IA-SDSS: A GIS-based land use decision support system with consideration of carbon sequestration

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ABSTRACT

Land use, land use change and forestry (LULUCF) can play a positive role in mitigating global warming by sequestering carbon from the atmosphere into vegetation and soils. Local entities (e.g. local government, community, stockholders) have been making great efforts in enhancing carbon sequestration (CS) of local forests for mitigating global climate change and participating in international carbon-trade promoted by the Kyoto Protocol. Approaches and tools are needed to assess the enhancement of CS through land use changes and proper policy decisions. This paper presents an integrated assessment framework and a spatial decision support system (IA-SDSS) as a tool to support land-use planning and local forestry development with consideration of CS. The IA-SDSS integrates two process-based carbon models, a spatial decision (EMDS) module, a spatial cost-benefit analysis (CBA) module, and the analytic hierarchy process (AHP) module. It can provide spatially explicit CS information as well as CS-induced economic benefits under various scenarios of the carbon credit market. A case study conducted in Liping County, Guizhou Province, China demonstrated that the IA-SDSS developed in this study is applicable in supporting decision-making on 'where' and 'how' to adopt forestry land use options in favor of CS.

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1. Introduction

As major indicators of human disturbances, land use changes significantly influence the carbon (C) fixation and flux (Post and Kwon, 2000). Appropriate land use changes and forestry activities have often been considered to be opportunities to reduce net CO_2 emissions to the atmosphere or to increase the net uptake of C from the atmosphere (IPCC, 1996, 2007). The Kyoto Protocol under the United Nations Framework Convention on Climate Change (UNFCCC) agreed by more than 150 nations confirms that the eligible land use, land use change, and forestry (LULUCF) activities in the forms of reforestation and afforestation as parts of the Clean Development Mechanism (CDM) could provide C credits for off-setting for green house gas emission of developed countries (UNFCCC, 1997, art.3.3 and 3.4).

CS through appropriate forestry land use practices (e.g. reforestation and afforestation) is regarded as a win–win strategy with benefits to the global climate change mitigation, environmental

conservation and rural poverty alleviation (FAO, 1999; Lal, 2002; Tschakert, 2004; Ponce-Hernandez, 2004; Lipper and Cavatassi, 2004; Pfaff et al., 2007). Reforestation and afforestation refer to the direct human-induced conversions of non-forested to forested land that was forested but has previously been converted to non-forested land and that has not been forested for a period of at least 50 years (UNFCCC, 1997, 2001).

The implementation of CS through reforestation and afforestation activities needs land-use planning considering benefits of CS. In the past decade, efforts have been made to assess the CS potential of terrestrial ecosystems (Lal, 2005; Shrestha and Lal, 2006; Roxburgh et al., 2006; Schaldach and Alcamo, 2006) and to analyze the relevant eco-environmental and economic issues (De Jong et al., 2000; Kerr et al., 2003; Wise and Cacho, 2005; Olschewski and Benitez, 2005; Antle et al., 2007; Caldwell et al., 2007; Perez et al., 2007). C balance has been taken as a principal criterion for sustainable forest management (Chertov et al., 2005), and the linkage of CS with local and regional sustainable development has been proposed (IPCC, 1996; Gundimeda, 2004; Yin et al., 2007). Ponce-Hernandez (2004) extended conventional land evaluation guidelines published by FAO with CS to a new land suitability assessment process for crop selection. Palma et al. (2007) took CS as one of criteria in the environmental assessment. CS has

significant effects on local land-use planning. From the local perspective, the CS potential will be an important criterion in land resource utilization evaluation and decision-making with ongoing C markets on voluntary basis.

Reliable, robust and cost-effective methods are required for accurately quantifying CS potential in terrestrial ecosystems (Lal, 2005; Zhao and Zhou, 2005; Niu and Duiker, 2006). Many methodologies have been developed for this purpose (Lal, 2005; Shrestha and Lal, 2006; Roxburgh et al., 2006; Schaldach and Alcamo, 2006). Models are currently acting as effective tools for assessing regional and global C cycles and their dynamics (Leith, 1975; Liu et al., 1997; Liu et al., 2002; Chen et al., 1999; Feng et al., 2007). They can also been used to predict the further trends of CS by terrestrial ecosystems under projected future climates and atmospheric CO_2 concentration (Cao and Woodward, 1998; Ju et al., 2007). Process-based models (Daly et al., 2000; Running and Coughlan, 1988) may be more reliable than statistical and parametric-based ones because of their foundation on mechanisms of C cycling in terrestrial ecosystems (Liu et al., 1997).

On the other hand, spatially explicit approaches have been developed for producing geo-referenced estimates of the CS potential (Liu et al., 1997; Chen et al., 2003; Ponce-Hernandez, 2004). The geographical information system (GIS) method is one of indispensable research approaches that can be combined with remote sensing and ecological models to assess C dynamics at different spatial scales (Lal, 2002). The characteristics of a few representative studies using GIS for estimating C potential are summarized in Table 1. In these studies, GIS is usually employed to process model inputs (climate, land cover and soil texture) and to visualize results (Ardö and Olsson, 2003; Ponce-Hernandez, 2004; Schaldach and Alcamo, 2006). However, no studies fully integrate process-based C models with GIS to estimate CS of terrestrial ecosystems affected by climate, atmospheric CO_2 concentration and forest age and to conduct land-use planning spatially considering the economic and ecological benefits from CS.

Since late 1970s, China has been engaging in forest plantations on large scales, and the total forest area increased from 122 million ha in late 1970s to 159 million ha in 2001 (China Year Book, 2002; SFA, 2006). These activities have had considerable consequences in C budget of China's terrestrial ecosystems (Wang et al., 2007; Thomas et al., 2007; Cao, 2008). At the local level (county, township, village), the land-use planning is generally closely associated with the need for economic development. The incentives for adopting land use strategies enhancing CS would result from market realization of the C value. This market force, if established fully in the near future, would dramatically alter the land use pattern at the grassroot level. A land use decision support tool that has the capability of estimating the CS potential and including the C value in the economic analysis would be urgently needed for improving CS by terrestrial ecosystems through proper land-use planning practices.

To satisfy this goal, an integrated land use assessment and spatial decision support system (IA-SDSS) was developed. This system was constructed on the ArcGIS 9.0 platform to spatially estimate CS potential using process-based C models, to compare ecological and economic benefits of different forest type and species options, to assess the suitability of different locations for CS land use activities. In this paper, the major characteristics of this system and its strategies to integrate different components are firstly highlighted. Then, functions of its components are described. Finally, a case study in Liping County, Guizhou Province, China was conducted to test the applicability of this system in land use assessment with consideration of CS benefits at a local scale.

2. IA-SDSS

2.1. Framework

The IA-SDSS was implemented with ESRI ArcGIS® 9.0 Visual Basic for Application (VBA) and integrates five core modular components (Fig. 1), including two C models (BEPS and InTEC), a common modelling tool named ecosystem management decision support (EMDS) developed by the USDA Forest Service Pacific Northwest Research Station (Reynolds et al., 1996, 2003; Reynolds, 2005), a spatial cost-benefit analysis (CBA) module and a analytic hierarchy process (AHP) module.

The Boreal Ecosystem Productivity Simulator (BEPS, Liu et al., 1997) is a process-based ecosystem productivity model used to calculate annual net primary productivity (NPP) at daily time steps. The Integrated Terrestrial Ecosystem C-budget model (InTEC, Chen et al., 2000, 2003) is employed to simulate forest C budgets spatially at annual steps by integrating the effects of climate, atmospheric CO_2, nitrogen (N) deposition and forest disturbance on CS (Chen et al., 2003; Wang et al., 2007; Ju et al., 2007). In the IA-SDSS, the NPP in a reference year simulated by BEPS at daily time steps is used as a benchmark to set the initial value of NPP in the InTEC model (Ju et al., 2007). The InTEC model simulates historical and future annual NPP and CS of each cell in the study area.

The CBA module is to conduct a spatial cost-benefit analysis based on data of cost (maintenance and opportunity), annual average income, and simulated CS which are organized as GRID layers. The output from CBA is the net present value (NPV) of each cell. NPV is also stored as a GIRD layer. The average of NPV in each assessment unit is calculated and input into the EMDS module. EMDS loads the knowledge base in the EMDS project environment (ArcMap*.mxd file) of ArcGIS 9.0, searches data through a Data Acquisition Manager from input map layers of a tabular attribute, drives NetWeaver engine to conduct logic operation, and finally produces a map layer representing the suitability of each assessment unit for reforestation. Ecological and economic benefits from CS, slope, and aspect are included in the assessment of suitability. The AHP module is used for selecting tree-species according to given assessment indicators and can also be employed to assign the weights for EMDS overlay layers. The IA-SDSS system enables the preparation of spatial dataset, the import and export of digital maps and the production of statistical charts.

