhood ties. We can see that except for Longmen, Pu’an, Yiwan, and Dai’ao groups, all other RGs are connected with each other, and these three groups are interlinked. The network of kinship ties formed four big clusters, each representing a big family with a distinct clan identity, such as the ones in Hedong, Yewan, and Zhihe (Fig. 4b). The graph of household neighborhood ties is more compact, which has more clusters, showing the spatial adjacent relationships of household locations among different households (Fig. 4d). The network of plot neighborhood ties is the tightest among the three types of social connections, with more RGs being connected (Fig. 4c).

4.2. Resilience response to PES disturbance

Fig. 5 shows the simulated dynamics of household livelihood resilience during 2013–2030, the main indicators measuring it, and the two network metrics based on our empirically grounded ABM. Most of the complex interplays described in Section 2 have been supported by the changing trends of indicators shown in Fig. 5. For example, the forest cover grows continuously following the implementation of PES programs. As a result, the proximity to the forest would be increasing (Fig. 5d), which brings about growth in wildlife crop damage as the predicted share of animal raiding climbs from 15% to about 50% during the simulation period (Fig. 5e). The logistic regression result also indicates that the proximity of cropland parcels to the forest edge has a significant positive impact on crop raiding (Table S1). The increased crop raiding by wildlife reduces crop yields for the remaining land parcels adjacent to forests (Zhang et al., 2018b), giving rise to an upward trend of cropland abandonment (Fig. 5h).

Regarding livelihood activities, an increasing number of households shift their labor from agricultural to non-agricultural employment, with households relying on non-agricultural activities increasing from 37% to about 60%. Specifically, the number of people pursuing local off-farm work and migration continuously grows with time (Fig. 5k & l). In contrast, agricultural diversity is decreasing over time (Fig. 5j). There would be fewer households engaging in crop production, animal raising, or GE cultivation. As more and more working age populations migrate to work in cities, the elderly, disabled, and children are left behind, thus the dependency ratio increases (Fig. 5f). The fuelwood use shrinks (Fig. 5g), because more family members work off-farm and fewer households raise animals. Thus they have less labor available to collect fuelwood, and also less demand for fuelwood. In addition, the highest education that a household received in the study area would also increase (Fig. 5i) and is supposed to reach 11 years by 2030.

The outflow of labor also has significant effects on rural social networks. Either the degree or the betweenness of households shows a downward trend (Fig. 5b & c), indicating households that stay in the countryside would have fewer acquaintances, and their influences in their respective networks would also fall. Therefore, we can see that the PES programs have long-term impacts on households’ livelihoods by altering their cropland holdings, changing the local environment, increasing crop damage rates, leading to increased cropland abandonment, reducing agricultural diversity, and increasing off-farm employment. These processes produce reciprocal feedback effects on socioeconomic and environmental outcomes, and further affect household livelihood decisions.

Consequently, we find that the overall resilience of the SES system shows a declining trend under PES intervention, which can attribute to the decrease in livelihood diversity and social network connections (Fig. 5a). In 2014 when we conduct our household survey, most households adopt part-time farming. However, the increased forest cover and wildlife crop raiding following the implementation of PES programs reduce the economic return from agricultural production. Due to the increased disturbance, most of the households have to quit farming completely and rely solely on off-farm work, which lowers their livelihood diversity. In addition, there are many rural farmers who either lack livelihood skills with mental/physical disabilities, or have to take care of other family members. It is difficult for them to transfer their livelihoods from farming to off-farm work. The reducing economic return from farming would make their livelihoods even tougher and reduce their resilience. The predicted decreasing trend of resilience under PES disturbance in our study area differs from Komarek (2018), who found the conservation agriculture had no negative effect on the resilience of grain yields to climate shocks in a western area in China. The discrepancy may have resulted from the difference in defining “resilience” and the selection of study area.

