Science of the Total Environment 554–555 (2016) 7–16

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Ecological risk assessment of ecosystem services in the Taihu Lake Basin of China from 1985 to 2020

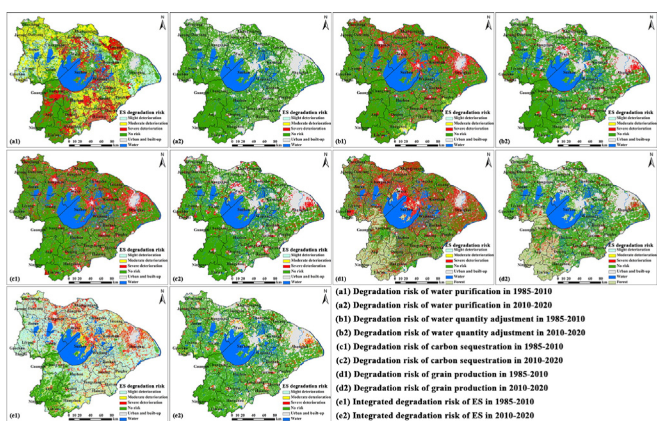
Xibao Xu [a,b,*], Guishan Yang [a], Yan Tan [c], Qianlai Zhuang [b], Hengpeng Li [a], Rongrong Wan [a], Weizhong Su [a], Jian Zhang [a]

[a] Key Laboratory of Watershed Geographic Sciences, Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, Nanjing 210008, China
[b] Department of Earth, Atmospheric, and Planetary Sciences, Purdue University, West Lafayette, IN 47907, USA
[c] Discipline of Geography, Environment and Population, The University of Adelaide, Adelaide 5000, Australia

HIGHLIGHTS

- A novel ecological risk assessment model of ecosystem services was developed.
- DNDC, SWAP, Biome-BGC and AEZ models were used for assimilation.
- Integrated degradation risk of four key ecosystem services was assessed.
- Land-use change posed a great degradation risk on ecosystem services in 1985–2020.
- Severe deterioration in 2020 would be centered in some small and less developed cities.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 20 December 2015
Received in revised form 17 February 2016
Accepted 17 February 2016
Available online xxxx

Editor: D. Barcelo

Keywords:
Land-use change
Ecosystem services
Integrated degradation risk assessment
Assimilation models

ABSTRACT

There are tremendous theoretical, methodological and policy challenges in evaluating the impact of land-use change on the degradation of ecosystem services (ES) at the regional scale. This study addresses these challenges by developing an interdisciplinary methodology based on the Procedure for Ecological Tiered Assessment of Risk (PETAR). This novel methodology integrates ecological models with a land-use change model. This study quantifies the multi-dimensional degradation risks of ES in the Taihu Lake Basin (TLB) of China from 1985 to 2020. Four key ES related to water purification, water quantity adjustment, carbon sequestration and grain production are selected. The study employs models of Denitrification-Decomposition (DNDC), Soil-Water-Atmosphere-Plant (SWAP), Biome-BGC and Agro-ecological Zoning (AEZ) for assimilations. Land-use changes by 2020 were projected using a geographically weighted multinomial logit-cellular automata (GWML-CA) model. The results show that rapid land-use change has posed a great degradation risk of ES in the region in 1985–2020. Slightly less than two-thirds of the basin experienced degradation of ES over the 1985–2010 period, and about 12% of the basin will continue to experience degradation until 2020. Hot spots with severe deterioration in 2010–2020 are projected to be centered around some small and less developed cities in the region. Regulating

* Corresponding author at: Key Laboratory of Watershed Geographic Sciences, Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, Nanjing 210008, China.
E-mail addresses: xbxu@niglas.ac.cn (X. Xu), gsyang@niglas.ac.cn (G. Yang), yan.tan@adelaide.edu.au (Y. Tan), qzhuang@purdue.edu (Q. Zhuang), hpli@niglas.ac.cn (H. Li), rrwan@niglas.ac.cn (R. Wan), wzsu@niglas.ac.cn (W. Su), jianzhang@niglas.ac.cn (J. Zhang).

http://dx.doi.org/10.1016/j.scitotenv.2016.02.120

accelerated urban sprawl and population growth, reinforcing current environmental programs, and establishing monitoring systems for observing dynamics of regional ES are suggested as practical counter-measures.