The major functions of the IA-SDSS are: (i) to simulate spatial and temporal dynamics of local C stocks and sequestration potential; (ii) to conduct spatially explicit modelling of economic cost-

Table 1
Representative studies involving carbon sequestration (storage) modelling integrated with GIS.

| Framework	Literature	Resolution	Carbon simulation	Motivation	Platform
Sudan soil organic carbon assessment system	Ardö and Olsson, 2003	1 km²	CENTURY model	Assess soil organic carbon	ArcView
AFFOREST sDSS	Gilliams et al., 2005	1 ha, 1 km²	Logistic growth function and Soil acidification model	Afforestation planning	ArcView 3.2
HILLS model system	Schaldach and Alcamo, 2006	1 km²	CENTURY model	Modelling land use changes	ArcGIS 8.3
GEFSOC soil carbon modelling system	Easter et al., 2007	4 km²	CENTURY and Roth C model	Soil carbon (C) inventory.	ArcView or ArcGIS
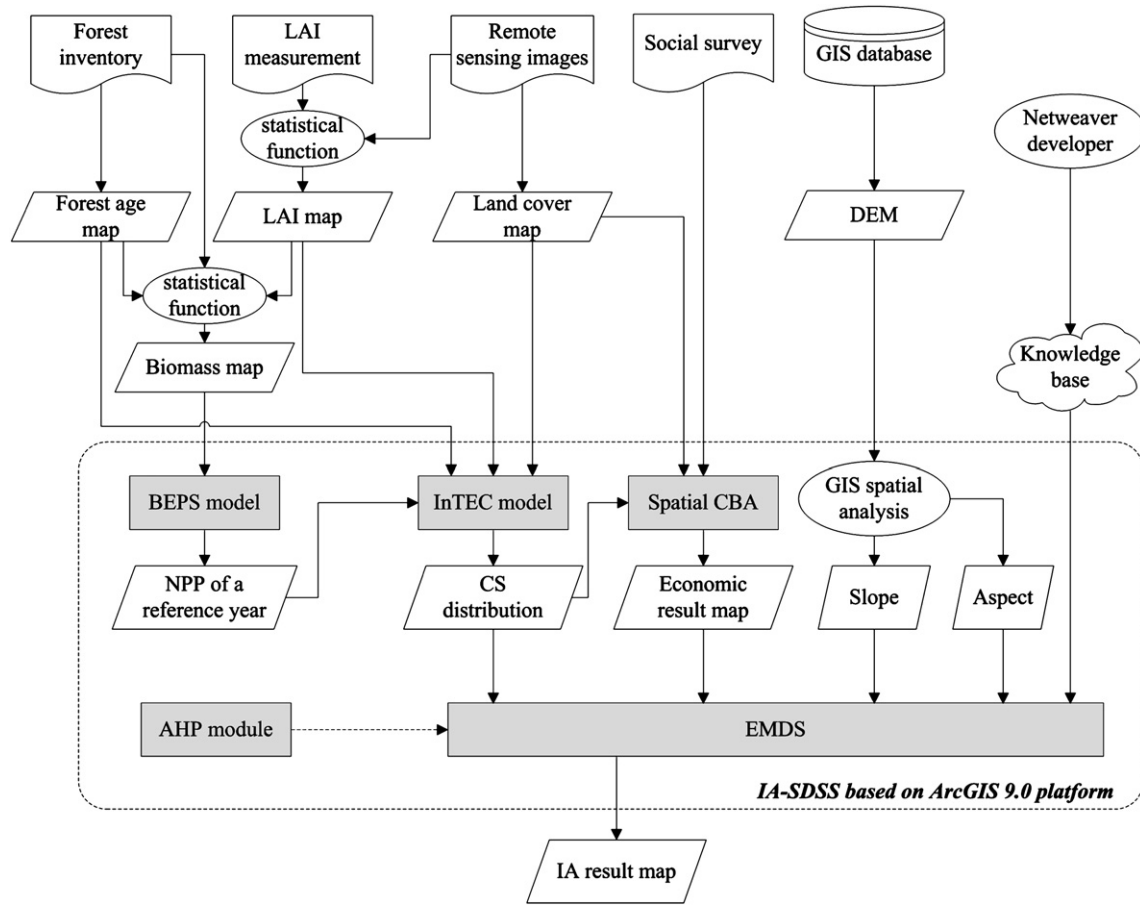
Fig. 1. The framework and structure of the IA-SDSS. The five core modules in shaded boxes are inter-related by data exchange as depicted by arrows.

benefit and trade-off with consideration of CS potential benefit which is calculated by multiplying simulated CS quantity with a given C price; (iii) to assess suitability of each assessment unit for different land use options; and (iv) to determine the priority of plantation species based on tree-species selection results using the AHP module.

2.2. Models, parameters and inputs

The BEPS and InTEC models are coupled to simulate CS for each cell. The NPP in a reference year simulated by BEPS at daily time steps is an input to InTEC. The InTEC model includes a component for calculating annual NPP by spatially and temporally scaling up the Farquhar's biochemiocal model (Farquhar et al., 1980; Chen et al., 2000), and a component for simulating soil C and N dynamics using algorithms adopted from the CENTURY model (Parton et al., 1987). The distinction of InTEC from other C models is the representation of the effect of forest age on NPP (Chen et al., 2002). The details of InTEC refer to the literatures (Chen et al., 2000, 2003).

In InTEC, historical NPP is calculated as

$$NPP(i) = NPP_u(i)Fnpp(a_i)/Fnpp(a_0). \tag{1}$$

where $NPP_u(i)$ is NPP value determined by non-disturbance factors (climate, CO_2, and N availability), $Fnpp(a_i)$ and $Fnpp(a_0)$ are normalized productivity values of a forest at ages a_i (in the ith year) and a_0 (in the starting year), respectively (Chen et al., 2003). They range from 0 to 1.0 and equal the NPP at given ages divided by the maximal NPP value when the forest growth peaks (Chen et al.,

2000, 2003). The variation of NPP with age is fitted by a generalized semi-empirical mathematical function (Chen et al., 2000):

$$NPP(\text{age}) = a\left(1 + \left(b(\text{age}/c)^d - 1\right)\big/\exp(\text{age}/c)\right) \tag{2}$$

where $NPP(\text{age})$ is the NPP as a function of age; and the parameters a, b, c and d are dependent on the site index.

NPP affected by non-disturbance factors $NPP_u(i)$ can be calculated as:

$$NPP_u(i) = NPP_u(0) \prod_{j=1}^{i} \frac{2 + \chi(j)}{2 - \chi(j)} \tag{3}$$

where $NPP_u(0)$ is the NPP value in the initial year; $\prod_{j=1}^{i} 2 + \chi(j)/2 - \chi(j)$ represents the integrated effect of non-disturbance factors on NPP. Eqs. (1)–(3) are combined to calculate annual NPP through iteration at given $NPP_u(0)$, climate, and atmospheric CO_2 concentration. $NPP_u(0)$ is tuned until the difference of NPP simulated by the InTEC and BEPS models in the reference year is smaller than a threshold (1% of NPP simulated BEPS).

Values of important parameters used in BEPS are listed in Table 2. Table 3 gives parameter values used in InTEC for the major forest cover types.

The main inputs for the BEPS model are leaf area index (LAI), land cover, biomass, soil available water-holding capacity (AWC) and daily meteorological data (air temperature, solar radiation, precipitation and specific humidity) (Table 4). InTEC is driven by spatial data sets of annual and growing-season mean temperatures, annual total precipitation, growing season length, remotely sensed

Table 2
BEPS model parameters and values for NPP calculation (cited from Liu et al., 1999; Chen et al., 1999; Xu et al., 2007).

Parameter (unit)	Conifer	Deciduous	Mixed	Crops	References
Maximum stomatal conductance (mm s^{-1})	2.25	4.5	3.38	2.0	Hunt et al., 1996; Matsushita and Tamura, 2002
Clumping index	0.5	0.7	0.6	0.9	Liu et al., 1997
Leaf nitrogen content (%)	1.2	1.2	1.2	1.2	Chen et al., 1999
Maximum leaf nitrogen content (%)	1.5	1.5	1.5	1.5	Chen et al., 1999
Maximum carboxylation rate at 25 °C (mmol m^{-2} s^{-1})	33	33	33	50	Bonan, 1995; Liu et al., 1999
Biomass of leaf (kg C m^{-2})	0.5	0.3	0.4	0.1	Foley, 1994; Matsushita and Tamura, 2002
Sapwood carbon of stem (kg C m^{-2})	9.2	8	8.5	0.1	Foley, 1994; Matsushita and Tamura, 2002
Biomass of root (kg C m^{-2})	2.3	1.7	2.1	0.1	Foley, 1994; Matsushita and Tamura, 2002
Leaf respiration coefficient (g C day^{-1} kg^{-1})	2.67	3.98	3.12	2.0	Foley, 1994; Matsushita and Tamura, 2002
Stem respiration coefficient (g C day^{-1} kg^{-1})	0.05	0.05	0.05	0.5	Foley, 1994; Matsushita and Tamura, 2002
Root respiration coefficient (g C day^{-1} kg^{-1})	0.2	0.2	0.2	0.1	Foley, 1994; Matsushita and Tamura, 2002

LAI and land cover, fractions of sand, clay, and silt in soils, NPP simulated by BEPS and forest age in a reference year, N deposition rates (Table 5). An annual value of CO_2 concentration is used for the study area in each year. The spatial variation of CO_2 is not considered.

2.3. Spatial cost-benefit analysis

A CBA module is used to estimate spatial variations in the economic cost-benefit trade-off with consideration of CS and to investigate the economic implications of C price. The spatially integrated assessment approach has been used in environmental economics (Bateman et al., 2006) and has the advantage in revealing the spatial distribution of assessment results. Some studies show that tree plantations can provide considerable C sinks and timber yields, but have the disadvantage of high investment costs and the need for access to long-term financing (Winjum et al., 1993; Masera et al., 1997; Sedjo, 1999). The NPV analysis method is adopted to compare the performance of land use options in making returns such as forestry products plus C credits. Forestry investment revenues are normally the total income from forests, and the costs include site preparation, planting, management, and loss of opportunities. The opportunity costs occur because new forests are established on land which otherwise would have been used for other purposes such as agriculture and grazing.

Based on the CS simulated by InTEC, CBA can be spatially conducted in conjunction with the economic data from social survey. C price is an important issue in CBA. In global change economics, a concept of 'social cost of C' (SCC) is developed to measure the

benefit of CS. SCC means the incremental damage to the Earth's environment in the next 100 years caused by one additional tone of C emitted to the atmosphere today. SCC is expressed as the economic value in the unit of dollar or pound per ton of C. It varies from US$ 30/t C to US$ 180/t C with some$_e$ uncertainties (Guo et al., 2006; Downing et al., 2005).

To assess the long-term benefits from adopting C-favorable land use practices, we calculate NPV per hectare of each forestry alternative (tree-species) using the following equation:

$$NPV = \sum_{t=1}^{n} \frac{I_t - C_t}{(1+r)^t}. \tag{4}$$

where *NPV* is the net present value cumulated to year *n*; *r* is the discount rate; I_t and C_t are the total net income and costs, for year *t*, respectively.