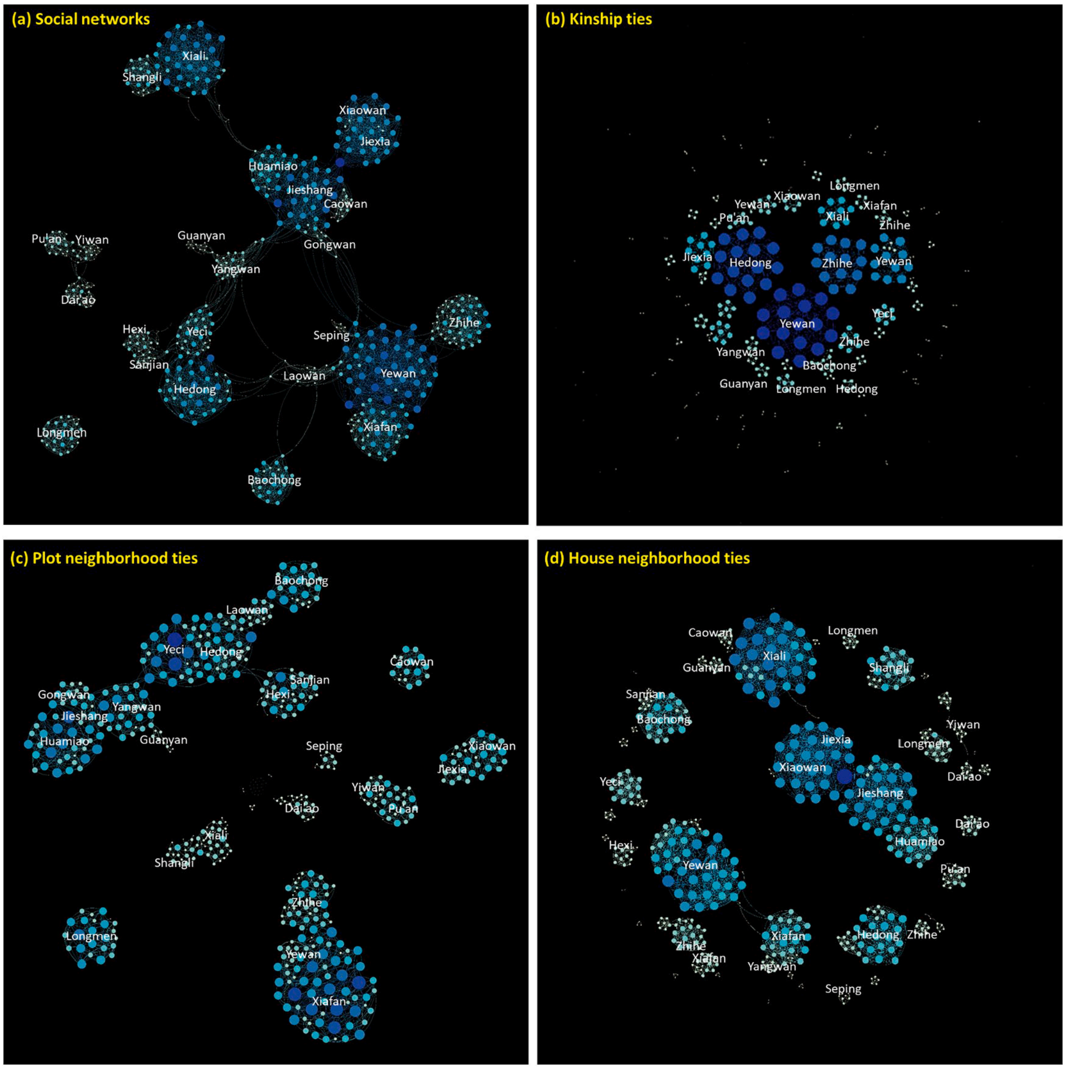

Fig. 4. Visualization of (a) social networks, (b) kinship ties, (c) plot neighborhood ties, and (d) house neighborhood ties for Huanghe village. Note: Each node indicates one household. The links indicate an undirected link between two households. The size of the nodes increases by household social integration measured by degree.

4.3. Predicted spatiotemporal patterns of resilience

We estimated the trends of livelihood resilience score for the 24 RGs in Huanghe village during 2013–2030. Among the 24 RGs, the mean highest values of resilience score are recorded in Yewan, Xiafan, and Gongwan, while the mean lowest in Yiwan, Guanyan, and Pu'an (see more details in Fig. S1).

Based on the geographical locations of the surveyed households, we created a heat map on the predicted household livelihood resilience in 2013 and 2030 using the Kernel Density tool in ArcGIS software (Fig. 6). Such a heat map may provide more detailed information on spatial distributions of livelihood resilience of households. Most of the high resilience hotspots are located in relatively lower elevations with higher population density and along the main road, such as the high-density clusters of resilience in Yewan, Xiafan, Hedong, etc. These households have more diversified livelihood choices, as the location privilege can bring opportunities for households nearby to start local businesses (e.g., sales of local products including GE, tea, and other forest products) and provisions of food and accommodation for tourists (e.g., hotels, restaurants). In contrast, households located in higher elevations and more remote areas, such as Yiwan, Seping, and Pu'an, have lower resilience scores.

We also created maps for the occurrence likelihood of crop raiding, cropland abandonment, and forest recovery for the 2225 cropland parcels in Huanghe village over space and time (Fig. 7). Because ABM involves stochasticity, for each parcel in each year, we calculated the proportion of the number of model runs with the occurrence of the incident in the total number of model runs as the likelihood of a given incident. In addition, we calculated the difference of the probabilities in the final year (2030) and the first year (2013) to represent the changes in the occurrence of the three incidents during 2013–2030. First, we detected several clusters of parcels with relatively high likelihoods of crop raiding by wildlife, especially in the west and northwest corner (Fig. 7a). These parcels are small in size, close to forest edges, and locate in high elevations. It is noteworthy that there are considerable increases in the likelihood for parcels to be raided by wildlife in the central, flat areas where most productive croplands are situated (Fig. 7b). As expected, the spatial patterns of parcels with high likelihoods to experience forest recovery are consistent with that of cropland abandonment, because forest recovery in this study occurs during the process of secondary succession following the abandonment of croplands. We observe that parcels with a high probability of being abandoned and then changed to forests are distributed mainly in the central, north, and southeast parts of the village (Fig. 7c). In addition, it is evident for an increasing trend of cropland abandonment during the simulated period in central, west and northwest corners (Fig. 7d), while the largest