1. Introduction

One of the great challenges of our time is providing food, timber, energy, housing, and other goods and services, while maintaining ecosystem functions and biodiversity that underpin their sustainable supply (Lawler et al., 2014). Approximately 60% of the world's ecosystem services (ES) are degraded or used in an unsustainable way, and the degradation of ES is expected to grow significantly worse throughout the first half of the 21st century (McNeely et al., 2011; Millennium Ecosystem Assessment, 2005). ES are largely and directly influenced by five main drivers: land-use change, invasive species, over-exploitation, pollution and climate change (McNeely et al., 2011). Among which, land-use change is a major driver of change in the spatial pattern and overall provision of ES (Goldstein et al., 2012; Lawler et al., 2014; Nelson et al., 2010). Degradation of ES is usually influenced by land-use change through two ways: changes in land-use patterns and land management (e.g., agricultural practices, forestry practices, fertilizer utilization). As there are spatial and temporal interactions and interdependencies of ES, it is significant to comprehensively assess the degradation of ES influenced by land-use change, which will pose a significant barrier to global or regional sustainability (Kragt and Robertson, 2014; Millennium Ecosystem Assessment, 2005; Zagonari, 2016). For example, increasing fertilization will increase grain production (GP) of the provisioning ES, while decreasing water purification and soil carbon stock of the regulating ES for the agroecosystems (Kragt and Robertson, 2014). At present, studies on the degradation of ES related to land-use change have attracted extensive attention around the world (Lawler et al., 2014; Nelson et al., 2010; Wong et al., 2015; Zagonari, 2016).

Ecological risk assessment (ERA) is a process that estimates potential adverse effects and risks that human activities and human-induced stressors pose on ecosystems or their components (Munns, 2006). The "three-step method" of ERA, namely problem formation, risk analysis, and risk characterization, has been widely accepted by scientists since the 1998 publication of the Environmental Protection Agency on "Ecological Risk Assessment Guidelines" (Environmental Protection Agency, 1998). Conventional ERA focused on the assessment of adverse effects caused by toxic chemicals. Now ERA is widely applied to the fields of water environment (Doria et al., 2009; Zhong et al., 2010), regional and integrated risk assessment (Cormier et al., 2000; Gao and Xu, 2013) as well as ES management and policy (Deacon et al., 2015; Landis, 2004). Sophisticated approaches to risk assessment have been developed. PETAR (procedure for ecological tiered assessment of risk) (Moraes and Molander, 2004), WOE (weight-of-evidence) (Burton et al., 2002; Landis, 2003), RRM model (relative risk assessment model) (Chen et al., 2012; Landis and Wiegers, 2007; Liu et al., 2010) and Bayesian network approaches (Landuyt et al., 2014; McDonald et al., 2015) are some examples.

However, the ERA of ES still faces two major challenges. Firstly, theoretical and analytical frameworks need further advancement. Exponentially increasing studies of ES have advanced classification, evaluation and mapping techniques of ES. Yet the linkage between ecological mechanisms and ES that create the end products remains understudied (Bennett et al., 2009; Daily and Matson, 2008; Fisher et al., 2008; Wong et al., 2015; Xu et al., 2014). Secondly, existing evaluation methods tend to focus on individual ES rather than take them as an integral system. This could lead to a biased assessment which fails to reveal the root mechanisms for ES degradation in a watershed and consequent environmental health risks (Chen and Liu, 2014). Methodologically, ERA also needs to have an interdisciplinary approach, drawing on insights from the disciplines of ecology, remote sensing and numerical modeling. Ecological models have a great deal of potential to address the problem that impedes ecologically related risk assessment. The inherent ecological complexity needs to link measurement endpoints and ES. It also needs to quantify service provision and possible adverse effects from human activities (Galic et al., 2012; Xu et al., 2014). Improved modeling approaches are therefore particularly needed to overcome the limitations of current approaches to ecological risk assessment (Chen et al., 2012; Forbes et al., 2009).

The Taihu Lake Basin (TLB), a core part of China's Yangtze River Delta, has experienced remarkable economic development (at an annual GDP growth rate of 15.7%), population growth (at an annual growth rate of 3.0%), and urbanization (at an annual growth rate of 9.2%) over the 1985–2010 period. Rapid industrialization and urbanization have dramatically changed land use/land cover patterns in the basin. This has, in turn, caused extensive degradation of ES, including water purification (Guo, 2007; Xu et al., 2010; Yang and Liu, 2010), carbon sequestration (Wang et al., 2016), water quantity adjustment (Yang et al., 2011a; Yin et al., 2009) and GP (Liu et al., 2015; Pan et al., 2015). Degradation of these ES has posed great threats to ecological security and new challenges to sustainable development in the region. The TLB has been classified as a metropolitan zone according to the *National Ecological Function Zones of China*, facing enormous challenges of water quality, biodiversity and air and soil pollution (Ministry of Environmental Protection of the People's Republic of China M, Chinese Academy of Sciences's, 2015). According to China's *National New-type Urbanization Plan* (2014–2020) (State Council of China, 2014), continued urbanization in the region will undoubtedly lead to growing demand for land resources. There is a pressing need to assess the degradation risk of ES induced by land-use change in order to facilitate science-based policy-making for a sustainable development in the region. Previous studies largely concentrated on the health risk assessment of pollution and heavy metals in Taihu Lake (Jiao et al., 2014; Yu et al., 2012; Zhong et al., 2010), the ecological risk of pesticide residues in the wetland (Qu et al., 2011), and the ecological risk of TLB based on a conceptual model comprised of risk sources, habitats and risk receptors at the regional scale (Gao and Xu, 2013). However, there is little literature about degradation risk of ES induced by land-use change in the TLB. This paper fills-in part of this knowledge gap by assessing the integrated degradation risk of ES induced by land-use change in the basin.