The NPV of each cell output from the CBA module is input into the EMDS module for calculating suitability of each assessment unit for enhancing CS through land use practices.

2.4. EMDS and NetWeaver knowledge base

The EMDS system is a product of the USDA Forest Service and available free of charge, It is suitable for conceptually broad and complex problems involving many, often abstracts and concepts, and can be used as an activate ArcMap™ extension in ArcGIS 9.0. It integrates the logic engine of NetWeaver™ (Rules of Thumb, Inc.) to perform landscape evaluations (Reynolds et al., 1996). Knowledge

Table 3
Carbon allocation coefficients, turnover rates and decomposition rates of the vegetation and soil carbon components (cited from Chen et al., 2000, 2003; Wang et al., 2007).

Symbol	Description (unit)	Conifer	Deciduous	Mixed Forest	Open land
Vegetation C					
f$_w$	NPP allocation coefficient to wood (−)	0.3010	0.4624	0.3817	0.3817
f$_{cr}$	NPP allocation coefficient to coarse root (−)	0.1483	0.1190	0.1536	0.1536
f$_l$	NPP allocation coefficient to leaf (−)	0.2128	0.2226	0.2077	0.2077
f$_{fr}$	NPP allocation coefficient to fine root(−)	0.3479	0.1960	0.2570	0.2570
K$_w$	Wood turnover rate (yr^{-1})	0.0279	0.0288	0.0279	0.0139
K$_{cr}$	Coarse root turnover rate (yr^{-1})	0.0269	0.0448	0.0268	0.0268
K$_l$	Leaf turnover rate (yr^{-1})	0.1925	1.0000	0.3945	0.3945
K$_{fr}$	Fine root turnover rate (yr^{-1})	0.5948	0.5948	0.5948	0.3000
Soil C					
K$_{ssl}$	Surface structural leaf litter decomposition rate (yr^{-1})			3.9*L_c*A	
K$_{sml}$	Surface metabolic leaf litter decomposition rate (yr^{-1})			14.8*A	
K$_{fsl}$	Soil structural litter decomposition rate (yr^{-1})			4.8*L_c*A	
K$_{fml}$	Soil metabolic litter decomposition rate (yr^{-1})			18.5*A	
K$_w$	Woody litter decomposition rate (yr^{-1})			2.88*L_c*A	
K$_{sm}$	Surface microbe decomposition rate (yr^{-1})			6.0*A	
K$_m$	Soil microbe decomposition rate (yr^{-1})			7.3*A*T_m	
K$_s$	Slow C decomposition rate (yr^{-1})			0.2*A	
K$_p$	Passive C decomposition rate (yr^{-1})			0.0045*A	

*A is the combined abiotic impact of soil moisture and soil temperature on the decomposition rate, based on the Century model and its adaptation to annual step calculations (Chen et al., 2000). L_c quantifies the impact of lignin content of structural materials on decomposition. T_m is the effect of soil texture on soil microbe C decomposition.

Table 4
BEPS model input data with their descriptions, file formats and data sources for the case study of Liping County.

Input data	Description	File format (or value)	Source
LAI	Leaf area index	Binary	Zheng et al., 2007
Land cover	Land cover information	Binary	RS image classification
AWC	Soil available water capacity (unit: m)	Binary	Tian et al., 2006
Biomass	Above-ground biomass (unit: kg m^{-2})	Binary	Zheng et al., 2007
Radiation	Daily solar radiation (unit: W m^{-2})	ASCII	Local meteorological station
Temperature	Daily maximal and minimal temperature (unit: 0.1 °C)	ASCII	Local meteorological station
Humidity	Daily relative humidity (unit: %)	ASCII	Local meteorological station
Precipitation	Daily precipitation (unit: mm)	ASCII	Local meteorological station

bases that describe logical relations among ecosystem states and processes of interest in an assessment are created in NetWeaver Developer where fuzzy logic-based reasoning can be implemented by logic operators such as OR and AND. The knowledge base consists of dependency networks that represent a hierarchical network for evaluating a proposition (Fig. 2). The result of an evaluation is a score named the Truth Value that expresses the degree to which the proposition is supported or refuted (Reynolds et al., 1996, 2003; Dai et al., 2004).

In EMDS, a resultant layer named Truth Value map presents the final suitability score of each assessment unit (e.g. administrative unit) by fuzzy logic-based reasoning (Miller and Saunders, 2002), similar to the way of weighted linear combination (WLC). The Truth Value is in the range from −1 to 1 to express the degree of supporting user-defined proposition (from no-support to fully-support).

For land-use planning considering CS benefits, the assessment of suitability for enhancing CS through land use practices is conducted at the scale of prescribed assessment unit based on four

Table 5
InTEC model input data with their descriptions, file formats and data sources for the case study of Liping County.

| Input data	Description	File format (or value)	Source
NPP	Reference year NPP from BEPS (unit: g m^{-2} yr^{-1})	Binary	Simulated from BEPS
LAI	Leaf area index	Binary	Zheng et al., 2007
Land cover	Land cover information	Binary	RS image classification
AGE	Forest stand age	Binary	Wang et al., 2007
Ndep	Nitrogen deposition rate (unit: g m^{-2} yr^{-1})	Binary	Wang et al., 2007
Cet	Evapotranspiration (unit: mm yr^{-1})	Binary	Wang et al., 2007
Clay	Percentage of clay in soil (unit: %)	Binary	Wang et al., 2007
Claysilt	Percentage of claysilt in soil (unit: %)	Binary	Wang et al., 2007
CO$_2$	Annual concentration value of carbon dioxide	ASCII	Ju et al., 2007
GHG	Annual relative value of Green House Gas (GHG) emissions	ASCII	Ju et al., 2007
Appt	Annual precipitation (unit: mm)	BIP, Binary	Ju et al., 2007
Length	Growing season length (unit: day)	BIP, Binary	Ju et al., 2007
Ta_a	Annual mean temperature (unit: 0.1 °C)	BIP, Binary	Ju et al., 2007
Ta_s	Average temperature in growing season (unit: 0.1 °C)	BIP, Binary	Ju et al., 2007
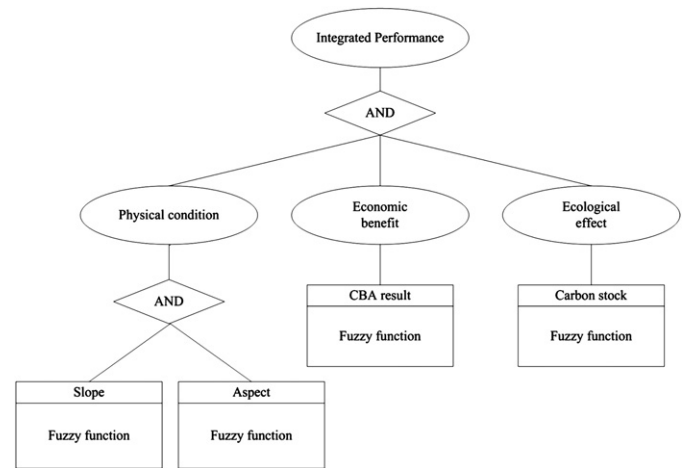
Fig. 2. The knowledge base created by NetWeaver Developer for CS land use decision-making. Ellipses express the dependency networks, diamonds express the logic operators, and the boxes express the data link referred to as fuzzy membership functions for evaluation.

indicators from three perspectives, including CS potential quantity, NPV benefit, slope and aspect. The weight for each perspective is assumed to be same (Fig. 2). For CS, slope and aspect indicators, the assessment is firstly conducted for each cell, and then aggregated to the prescribed assessment unit (for example, township). The suitability of each IA factor is determined using the normalized fuzzy function which is built according the minimal and maximal values of this factor. For example, northbound and southbound aspects represent no-support and full-support for local vegetation growth. Generally, plantations on steep slopes will have great capability of protecting soil and water. Therefore a larger slope is given a higher score towards the full-support. The high NPV values and CS potential represent the high degrees of support.

IA results are mapped using the knowledge base model shown in Fig. 2. This knowledge base model encapsulates the assessment criteria and logic relations between assessment elements in an explicit form so that they can be easily examined, explained, and modified. It provides not only a tool for integrated assessment, but also a useful aid for decision-makers to use spatial information and to explain the basis for their decisions.

2.5. Ranking tree-species by AHP

AHP is one of extensively used multi-criteria decision-making methods (Saaty, 1994) and can effectively handle both qualitative and quantitative data. Essentially it is based on Pair-wise Comparison Matrices (PCMs) of elements in a decision hierarchy with respect to the parent element at the next higher hierarchical level. In a typical three-layers hierarchy including one objective in the first layer, n criteria ($B_1, B_2, …, B_n$) in the second layer and m alternatives ($A_1, A_2, …, A_m$) in the third layer, key steps used to get the weights of alternatives are shown in Fig. 3.

(i) To compare each criterion and create a PCM. The sum of every row M_i is calculated as:

$$M_i = \sum_{j}^{n} b_{ij}, (i = 1, 2, …, n).$$ (5)

where b_{ij} is the element of the corresponding pair-wise comparison matrix B for the criteria layer. The diagonal elements of B equals to 1.0 and $b_{ij} = 1.0/b_{ji}$.
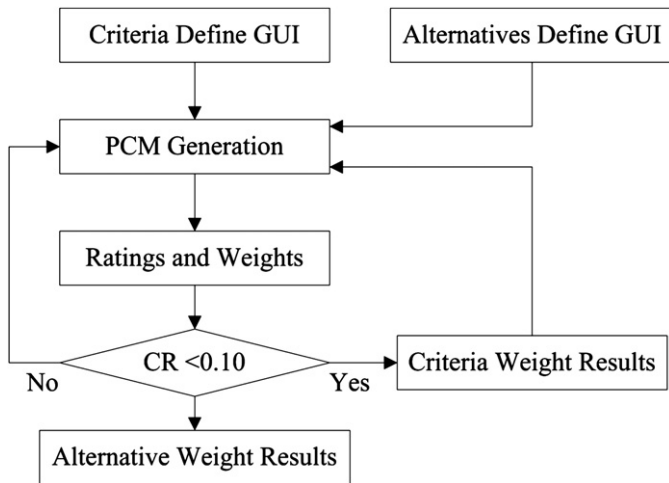
Fig. 3. Key steps in the AHP module development. The first step is to define criteria for decision model through the criteria define GUI. Then, the weights of the criteria are calculated by Eqs. (5)–(8). Finally, all the weights of the alternatives are calculated by Eq. (9).