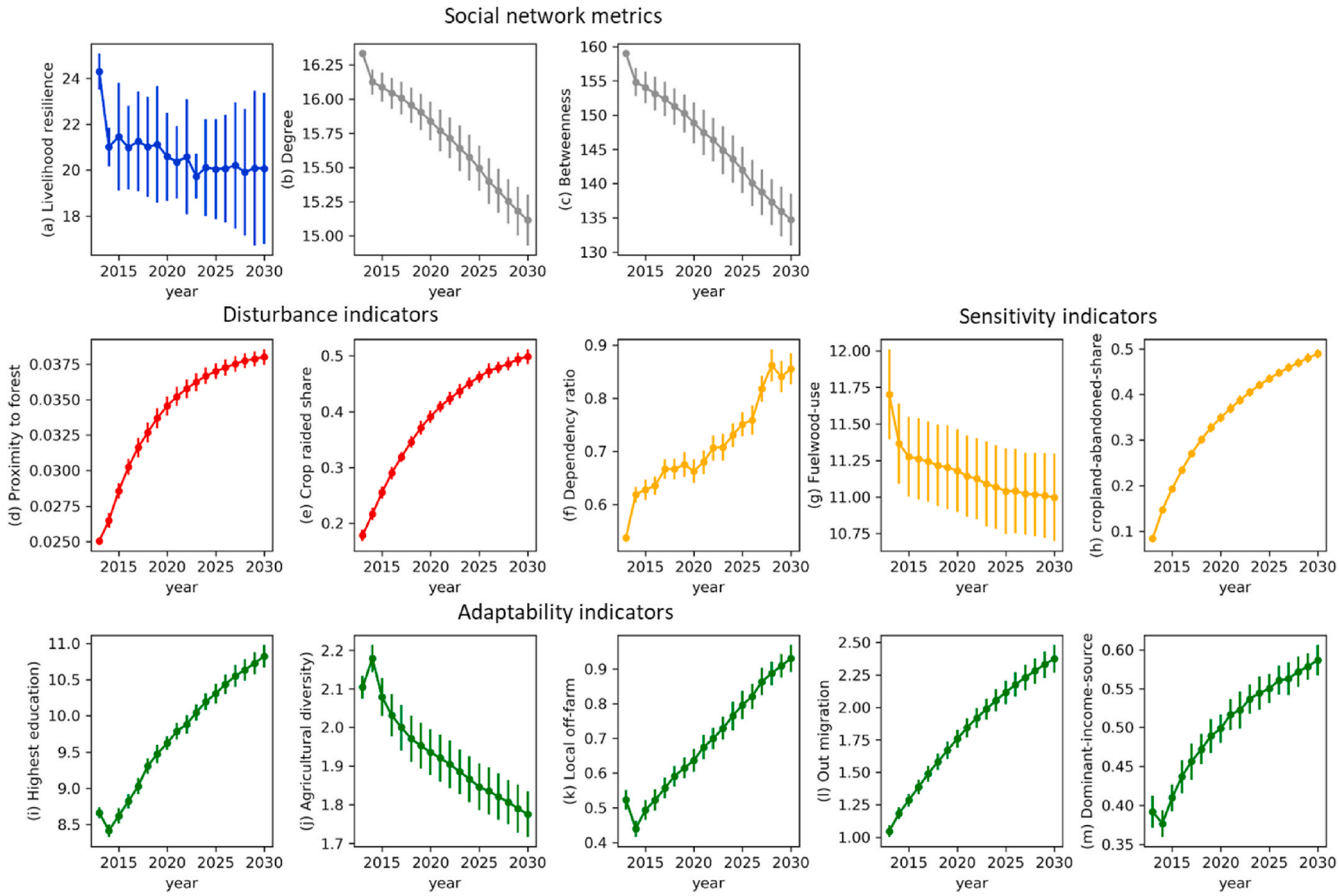

Fig. 5. Time series of household resilience and its measurement indicators.