This study seeks to increase understanding of the degradation risk of ES induced by land-use change in 1985–2010 and predict the future possible changes in the degradation risk of ES by 2020 in the TLB. A comprehensive risk assessment model of ES is constructed, which integrates four ecological models with a land-use change model. Based on the fundamental importance of ES and facing great challenges of degradation risk in the basin, three key regulating ES (water purification, water quantity adjustment, carbon sequestration) and one provisioning ES (GP) are particularly considered in the assessment. Land use in 2020 was projected with a geographically weighted multinomial logit-cellular automata (GWML-CA) model. Four ecological models, including modified Denitrification-Decomposition (DNDC), Soil-Water-Atmosphere-Plant (SWAP), Biome-BGC and Agro-ecological Zoning (AEZ), are used to derive key indicators that measure the degradation of ES. This study identifies the major degradation risk areas and draws out policy implications to maintain or even enhance ES for sustainable development in the basin throughout the next decades.

2. Material and methods

2.1. Study area

The TLB, situated on the east coast of China (within E119°3′1″-121°54′26″, N30°7′19″-32°14′56″), encompasses one municipality (Shanghai) and the majority of two provinces (Jiangsu, Zhejiang) (Fig.1). The basin has a typical subtropical monsoon climate, with an annual mean temperature of 15–17 °C and annual mean precipitation of 1010–1400 mm. Its average elevation is 34.4 m, varying between −4 m and 1559 m. The dominant soil types are yellow brown soil, red soil and paddy soil (agricultural land). There are about 200 rivers and 9 lakes (area above 10 km^2) within the basin, and Taihu Lake (2238.1 km^2) is the largest one as the third largest freshwater lake in China. The basin is one of the most populous and developed regions of China, with 0.38% of the total land area of China supporting 4.8% of the nation's population (1.34 billion) and producing 11.6% of the gross domestic product (GDP) (USD 6471.2 billion), according to the 2010 China census. During the 25-year period to 2010, the urban-built area grew substantially (by 2.5 times the 1985 level).

2.2. Risk assessment of ES: an interdisciplinary approach

Built on the PETAR principle, this study establishes an interdisciplinary approach to the ERA of ES in the basin. The approach, as depicted in Fig. 2, has a focus on four key ES related to three regulating ES (water purification, water quantity adjustment, carbon sequestration) and one provisioning ES (GP). Four indicators that measure respective ES are used: nitrogen emissions (NE), coefficient of water quantity adjustment (WQAC), net ecosystem production (NEP), and grain productivity (GP). The process of ERA at the regional scale involves four major steps: field observation and data processing; deriving indicators and projecting land-use change with numerical models; establishing risk assessment models; and integrated degradation risk assessment of ES.

2.3. Model specifications and indicators

The integrated degradation risk of ES is a function of degradation risk levels of four key ES, which is expressed with Eq. (1):

$$R_{ij} = W_Q * RQ_{ij} + W_V * RV_{ij} + W_C * RC_{ij} + W_G * RG_{ij} \quad (1)$$

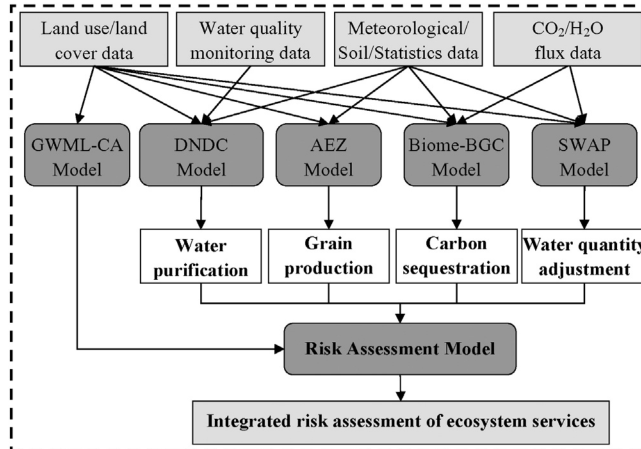


Fig. 2. Framework of the integrated degradation risk assessment of ES.

where R_{ij} indicates the integrated degradation risk level for the grid cell ij; RQ_{ij}, RV_{ij}, RC_{ij} and RG_{ij} are the degradation risk levels of water purification, water quantity adjustment, carbon sequestration and GP for each grid cell, respectively. For the forest ecosystem, the RG_{ij} (GP) was assumed to be 0 and thus was excluded. W_Q, W_V, W_C and W_G denote the weights for four key ecological services, respectively. In this study, these weights were set be equal, assuming that they play an equivalent role in supporting regional sustainability.