(ii) The weight of each criterion w_{ci} can be determined by the following formula:

$$w_{ci} = M_i \bigg/ \sum_{i=1}^{n} M_i \qquad (6)$$

(iii) To check for the consistency of PCM. Eigenvector W is derived from:

$$BW = \lambda_{\max} W \qquad (7)$$

Where $\lambda_{\max}$ is the maximum eigenvalue of B, $W = (w_{c1}, w_{c2}, \ldots, w_{cn})^T$.

The Consistent Index (CI) and the Random Consistency Ratio (CR) are defined as:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \text{ and } CR = \frac{CI}{RI} \qquad (8)$$

where RI is the Random Index and defined with a constant value according to the number of criterion (Saaty, 1994). If the CR value is smaller than 0.10, it indicates that the consistency in the judgments made in the PCM creation is acceptable, Otherwise, the corresponding pair-wise comparison matrix B is reconstructed and steps (i) to (iii) are repeated.

(iv) To calculate the weight $w_{Ai,j}$ for alternatives ($j = 1, 2, \ldots, m$) with respect to criterion i and check their consistency using Eqs. (5)–(8). Then, the total weight w_{Aj} is calculated as:

$$w_{Aj} = \sum_{i=1}^{n} w_{Ai,j} \cdot w_{ci} \qquad (9)$$

A three-layer AHP decision model is designed in this study aiming at determining priorities of tree-species selection to resolve the problem on 'how' to do plantation. The tree-species selection is regarded as the objective in the first layer, pre-defined criteria (e.g. CS, economic benefit and ecological effect, etc.) are in the second layer and all the alternatives (tree-species) are in the third layer.

2.6. Integration and GUI implementation

The IA-SDSS system is developed in the ArcGIS 9.0 platform and uses components provided by the ArcObjects of ArcGIS. At current stage, it has to be runs as VBA macros in the ArcGIS environment.

VBA provides an integrated programming environment, the Visual Basic Editor (VBE), which lets developers create a new button, tool, combo box, then attach codes to these entities' events (ESRI, 2004). The BPES model written in C++ language was encapsulated to a standard executable file which can be run directly. The C++ code of InTEC was compiled as an ActiveX Dynamic Link Library (DLL) which can be called by the VBA-scripts of commands (buttons) in IA-SDSS (Fig. 4). Rendered as an ArcGIS extension, EMDS takes advantage of ArcGIS's data management operations to prepare input tables (e.g. attribute tables) of knowledge bases created by NetWeaver Developer, which is an external development tool. Results of an EMDS assessment are displayed as maps, graphs, and tables in the data view of ArcMap.

The main GUI, forms or dialogs of IA-SDSS are shown in Fig. 5, A tool bar designed consists of several commands (buttons) for running the BEPS and InTEC models, converting data, setting model parameters, conducting CBA and AHP. The main functions of buttons are shown in Fig. 6.

3. Case study

3.1. Study area and data sources

The IA-SDSS developed is tested in Liping County, Guizhou Province, China. This county is a representative of rural counties in southwestern China (Fig. 7). It has an area of 4.44×10^5 ha located at $25°44'–26°31'$N and $108°37'–109°31'$E. The entire area falls within the monsoon moist climate region of the middle subtropical zone. Its annual rainfall ranges from 1100 to 1700 mm. Forests account for about 60% of this county (LSB, 2003), including mostly plantations of Chinese fir and Masson pine of various ages with some native mixed hardwood forests. Its population of 503,000 is predominantly in rural area (92%) and relies heavily on forestry and agriculture as sources of income (LSB, 2003).

Liping has been a pilot site of the State Natural Forest Protection project and the 'Grain-For-Green' project which converts agricultural land on slopes greater than 25° to forestland (SFA, 2005a,b). It was also a study region of the "Confronting Global Warming: Enhancing China's Forest Carbon Sequestration" project sponsored by the Canadian International Development Agency (CIDA) and the Chinese Academy of Sciences (Chen et al., 2007). Through these projects, a lot of ecological, soil, climate, social, and economic data for this area were collected, facilitating our study.

Land cover information is crucial in quantifying surface parameters such as LAI and is required by the BEPS and InTEC models. Two Landsat ETM+ images at a spatial resolution of 30 m obtained on May 14th and May 21st, 2000 were employed to produce a land cover map using a modified decision tree classification algorithm (Jin et al., 2007). The classification was implemented using the ENVI 4.1 software. Six land cover types were classified in Liping County including conifer, deciduous, mixed forests, crops/shrubs, water and open lands (Fig. 7). LAI was retrieved using a statistical model (Zheng et al., 2007) developed according to the Reduced Simple Ratio (RSR) calculated from remote sensing images and the measurements of LAI with a hemispheric photography technique and optical instrument TRAC (Chen and Cihlar, 1995).

The other spatial data collected from Chinese Academy of Sciences, Liping County Forest Bureau and the CIDA research team mainly include digital elevation model (DEM) with a spatial resolution of 90 m, a soil map at 1:1,000,000 scale, a township vector map at 1:10,000 scale. Ground-collected data include statistical tables from the Liping County government, social and economic survey data collected from the county by the CIDA research team, regulations and instructors from Chinese State
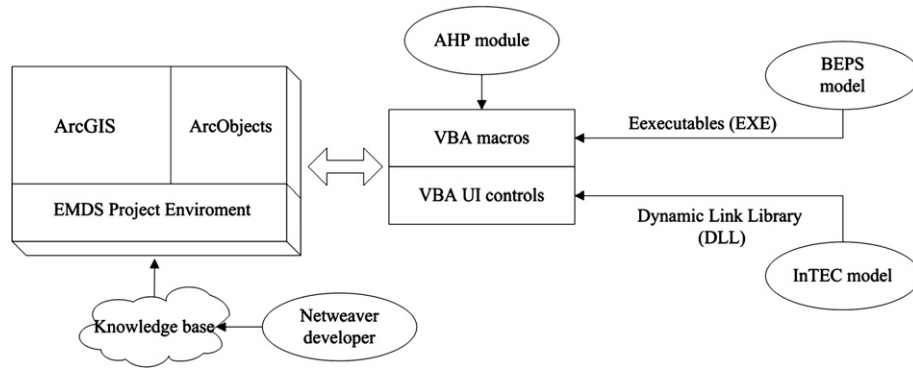
Fig. 4. The technical route for the IA-SDSS implementation.

Forestry Administration and other published documents. Meteorological data used to drive BEPS, including daily maximum and minimum air temperature, vapor pressure deficit, precipitation and sun-radiation for year 2000 were obtained from a meteorological station located in the county. AWC was estimated according to the textural information in the soil map. Biomass data of forests were derived from remote sensing and forest age inventory data (Zheng et al., 2007).

The climate data used to drive the InTEC model is a combination of historical and projected climate data. Monthly climate data (temperature, precipitation) at a resolution of 90 m from 1901 to 1998 were interpolated using a bilinear interpolation algorithm from a global 0.5° dataset produced based on weather station data

by the UK Climate Research Unit (News et al., 2000). The climate data during 1999–2100 was generated from the future climate projected by the B2 run of the second version of the first generation of Canadian coupled general circulation model (CGCM2). To adjust for climate model bias, the additive departures for temperature and multiplicative departures for precipitation during 1999–2100 relative to the 1989–1998 mean climates was interpolated to a resolution of 90 m in the same way for historical climate data. The interpolated climatic anomalies were applied to the historical climatology during 1989–1998 to produce time series of future climates during 1999–2100 for each pixel (Ju et al., 2007). Atmospheric CO_2 concentration is assumed to increase linearly to 600 ppmv in 2100.
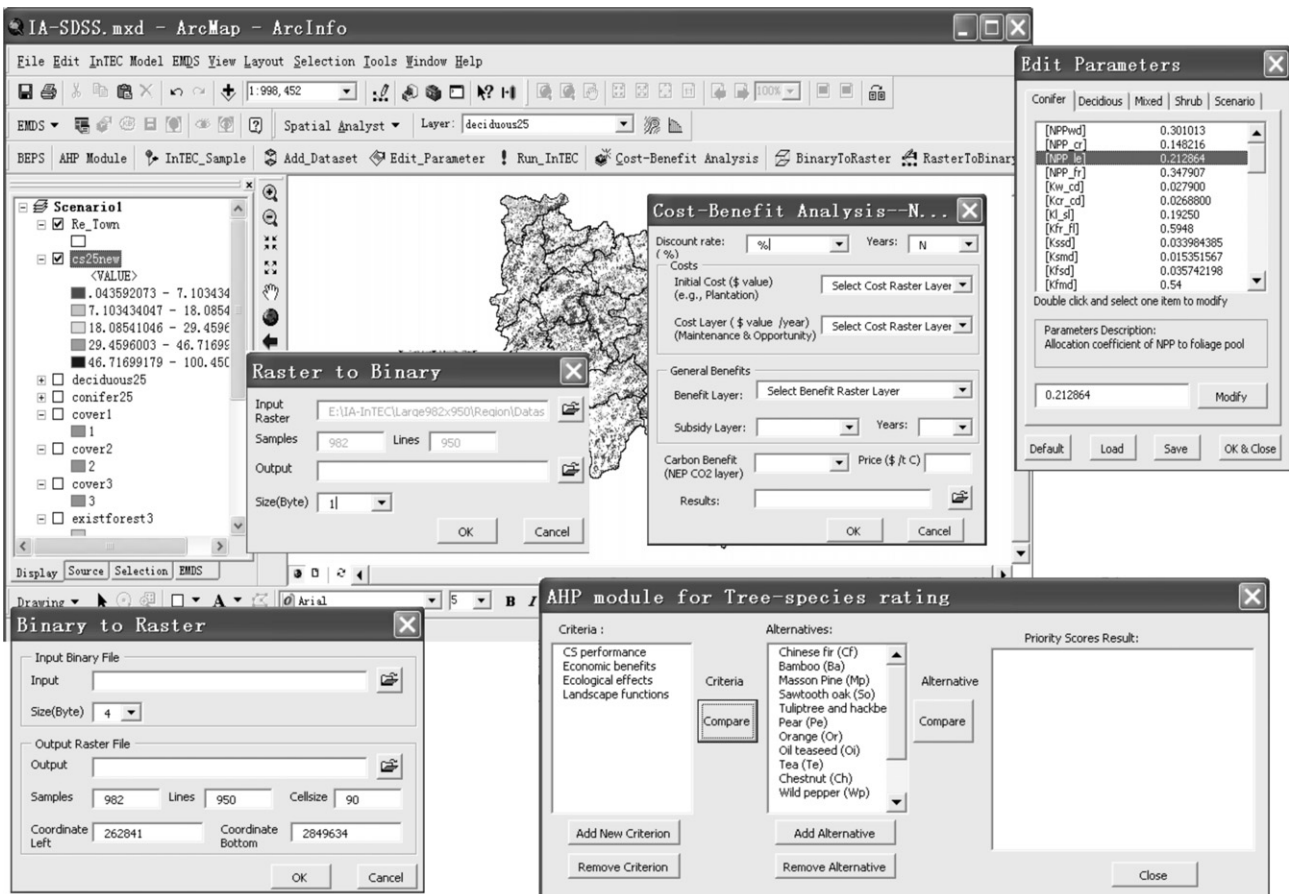