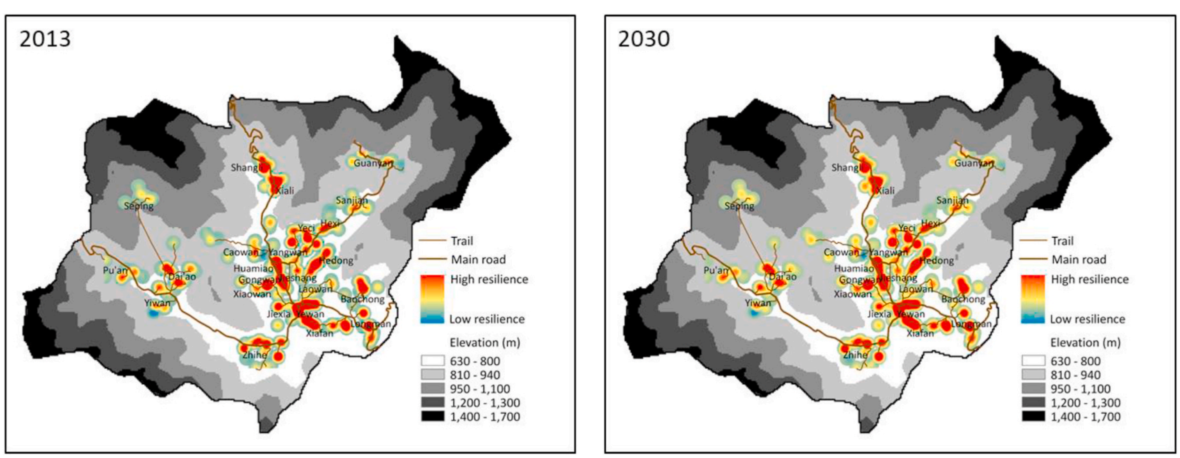

Fig. 6. Hotpots of household livelihood resilience score in 2013 and 2030.

positive changes in the likelihood of forest recovery can be seen in the westernmost part of Huanghe village (Fig. 7f).

4.4. Factors affecting livelihood resilience

Tables 3 and 4 report the simulated effects of social networks (manifested by two network metrics of node degree and betweenness) and other factors on livelihood resilience over the period of 2013–2030. Fig. 8 exhibits the predicted magnitudes and temporal trends of effects of degree and betweenness. As expected, both metrics of the degree and betweenness have significant positive impacts on households' livelihood resilience, indicating that social networks play a major role in resilience building among the households in the communities. The estimated regression coefficients of degree range from 1.054 to 2.252 during 2013–2030. That is, an increase of 10% of the degree (i.e., the direct link a household has with others increases by 10%), the indicator value of resilience would increase by 0.105–0.225 during the simulation years. The positive relationship between degree and resilience suggests that having more direct social connections with other households in the village is crucial for resilience building in rural areas. Similarly, the

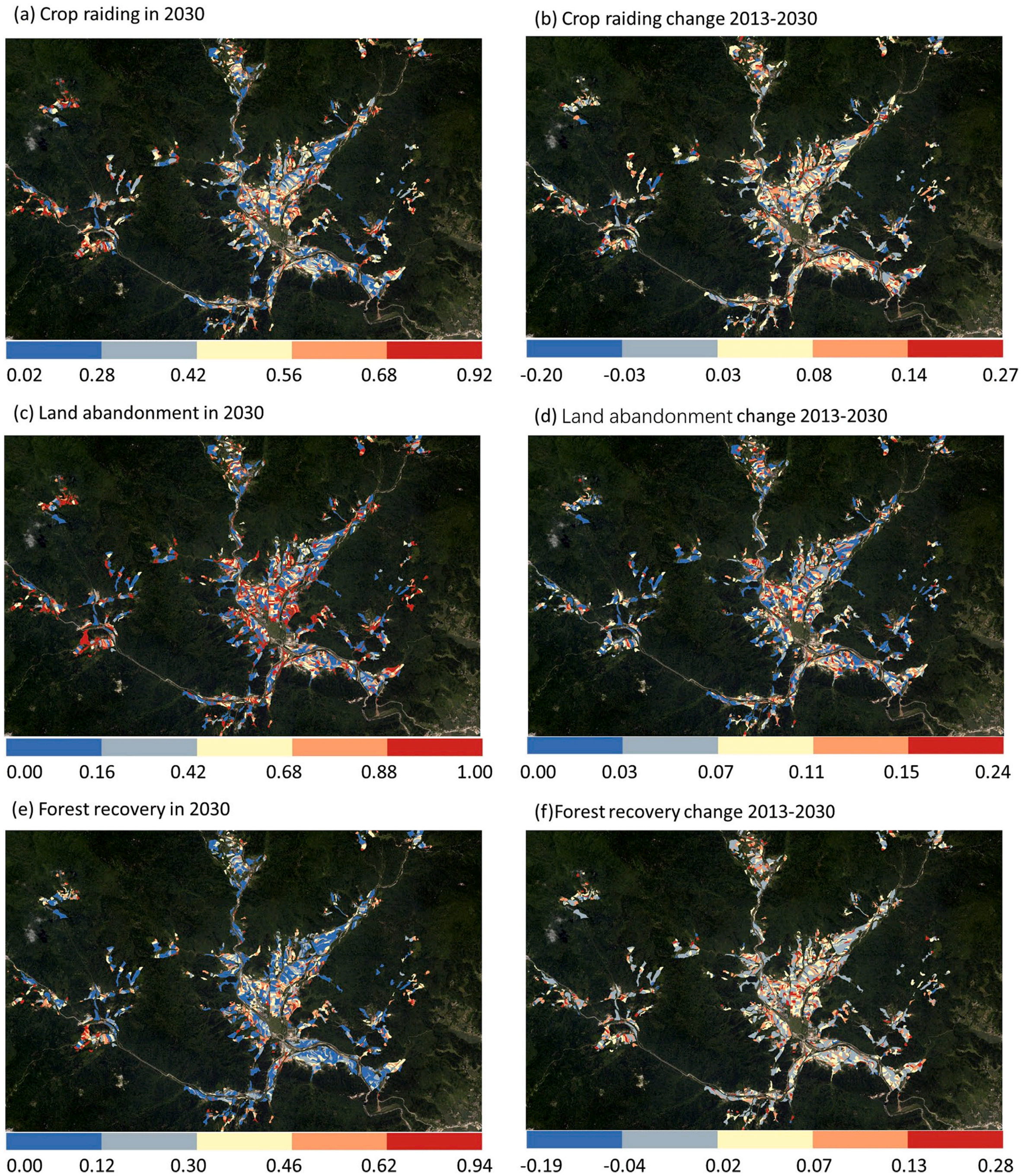

Fig. 7. Spatial patterns of likelihoods of cropland parcels been raided by wildlife, abandoned, and reforested during 2013 and 2030. The values are divided into 5 levels using the Natural Breaks (Jenks) method.

impact of the betweenness is also positive but smaller than the degree index. The impacts of degree and betweenness fluctuate over time and show decreasing trends. This may be explained by the significant decrease of the degree and betweenness caused by out-migration (Fig. 5b & c), as the removal of important nodes would significantly reduce the connectivity of subgroups in the network, which would contribute to resilience decrease.

The significant effects of other factors should also be mentioned. We find that labor availability, household head's education, distance to the forest, and RG size all positively affect household livelihood resilience. In contrast, household head's age, cropland area, and EWFP payment contribute negatively to livelihood resilience. Specifically, households that have more working age members with younger and more educated household heads, and live in larger groups would be more resilient, which is consistent with findings in other studies (Alam et al., 2018; Fang et al., 2018; Sikder and Higgins, 2016). Interestingly, we find that a larger cropland area is linked to lower resilience, which suggests cropland has essentially lost its original social security function (Wang et al., 2020a). Regarding the two PES programs, EWFP payment contributes negatively related to livelihood resilience, while CCFP has a positive impact on resilience, but the impact is only statistically significant in a few years. With regard to EWFP payment, it has a significant positive impact on cropland abandonment (see Tables 3 and 4 in Zhang et al., 2018) and a negative impact on local off-farm work (Table S5), which lowers a household's adaptability and increases its sensitivity to disturbances.

Table 3
Simulated effects of social networks measured by degree on livelihood resilience under payments for ecosystem services.

Year	Labor availability	Head's age	Head's education	Cropland area	Distance to forest	Remittances	CCFP payment	EWFP payment	RG size	Degree	Constant	R^2
2013	7.044***	−0.183***	0.541**	−0.865***	0.083***	1.448***	0.248	−2.744***	0.071**	1.237**	13.616**	0.749
2014	3.662***	−0.192***	0.328	−1.140***	0.037***	1.384***	0.193	−1.662***	0.028	2.247***	17.925***	0.637
2015	3.780***	−0.196***	0.321	−1.135***	0.045***	1.217***	0.659	−2.649***	0.012	1.658***	25.366***	0.611
2016	4.169***	−0.207***	0.485**	−1.082***	0.053***	1.301***	1.041	−2.239***	0.035	1.443**	18.588***	0.62
2017	4.659***	−0.195***	0.569**	−1.066***	0.060***	1.296***	0.510	−2.542***	0.050	1.796***	18.507***	0.64
2018	5.085***	−0.231***	0.375*	−1.028***	0.063***	1.168***	0.810	−2.455***	0.059*	1.962***	19.282***	0.673
2019	5.417***	−0.231***	0.295	−0.998***	0.070***	1.267***	0.478	−3.133***	0.057*	1.633***	23.973***	0.684
2020	5.590***	−0.220***	0.169	−0.935***	0.071***	1.303***	0.609	−2.942***	0.049	1.635***	20.869***	0.68
2021	5.830***	−0.226***	0.160	−0.947***	0.072***	1.210***	0.223	−3.116***	0.054*	1.751***	24.230***	0.69
2022	5.063***	−0.172***	0.407**	−1.055***	0.052***	1.283***	0.697	−2.582***	0.040	1.404***	18.159***	0.699
2023	5.774***	−0.233***	0.461**	−0.899***	0.088***	1.415***	0.065	−2.705***	0.061*	2.127***	18.338***	0.696
2024	6.240***	−0.242***	0.904***	−0.858***	0.096***	1.170***	1.335**	−2.555***	0.060*	2.252***	10.683*	0.692
2025	6.473***	−0.216***	0.589**	−0.836***	0.095***	1.713***	1.149*	−2.512***	0.058	1.788***	7.181	0.701
2026	6.712***	−0.177***	0.575**	−0.814***	0.098***	1.812***	0.099	−2.710***	0.076**	1.442**	9.92	0.719
2027	6.810***	−0.243***	0.731***	−0.720***	0.098***	1.310***	0.815	−2.626***	0.120***	1.054*	13.910**	0.706
2028	6.829***	−0.253***	0.555**	−0.685***	0.099***	1.144***	0.618	−2.390***	0.106***	1.110*	16.607**	0.693
2029	6.738***	−0.271***	0.511**	−0.660***	0.095***	1.138***	0.062	−2.604***	0.115***	1.066*	22.017***	0.691
2030	6.822***	−0.282***	0.292	−0.662***	0.092***	0.963***	1.118**	−2.502***	0.085**	1.432**	20.191***	0.673

Note: *p < 0.10. **p < 0.05. ***p < 0.01.