Fig. 5. Main interface with core forms of IA-SDSS including an integrated tool bar containing all function commands.
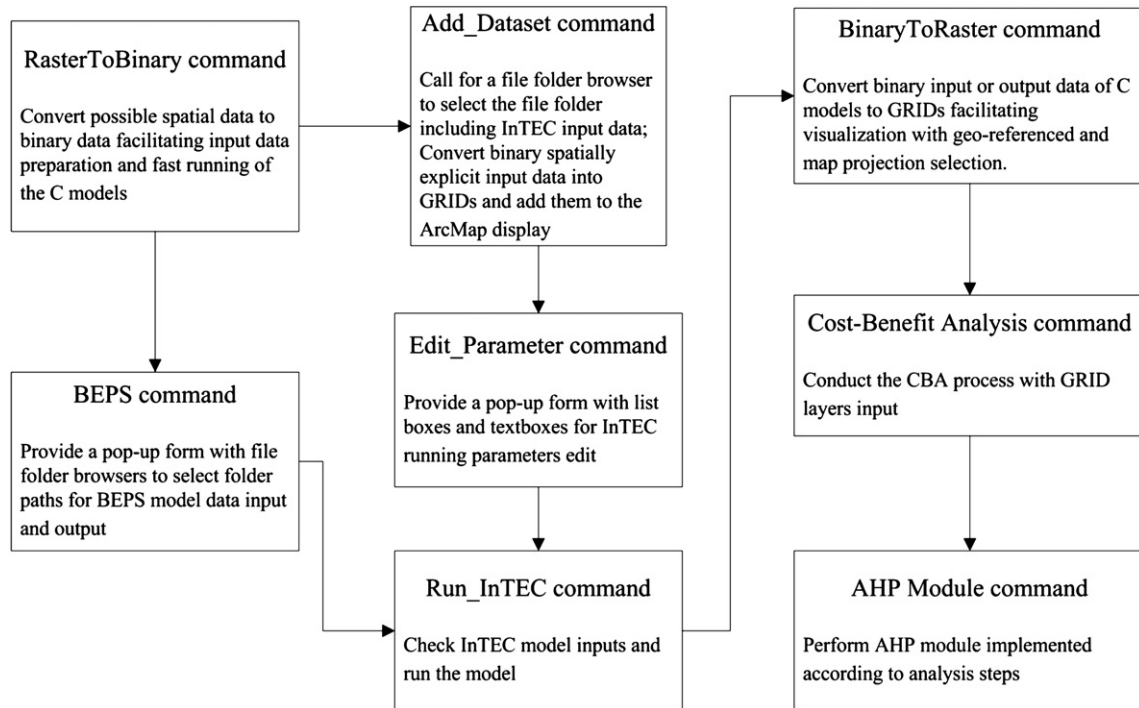
Fig. 6. Main commands with function descriptions in the integrated tool bar of IA-SDSS. Arrows indicate the workflow for the applications of IA-SDSS.

3.2. Scenarios design

The purpose of designing scenarios in an analysis is to explore alternative future conditions ("what-if" scenarios) and their implications. Three scenarios are designed for the IA-SDSS application: (i) conservation of existing forests; (ii) reforestation with conifer on croplands with the slope greater than 25°; and (iii) reforestation with deciduous on croplands with the slope greater than 25°. Reforestation scenarios can be investigated with

a knowledge base shown in Fig. 2. In the investigation of existing forests, a current land cover map was used to drive the InTEC model whereas in simulations of different reforestation scenarios, the InTEC model was run twice with assumptive land cover maps for conifer and deciduous covering the entire reforestation areas. Since the InTEC model has parameterization schemes only for four forest types—conifer, deciduous, mixed and shrubs rather than various tree-species. When applying InTEC, we follow Chen et al. (2000, 2003), in taking crops as shrubs for terrestrial ecosystem C budget
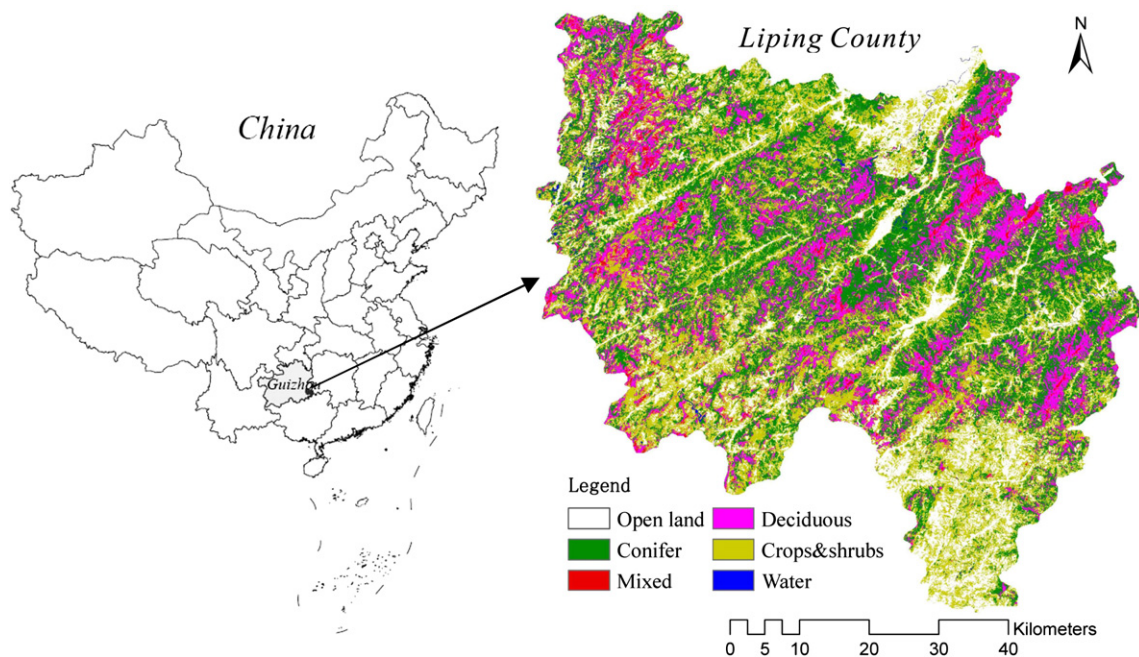

Fig. 7. Location of the case study area and classified land cover map form remote sensing images.

balance calculation, then get spatial patterns of C sources and sinks in different scenarios by using corresponding classification masks. Moreover, we consider just conifer, deciduous and mixed forests in the scenario of existing forests conservation because the shrub forests in Liping County are relative rare and mixed with other types of land use (e.g. crops). In this study, township is taken as the assessment unit.

3.3. Results

BEPS was firstly run to calculate the annual NPP in the reference year 2000. This NPP map is used as one of inputs to InTEC. The outputs from InTEC include annual net CS, NPP, ecosystem C stocks, soil and vegetation C stocks. InTEC was run for three times to extract CS outcomes in years 2000, 2025 and 2050. Year 2000 is regarded as a baseline for CS estimation and also a starting year for plantation. Year 2025 is for assessing the impacts of reforestation impacts on CS since the rotation period of all tree-species in Liping County is almost 25 years and the published economic data considers this forest rotation period (Zhou et al., 2007a), and year 2050 is for estimating the long-term trend of CS in forests.

The age–NPP relationship is critical in the CS potential simulation of a specific area for a long-time period. In this study, the parameters *a*, *b*, *c* and *d* in Eq. (2) are estimated based on the published empirical growth model of Masson Pine (*Pinus massoniana*) created using data collected in areas near by Liping (Ding et al., 1993). Masson Pine is the dominant tree-species of Liping County. In the simulations of different reforestation scenarios, no NPP in a reference year can be used to determine the initial NPP value in InTEC. With the assumption that the NPP-age relationship is same for all cells in an area of 11×11 cells, after reforestation annual NPP values can be calculated by:

$$NPP(i) = Fnpp(i) * \frac{\overline{NPP}}{Fnpp(\overline{age})} * \chi(i) \qquad (10)$$

where $\overline{NPP}$ and $\overline{age}$ are the mean NPP and age values in an area of 11×11 cells surrounding a cell, $\chi(i)$ represents the integrated effects of the changes in climate, atmospheric CO_2 concentration and N deposition on annual NPP.

3.3.1. Performance of the C models

The BEPS and InTEC models were applied and validated in total forests of China (Wang et al., 2007) and site of Liping County (Shao et al., 2007). Shao et al. (2007) validated the performance of InTEC by using the measured forest soil organic carbon (SOC) density for sites just in the Liping County with the simulated values with $R^2 = 0.63$ ($N = 16$). Furthermore, the simulated average NPP of reforested trees in this study reaches about 400 g C/m²/yr after the plantation, which is an acceptable value, in the range of the NPP changes (from 116 g C/m²/yr to 645 g C/m²/yr) of forest ecosystem in subtropical zone of the west China (Feng et al., 1999).

Fig. 8 shows the simulated historical and future NPP by InTEC during the period from 1901 to 2050. The existing forests will have lower mean NPP values than reforestated forests in 2050 because of the age effect on forest NPP. The simulated average NPP values show considerable fluctuations because forest disturbances caused sizeable reduction in NPP in some years. Since the economic development of Liping County has been mainly supported by forestry production over last two decades, most existing forests have stepped into the mature period. Starting from the a value of 279 g C/m²/yr in 2000, the mean NPP of existing forests gradually grows to 350 g C/m²/yr in 2014 and then drops slowly. From 2000 to 2025, NPP increases to 391 and 427 g C/m²/yr for reforested conifer and deciduous, respectively.

3.3.2. CS potential of existing forests

The C budget of existing forests varies from cell to cell. Accumulated CS over the period from 2000 to 2025 ranges from 1 t C/ha (weak sink) to 100 t C/ha (sink). After 2025, some existing forests shift from C sinks to C sources. Accumulated CS ranges from −14 t C/ha (weak source) to 183 t C/ha (sink) over the period from 2000 to 2050 (Fig. 9). The accumulated C source in non-productive forests is larger for the longer period from 2000 to 2050 because of the longer integrations time. The accumulated sink is not much larger for the longer period from 2000 to 2050 than the shorter period from 2000 to 2025 because of the forest stand age effect. For the longer period, there will be larger fractions of old forests with lower productivity, causing smaller sinks, or CS potential per unit time. Deciduous forests have better CS performance than conifer and mixed forests. The parts of northeastern and western forests of Liping County have greater potentials of CS than other forest areas (Fig. 9). Although the rate of CS decreases, the accumulated CS increases with the accumulation of time. The total quantities of CS of existing forests are 3.08×10^6 t C in 2025 and 4.64×10^6 t C in 2050.

3.3.3. CS potential of reforestation

In the simulation to investigate the effect of reforestation on CS, the C in the soil of croplands in the initial plantation year in 2000 is assumed to be 40% of that in the soil of forest with similar site conditions. The above-ground biomass was removed in 2000 and forest started to grow at the rate simulated by the InTEC model following reforestation. According to the 'Grain-For-Green' project of China, which aims at converting agricultural land on slopes greater than 25° to forestland (SFA, 2005a,b), all croplands in Liping County satisfied the 'Grain-For-Green' project requirement are assumed as the reforestation areas in this study. There are 5.57×10^3 ha reforestation areas, equivalent to the 1.25% of the total areas of Liping County, sporadically distributed in the northwest, southwest and south. The CS values of reforestation with conifer trees vary from −25 t C/ha to 147 t C/ha with a mean value of 35 t C/ha for the period from 2000 to 2025. And the CS values of reforestation with deciduous trees vary from −21 t C/ha to 119 t C/ha with a mean value of 40 t C/ha for the period from 2000 to 2025.

After reforestation, the soil C continuously decreases until C input from litters becomes larger than C loss through the decomposition of dead organic matter in the soil. With NPP increase, vegetation C increases. CS of a forest may be negative as a source after reforestation. Then, CS will increase to a positive value. Simulations show that 93.84% of reforested conifer forests are sinks and 94.75% of reforested deciduous forests are sinks in 2025. Those areas with positive CS values imply that there will be C sinks and suitable for tree growth. These results suggest that reforestation has a greater CS potential than the conservation of existing forests.
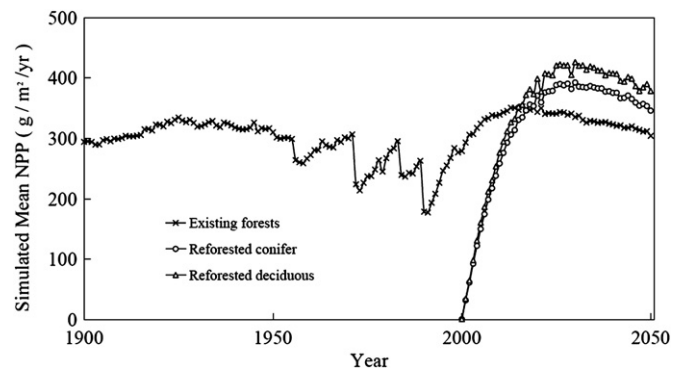

Fig. 8. Simulated the mean NPP values of existing forests from 1990 to 2050, reforested conifer and deciduous from 2000 to 2050.
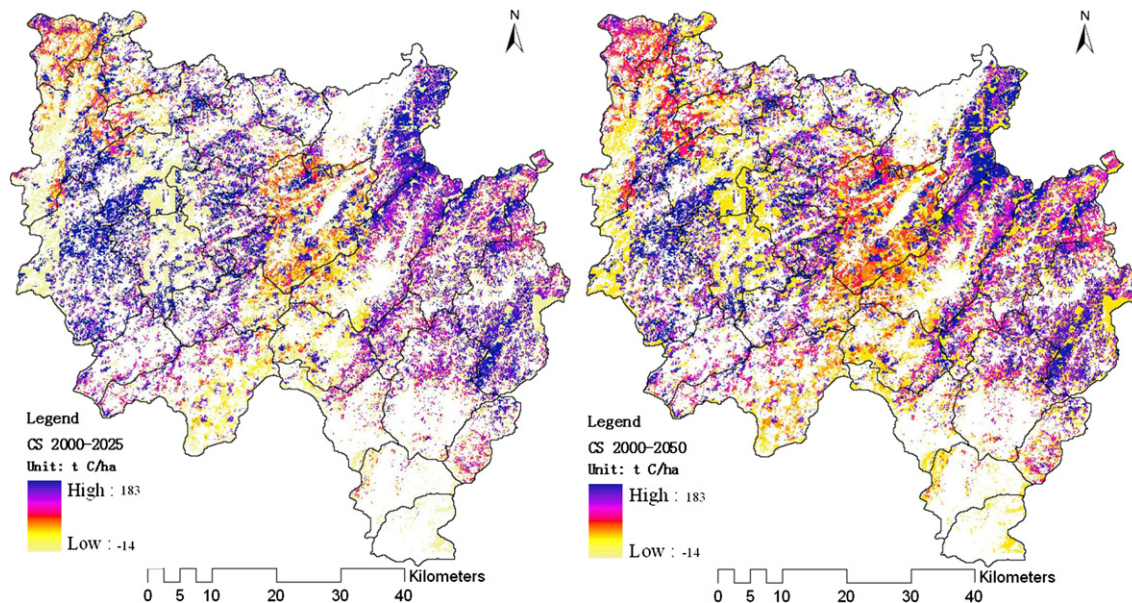
Fig. 9. The spatial-temporal dynamics of CS in existing forests. The left part shows the quantity of CS in existing forests (conifer, deciduous and mixed) during the period from 2000 to 2025. The right part shows the C sequestered by the existing forests during the period from 2000 to 2050.

That is, the C mitigation potential of reforestation will be greater than the conservation of existing forests in Liping County.

3.3.4. Spatial cost-benefits analysis

The benefits of CS include its economic and ecological values. And the C price in the future C credit markets influences directly economics of forestry practices. Based on our CS simulation results, the net benefits including the potential C payment could be calculated by multiplying a C price value with the CS quantity. Two C price values were considered with a lower price of US$50/tC and a higher price of US$100/tC. The InTEC model has parameterization schemes only for four forest types—conifer, deciduous, mixed and shrubs rather than various tree-species, while economic survey data is based on tree-species. We therefore match model-simulated cover type-based CS values with species-based economic values: using average values of all conifer tree-species including Chinese fir (*Cunninghamia laceolata*) and Masson Pine (*P. massoniana*) for specified conifer, using average values of all deciduous tree-species including Bamboo (*Phyllostachys*), Pear (*Pyrus sorotina*), Orange (*Citrus reticulate Blanco*), Oil teaseed (*Camellia oleifera*), Tea (*Melaleuca altermifolia*), Chestnut (*Castanea mollissima Blume*), Tuliptree and hackberry (*Liriodendron chinense*), Sawtooth oak (*Quercus acutissima*) and Wild pepper (*Zanthoxylum bungeanum Maxim*) for specified deciduous (Table 6).

The calculation of the NPV value is based on Eq. (4) with an assumptive 5% discount rate (Zhou et al., 2007a). It equals the discounted total income of forests, including CS economic benefit, plus general gross return including the sales of fruit products, interplanted agricultural products, mushrooms and so on (item #3) and the lumber sales, minus the total cost, including the discounted total costs from forests maintenance (item #2), plantation initial cost (item #1) and the opportunity cost (item #4) in Table 6. It indicates that reforestation normally will not generate enough income over a short period without lumber or CS benefits. Traditional economic survey from peasant households are based on the general conditions about timber yields, which cannot reflect the spatial and temporal dynamics of wood growth. Although InTEC is not a timber yield model, it can also estimate the C of different biomass C pools including foliage and wood above the ground. According to specific

biophysical coefficients allocating NPP to biomass pools for conifer and deciduous, the CS in wood can be calculated. Based on an average density of trunk volume of 0.45 t/m^3 of Liping County and the default C content of 0.50 recommended by IPCC (2000), the lumber quantities are obtained. The timber yields of reforested conifer vary from 12.02 m^3/ha to 167.89 m^3/ha with a mean value of 55.74 m^3/ha, and the timber yields of reforested deciduous species vary from 12.35 m^3/ha to 160.40 m^3/ha with a mean value of 63.33 m^3/ha from year 2000–2025. The benefit from timber sales is the production of the quantity of wood and the price of US$ 91.12/m^3 (Zhou et al., 2007a).