Table 4
Simulated effects of social networks measured by betweenness on livelihood resilience under payments for ecosystem services.

Year	Labor availability	Head's age	Head's education	Cropland area	Distance to forest	Remittances	CCFP payment	EWFP payment	RG size	Betweenness	Constant	R^2
2013	7.042***	−0.183***	0.542**	−0.866***	0.083***	1.446***	0.248	−2.739***	0.070**	0.570**	14.437**	0.749
2014	3.657***	−0.193***	0.329	−1.141***	0.037***	1.384***	0.197	−1.657***	0.027	1.026***	19.410***	0.638
2015	3.775***	−0.197***	0.322	−1.136***	0.044***	1.217***	0.661	−2.643***	0.011	0.762***	26.445***	0.612
2016	4.164***	−0.207***	0.486**	−1.083***	0.053***	1.300***	1.044	−2.230***	0.034	0.669***	19.500***	0.620
2017	4.653***	−0.195***	0.570**	−1.067***	0.059***	1.296***	0.513	−2.535***	0.049	0.825***	19.665***	0.640
2018	5.081***	−0.231***	0.376*	−1.029***	0.063***	1.166***	0.811	−2.449***	0.058*	0.897***	20.586***	0.673
2019	5.413***	−0.232***	0.296	−0.998***	0.070***	1.266***	0.479	−3.128***	0.056*	0.748***	25.050***	0.684
2020	5.585***	−0.220***	0.171	−0.936***	0.071***	1.302***	0.610	−2.933***	0.048	0.759***	21.896***	0.681
2021	5.827***	−0.226***	0.161	−0.948***	0.071***	1.209***	0.224	−3.110***	0.053	0.803***	25.379***	0.69
2022	5.061***	−0.172***	0.408**	−1.056***	0.051***	1.280***	0.700	−2.577***	0.039	0.649***	19.084***	0.700
2023	5.771***	−0.233***	0.463**	−0.900***	0.088***	1.413***	0.061	−2.700***	0.060*	0.971***	19.784***	0.696
2024	6.237***	−0.243***	0.905***	−0.858***	0.095***	1.169***	1.332**	−2.551***	0.060*	1.024***	12.218*	0.692
2025	6.470***	−0.216***	0.590**	−0.837***	0.094***	1.711***	1.145*	−2.504***	0.056	0.825***	8.355	0.701
2026	6.710***	−0.177***	0.576**	−0.814***	0.098***	1.810***	0.096	−2.703***	0.075**	0.666**	10.859*	0.719
2027	6.807***	−0.243***	0.731***	−0.721***	0.097***	1.310***	0.814	−2.621***	0.120***	0.486*	14.598**	0.706
2028	6.827***	−0.253***	0.555**	−0.685***	0.099***	1.143***	0.616	−2.386***	0.106***	0.509*	17.338***	0.693
2029	6.736***	−0.271***	0.511**	−0.660***	0.095***	1.138***	0.061	−2.597***	0.114***	0.497*	22.687***	0.691
2030	6.820***	−0.282***	0.291	−0.663***	0.092***	0.962***	1.116**	−2.494***	0.084**	0.664**	21.109***	0.674

Note: *p < 0.10. **p < 0.05. ***p < 0.01.

5. Discussion

5.1. Resilience thinking with the role of social networks

Social networks are increasingly recognized as crucial resources for building adaptive capacity, and thus enhance resilience to socioeconomic and environmental disturbances (Ayuttacorn, 2019; Cassidy and Barnes, 2012; Rockenbauch and Sakdapolrak, 2017). For instance, social networks can facilitate information and material flow and exchange that help stabilize the structure and function of social-ecological systems, especially those vulnerable to socioeconomic and environmental disturbances. However, the actual role that such social networks play in natural resource-dependent communities (such as CPSA) that faced with variations in SES induced by PES has not yet been understood. This study aims to examine the effects of social networks on the livelihood resilience of the rural SES in one of the 14 CPSA of China. We examined the social networks through three types of ties, kinship ties, house neighborhood ties, and cropland plot neighborhood ties. Through the lens of these three ties, a full range of perspectives regarding how social networks function can be derived and examined. The kinship ties and neighborhood ties rely on the connections at the organizational level where individuals and households and their interactions undergird the structure and function of the main socio-economic system, while the interactions between human agents (e.g., individuals and households) and the environment (i.e., land) lead to how the ecological system changes as manifested by cropland plot neighborhood ties. The essential feedbacks with the SES are heavily dependent on these ties, maintaining an equilibrium of complexity. When an external force was imposed on the SES, it may or may not cause significant changes as cascading effects propagate through these ties as well as their interactions. To capture the complex effects relating to the ties, two of the most widely applied metrics in social network analysis, i.e., the degree and the betweenness, are used to measure the structure of each household's social connections established in the village. Results from an empirical ABM and statistical models developed in this study clearly show that social networks significantly impact household livelihood decision-making and resilience building. First, the social network contributes positively to the adoption of local off-farm employment and out-migration (Table S5 & S6). Recent studies have also outlined its crucial role in the application of new techniques (Fischer, 2013; Ramirez, 2013), diffusion of agricultural information and innovation (Beaman and Dillon, 2018; Xiong et al., 2018), and practice of low carbon behaviors (Yin and Shi, 2019). Thus, understanding social networks and their effects on household livelihoods can assist the design of rural development programs.