GIS-based economic analysis method highlights the spatial dimension of CBA decisions, showing the same land use options yield market gains or losses depending upon the location chosen. With the support of the spatial CBA module, the NPV of reforestation options of each cell is aggregated to the township level and shown in Fig. 10.

In the conifer reforestation scenario, the NPV values of majority townships are negative with the price of US$ 50/t C, and only three townships have positive NPVs at the higher price US$ 100/t C. If all the townships are maintained with positive NPVs, the C price needs to increase to US$332.90/t C. On the other hand, in the deciduous reforestation scenarios, the NPVs of more than half townships are positive with the lower C price (US$ 50/t C) and only one township appears to be negative with the higher price (US$ 50/t C). Under this scenario, a price of US$69.41/t C can maintain the positive NPV for all townships. It indicates that reforesting conifer at Liping County is

Table 6
Economic statistical data for reforestation in Liping County derived from Zhou et al., 2007a.

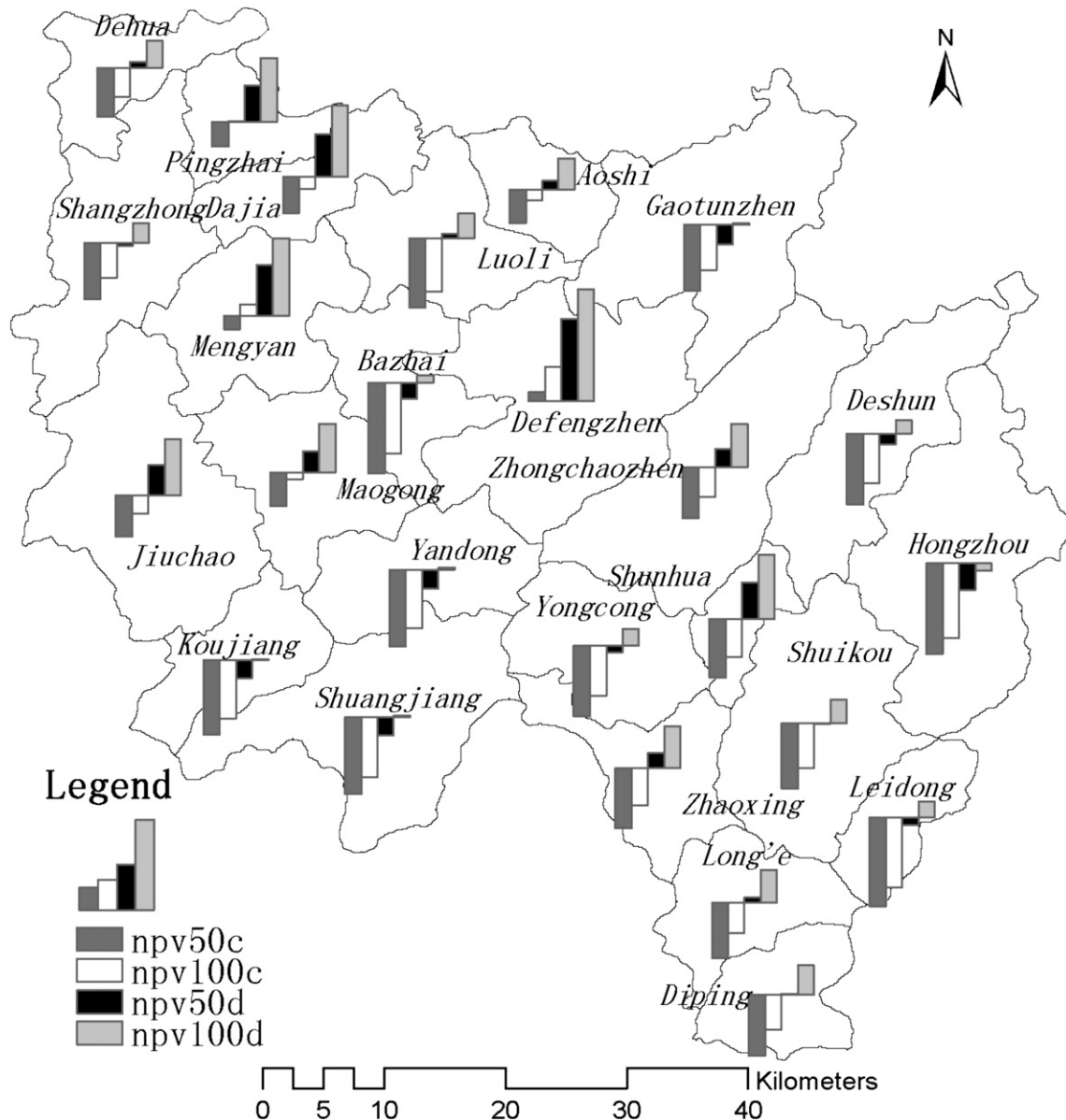| Tree-species	Seeding (item #1) (US$ ha^{-1})	Maintenance (Fertilizers, Pesticides, Irrigation, Forest protection (item #2) (US$ ha^{-1})	Annual gross return (item #3) (US$ ha^{-1})	Annual opportunity cost (item #4) (US$ ha^{-1})
Conifer	102.70	141.99	100.53	456.40
Deciduous	64.64	115.53	130.34	456.40

Fig. 10. Statistical values of NPV (unit: US$ ha^{-1}) averaged of reforestation scenarios in each township of Liping County in year 2025. Npv50c is the CBA result considering CS benefit with the lower C price (US$50/tC) and npv100c is with the higher C price (US$100/tC) for the reforested conifer. Npv50d and npv100d are the results for the reforested deciduous considering the lower and higher C prices.

not economically viable because of the high opportunity cost, unless the C price in the market becomes very high (over US$300/t C). With the high CS quantity and traditional forestry income (Table 6) of deciduous species, the reforested deciduous forests become economically beneficial at a moderate C price of about US$70/tC.

3.3.5. IA with EMDS

Due to the lack of data on the evaluation of social effects (social culture opinions) and other eco-environmental benefits (e.g. biodiversity, conservation of water and soil, improvement of water quality) of specific forestry land use options in the scenarios designed in Section 3.2. In this study, we mainly investigate the spatial variation of CS and its economic benefit with consideration of the potential C credit value, as the ecological factor, by using a GIS-based methodology. Since the CS potential is modeled at the cover type level rather than tree-species level, the additional C credit value is the key indicator in economic consideration. We took

the CBA result of reforested deciduous with the higher C price (US$100/tC) as an example.

Fig. 11 shows IA performance scores from EMDS of IA-SDSS (Reynolds et al., 1996, 2003; Dai et al., 2004), expressing the degree to which the data support the propositions that the township is suitable for reforestation with deciduous tree-species. The variability in IA performance scores is considerable, ranging from −1.00 (no-support) to 0.677 (strong support). The townships classified for strong support are suitable for forestry CS practices. This is the spatial information we endeavor to obtain. The resulting map shows that Defengzhen, Dajia and Mengyan townships have the higher scores and favorable for reforestation with deciduous forests because these townships have better CS performance and higher timber yields according to the model simulations. Actually, the reforestation areas are all croplands with the slope greater than 25°, and the differences of geophysical conditions between townships are very slight. The results imply that the benefits (including
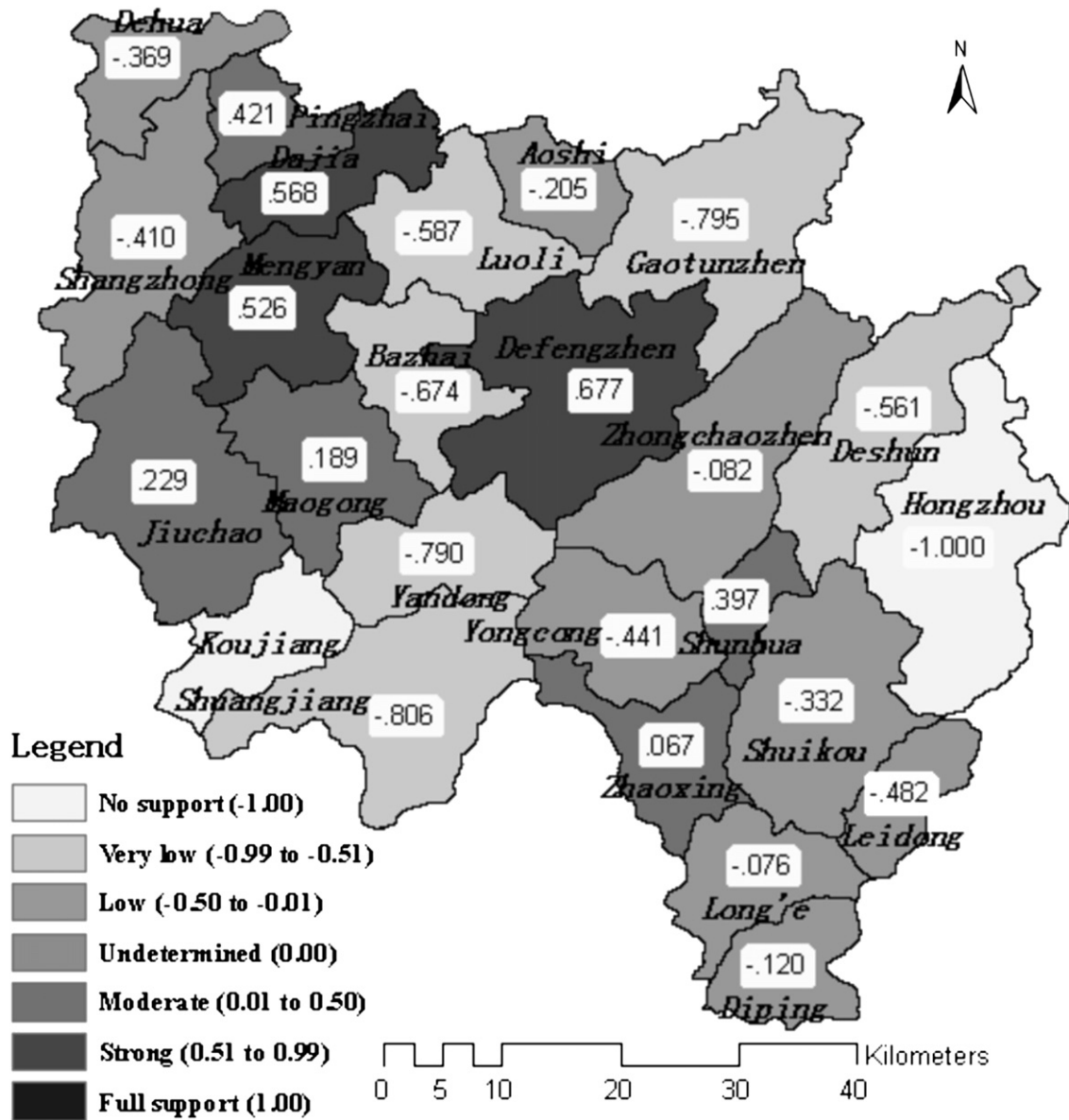
Fig. 11. Spatial distribution of IA scores of the scenarios from EMDS. Legend expresses the Truth Values in IA performance scores indicating the suitability degree of each township to the reforestation strategy with deciduous.

economic and ecological perspectives) from CS are very important issues influencing the assessment consequence and the incentive of local government participating in the CS land use practices.

3.3.6. Tree-species selection by AHP

The AHP method can easily be used to reduce subjective influence on factor weights through pair-wise comparisons, allowing users' participation in tree-species selection in forestry practices. A nine-point scale recommended by Niemura and Satty (2004) is adopted. A plantation strategy is implemented based on a three-layer hierarchy AHP decision model including tree-species selection as the objective in the first layer, four criteria (CS, economic benefit, ecological effect and landscape function) in the second layer and eleven alternatives (tree-species) in the third layer (Fig. 12). Through pair-wise comparison by the AHP GUI module, different weight schemes can be obtained by considering different priorities.

In Liping County, Tea has the maximal economic benefit, followed by Chestnut, Tuliptree and hackberry, Pear, Masson Pine,

Orange, Wild pepper, Chinese fir, Bamboo, Sawtooth oak, and Oil teaseed. In the alternative comparison of CS performance, all the tree-species are divided into two classes (deciduous or conifer). Deciduous and coniferous have different rank values (assigning 7 and 5 representing 'very strongly dominant' for deciduous trees and 'strongly dominant' for others) and all the alternatives are equal with respect to the ecological criterion in the assumption due to lack of data about ecological and landscape evaluations of each tree-species. We divided the tree-species into two groups (economic or fruit trees and ecological trees). Pear, Orange, Chestnut, Oil Tea-seed and Wild pepper are the economic trees having low ecological and landscape performance (assigning 1 to them) and other tree-species are ecological trees assigned 7 representing very strong dominant. Assigning the weight of IA factors is not a fixed process, thus, two different schemes (S1 and S2) were taken into account using the AHP method. In scheme 1, different weights are given to different criteria (0.36 for CS performance, 0.08 for economic benefits, 0.28 for ecological effects, and 0.28 for
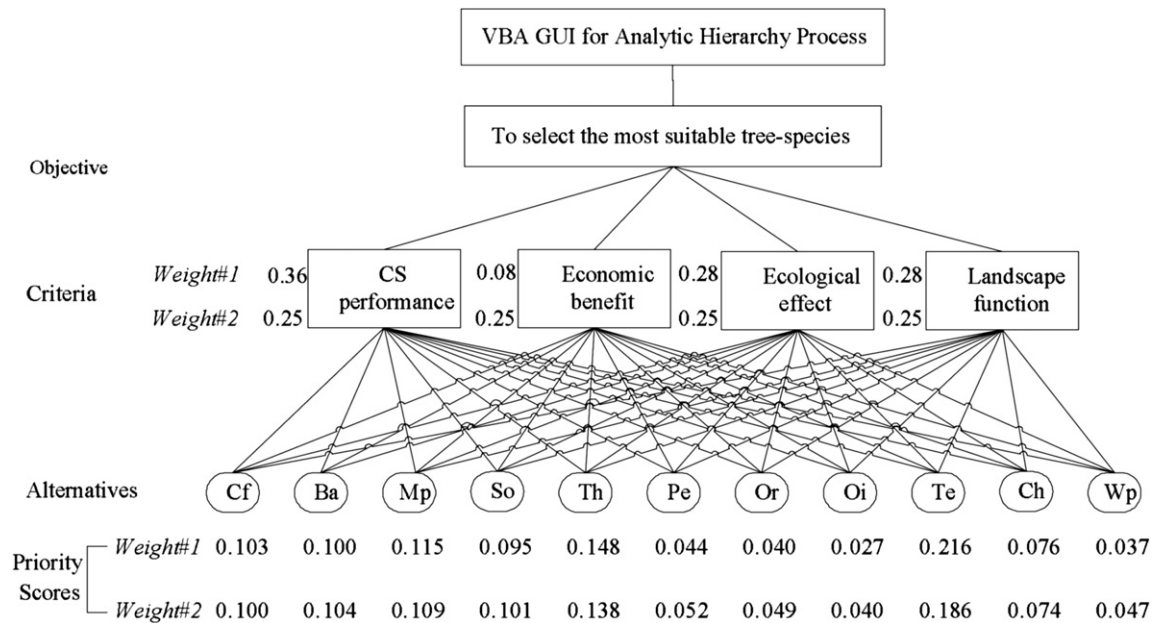
Fig. 12. AHP decision-making process and two weighting schemes.

landscape function). In scheme 2, a weight of 0.25 is assumed for each criterion. The rank value of a species with respect to ecological criterion is kept unchanged in schemes 1 and 2. In these two schemes, the most suitable tree for plantation is Tea which is followed by Tuliptree and hackberry, Masson Pine, and Oil teaseed, Wild pepper, Orange, Pear and Chestnut are the lowest trees in rank.

4. Discussion and conclusions

In this article, we present approaches integrating mechanistic C models with remotely sensed data and a GIS platform to investigate the total CS potential (including vegetation and soil C) of local forests. We also address issues related to the spatially explicit integrated assessment on CS land use options, which have not been address in previous studies (Han and Kim, 1989; Zhu et al., 1996), although other CS simulation studies have been conducted mainly on CS in soils after changes in land use (Ardö and Olsson, 2003; Ponce-Hernandez, 2004; Schaldach and Alcamo, 2006; Easter et al., 2007). The major contributions of this paper include:

(1) The development of a capacity to simulate the spatial-temporal dynamics of CS potential under different land use conditions at regional scales. Various forestry activities have different C mitigation potentials depending upon local ecosystem features. In Liping County, the unit area C mitigation potential through reforestation is greater than the conservation of current forests.

(2) Integration of process-based C models, considering non-disturbance and disturbance factors, in a GIS platform to simulate the future CS potential of different land use scenarios for decision support regarding forestry land use policy. BEPS and InTEC are reliable C cycle models useful for reducing uncertainties in the C sink/source estimation (Liu et al., 1997; Chen et al., 1999, 2003). With GIS integration, the modelling results can be geo-visualized, facilitating direct spatial analysis.

(3) Inclusion of GIS-based integrated assessment as part of the decision-making tool. The spatial CBA method allows the extraction of spatial variation, prior to directly using statistic data

for the entail region. CS benefits including the C price will be the most important issues to be considered in reforestation CDM projects. As ArcGIS 9.0 software extension component, EMDS provides not only a tool for integrated assessment but also a ready aid for policy making through the use of the spatial information. In our study, the IA-SDSS is implemented in EMDS and can utilize all existing functions for fuzzy logic-based decision.

In the applications of land use decision support system considering CS potential, uncertainties frequently exist in the simulation of CS. Although this paper aims at developing a decision support system for CS purposes, the system needs further improvements. The performance of the IA-SDSS developed here can be further improved by the following efforts: (1) to improve accuracy of input data and parameters used in the C cycle models. Input data often came from data sources of different spatial resolutions, which need to be resampled to the same grid, and errors may occur due to the resampling. Currently, most biophysical parameters used in the C cycle models adopt the default values partially tested in China (Zheng et al., 2007; Zhou et al., 2007b). Detailed calibration of models parameters will increase the reliability of simulation results. The IA-SDSS provides a dialog window (see Edit Parameters form in Fig. 5) for users to modify these parameters according to new information; (2) to adopt a local age–NPP curve for each tree-species or find a "dominant factor influencing forest growth" for a particular local application, similar to the strategy adopted by Chen et al. (2003) in future CS potential simulation. In this case study, the age–NPP curve of dominant forests species is applied for all coniferous and deciduous forests since we are unable to collect data to derive age–NPP curves for all forest species. This simplification might result in uncertainties in final assessment results; (3) to conduct sensitivity analysis on the discount rate and different land use scenarios. In the case study, a constant discount rate is employed. The spatial CBA module can allow various scenario analyses using different discount rates, C simulation periods and C prices; and (4) to collect a comprehensive set of indicators for the construction of the knowledge base. In this study, we considered only several factors due to insufficient data availability. But users can create their own knowledge bases with

CS factors according to the requirement of specific spatial problems using the methods proposed in this study.

At the present, the whole system can be implemented within the ArcGIS 9.0 platform, although the conversion and linkages of data between the modules of IA-SDSS are still needed with the support of ArcGIS and other software like EMDS. It therefore requires further technical development before it can be used widely. However, the current IA-SDSS can meet the need of decision-makers with certain professional knowledge and skills. In conclusion, the IA-SDSS can provide a flexible tool with spatially explicit approaches to land use decision-making (where and how, even how long to sequestering C by forest plantation). It can be used as a tool for local governments to make effective decisions for sustainable forestry land use with consideration of CS benefits.

Acknowledgements

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