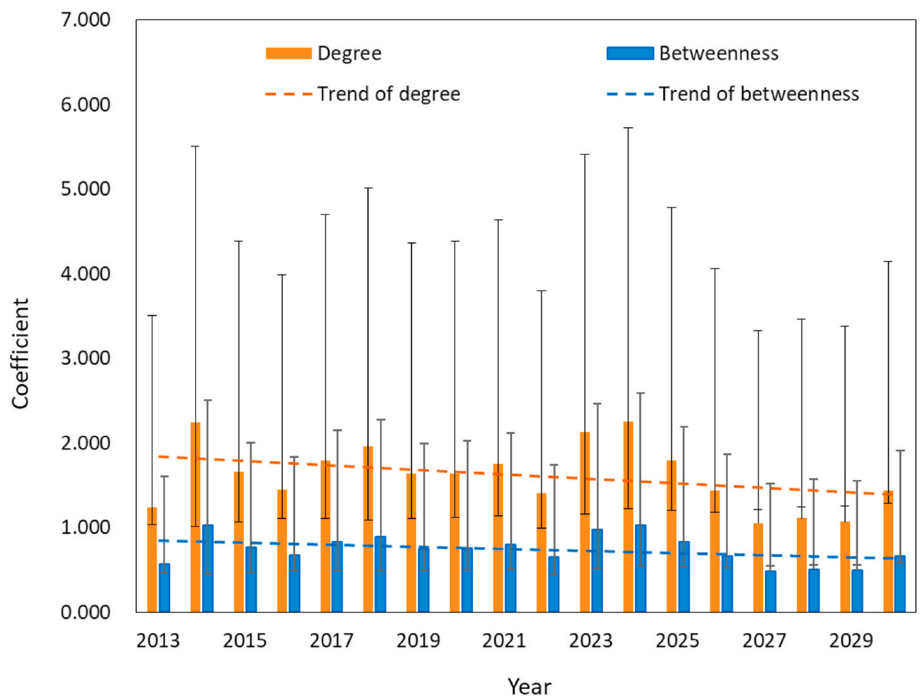

Fig. 8. Simulated dynamics of social network effects on household livelihood resilience manifested by degree and betweenness.

Policymakers may use social networks to spread information and technology, and promote efficient practices.

Second, social networks, as measured by the degree and betweenness, have significant positive impacts on livelihood resilience. The degree represents the number of direct links a household has with other households in the social networks. A household with a higher degree is endowed with more resources and opportunities through direct connections to other households, which enhance their ability to diversify livelihoods (Xia et al., 2020). The betweenness refers to the number of times a household acts as a bridge along the shortest path between two other households. Households with higher betweenness are those bridging nodes supporting the social networks, passing information through kinship or neighborhood ties (Rathwell and Peterson, 2012). They locate in more central positions in their social networks and are likely to have a wider range of livelihood strategies, thus are more resilient. This result is in accord with recent studies in other developing countries (such as South Africa and India), indicating that the node degree and betweenness are positively linked to income diversification (Johny et al., 2017), food security (Claasen and Lemke, 2019), adaptive capacity (Schramski et al., 2017), and thus livelihood resilience (Cassidy and Barnes, 2012). The heatmaps of livelihood resilience also show that households situated in larger resident groups with more social connections are much more resilient than households in relatively isolated areas. In addition, our results show that both effects of degree and betweenness decrease over time, which may attribute to the rapid changes in the structure of social networks in rural China. Due to rapid urbanization, industrialization, and massive rural-to-urban migration, the traditional agricultural society has been experiencing dramatic transformations. Consequently, the rural community solidarity and cohesion are disintegrating, and the traditional local social communities may lose their effectiveness in livelihood support (Ma et al., 2018; Yang et al., 2020). The atrophy of social networks in rural areas would make the households left behind in the countryside more difficult and less resilient to disturbances and shocks. Thus, it is essential to enhance social connections among households and establish formal and informal social organizations for households that are left behind in the countryside in the great transformation of the Chinese agrarian society.

5.2. *Strengths and limitations*

Relying upon detailed household survey data in a poor rural area in China, we develop an ABM to understand the complex dynamics of the SES, evaluate the role of social networks in livelihood resilience. The ABM can simulate dynamics in both the social system (including individual demographic processes and household livelihood decisions) and the ecological system (including wildlife crop raiding, cropland abandonment, and secondary forest succession). These two systems interact with each other through reciprocal feedback loops with complex mechanisms that require sophisticated approaches to uncover. It is the reciprocal feedbacks between the ecological system to the social system that makes the conventional econometric modeling relaively ineffective in understanding the dynamics of SES, compared with the approach with ABM. More importantly, our ABM can simulate the evolution of social networks over time and their impacts on household behaviors, which is rather valuable as empirical network data at multiple time points can be difficult and costly to collect. By integrating with GIS, ABM can represent micro-level human behavior in the landscape change processes in a spatially explicit manner (Heppenstall et al., 2021).

As a bottom-up approach, our ABM model is capable of generating surprise outcomes that emerge from nonlinear interactions within the SES. The nonlinearity can be well illustrated by the results from the temporally varying associations between the PES programs and household resilience (Tables 3 and 4). Specifically, the model produced opposite effects between CCFP (positive) and EWFP (negative) on building household resilience. This result is consistent with our previous findings that CCFP can stimulate household to shift labor allocation from on-farm to off-farm employment, especially rural-to-urban migration, whereas EWFP tends to demotivate labor out-migration because the generous compensation the household received from EWFP reduce the need for alternative income sources (Zhang et al., 2018a). Since out-migration constitutes a critical part of household resilience in adaptation to external disturbances (see adaptability indicators in Table 1), CCFP can enhance household resilience by freeing farm labor after converting the marginal cropland to forests, and the freed farm labor can seek better opportunities, including out-migration. In contrast, EWFP, which does not involve land conversion, may increase household sensitivity to disturbance (see sensitivity indicators in Table 1) as a result of induced cropland abandonment (Wang et al., 2019; Zhang et al., 2018b). This nonlinear variation likely involves feedbacks from other processes within the SES. Song et al. (2018) found that CCFP does not have a significant influence on household fuelwood use, while EWFP is strongly associated with more fuelwood use, which also affects the livelihood resilience (Table S7 in Section S1.3.3). Such a policy outcome is highly valuable for policy-makers to finetune existing environmental policies or create more effective new environmental policies. These results demonstrate that the ABM is a valuable tool in projecting the short- and long-term effects of environmental policies on the dynamics of the complex SES. It should be noted that the primary aim of our ABM is to understand the emergence of the complexity (indicated by resilience and social network) from the farmers' decisions, and how that can help us better uncover the mechanisms involving feedbacks in the SES, rather than predicting what would happen in the real world although the model has been calibrated to be more realistic to many other models. Here, in our model, the emergence outcomes on resilience is a result of both initial condition (set up by our survey data) and feedbacks operating during the model simulations. As time goes on, we are extrapolating further away into the future, and thus the realistic aspect of the model results diminishes.

The method of establishing households' social network based on the naming rule and spatial adjacency (house and plot neighbors) is an innovation of this study, which is less time and money consuming than the name generator and name interpreter methods that are often used to gather empirical network data (Bourne et al., 2017; Cassidy and Barnes, 2012; Xia et al., 2020). However, although most household heads' were born before the 1980s (more than 95%) and adopted generation and family names, there are still some households that do not follow the tradition, thus the kinship ties identified based on the naming rule are not always complete. It should be noted that the kinships out of marriage are not considered in this study as we cannot derive such information based on the census data only. In addition, human behaviors are rather complex. They may not exchange resources and information only with these blood-based relatives or location-based neighbors. Some households may not live in the village despite having a rural household registration (rural "*hukou*") because the rural hollowing problem is quite pervasive in rural China (Liu et al., 2014). Thus, we need to conduct another survey to investigate who they actually share or exchange information, labor, money, food, and other livelihood materials. In addition, social networks are treated as non-directional and unweighted in this study. However, social networks have a strength (e.g., strong versus weak ties) and a direction (e.g., household A may ask household B for social support, but B may not turn to A when need help) (Claasen and Lemke, 2019; Dapilah et al., 2019).

6. Conclusions

Paments for Ecosystem Services (PES) schemes bring opportunities for poverty reduction while promoting environmental conservation, but changes in socioeconomic and environmental conditions following the implementation of PES programs (e.g., increased forest cover, increased crop raiding, and out-migration) generate certain disturbances for livelihood resilience. This paper examines how rural social-ecological system (SES) respond to two nationwide PES programs in one of the 14 contiguous poverty-stricken areas (CPSA) of China, evaluates the livelihood resilience in different communities, and assesses the impacts of social networks on livelihood resilience for the households in the study area. Simulation results from our agent-based model (ABM) show that the livelihood resilience of rural households in the SES system is expected to decline during 2013–2030 under PES intervention primarily as a result of reciprocal feedback loops between the natural and social systems. Households located in relatively lower elevations with higher population density and along the main road are more resilient to disturbances. As expected, social networks impose significant positive impacts on livelihood resilience and that households with higher degree and betweenness are associated with greater resilience. In addition, numerous other factors also affect livelihood resilience. For example, households that have more working age members with younger and more educated household heads, live in larger resident groups and further from forests would be more resilient. As time goes on, cropland has gradually lost its original social security function and contribute negatively to livelihood resilience. EWFP payment contributes negatively to livelihood resilience, while CCFP has a positive impact on resilience. Therefore, this study adds values to the existing literature by empirically examining the role that social networks play in natural resource-dependent communities faced with variations in SES induced by PES. Moreover, the ABM model developed in this study can be used to evaluate the long-term effects of environmental policies, and improve our understanding of the dynamic interplay of the human and natural systems.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jrurstud.2021.05.017.

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