According to the *Technical Criterion for Eco-Environmental Status Evaluation* (HJ/T192-2006), issued by the Ministry of Environmental Protection of China (Ministry of Environmental Protection of the People's Republic of China's, 2006), the extent of change in each ES can be divided into four scales: severe deterioration (decreasing by 30% or more), moderate deterioration (decreasing by 15–30%), slight deterioration (decreasing by 5–15%) and no risk (decreasing by <5% or increasing). These four scales for each ES were normalized, as apparent in Table 1. The severity of ‘integrated degradation risk of ES’ was also classified into four scales according to the numerical range as shown in Table 1. Degradation of ES for water bodies (lakes, rivers) was not considered in the integral assessment as this study focuses on degradation risks of ES induced by terrestrial land-use change. Due to high complexity and spatial heterogeneity of urban ecosystems, the characteristics

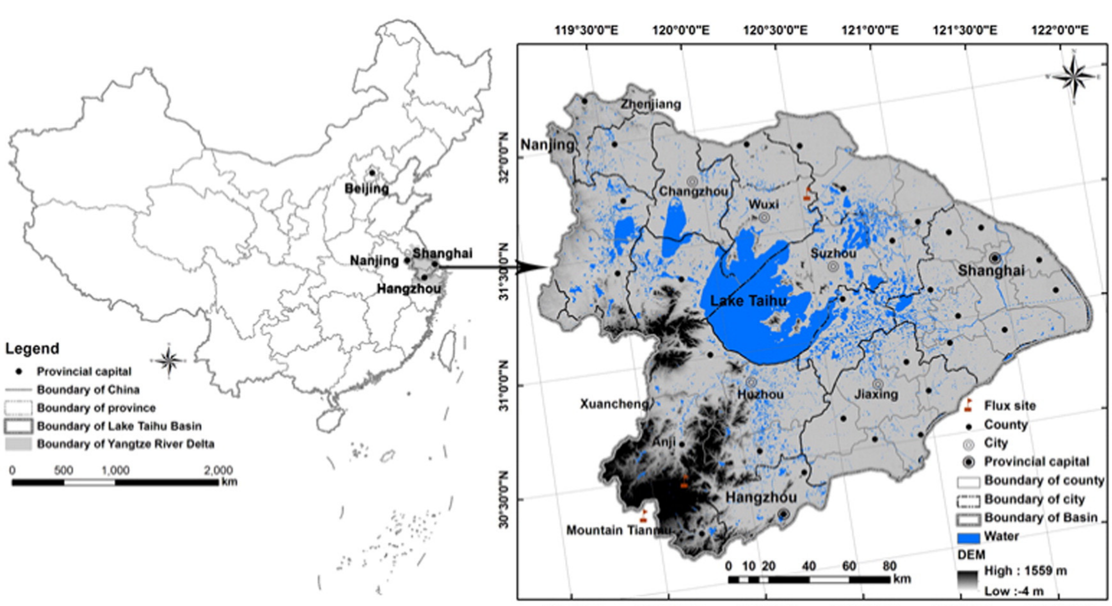


Fig. 1. Location of the Taihu Lake Basin.

Table 1
Criterion in degradation risk assessment of ES.

		No risk	Slight deterioration	Moderate deterioration	Severe deterioration
Water purification (NE)		<5% (0)	5–15% (1)	15–30% (2)	>30% (3)
Carbon sequestration (NEP)		>−5% (0)	−5–−15% (1)	−15–−30% (2)	<−30% (3)
Water quantity adjustment (WQAC)					
Grain production (GP)					
Integrated risk level	Cropland[a]	0	1–5	6–8	9–12
	Forest[b]	0	1–4	5–6	7–9

[a] Four indicators (NE, WQAC, NEP and GP) are measured.
[b] Three indicators (NE, WQAC and NEP) are measured.

and mechanisms of three key ES (water purification, water quantity adjustment and carbon sequestration) of urban ecosystems still remain limited, and suitable models that can be applied to estimate these three ES of urban ecosystems are scarce. Thus, degradation of ES for urban ecosystems was also not considered in this study, and four key ES for water bodies and urban ecosystems (transforming from cropland and forest) were assumed as zero, which would lead to overestimate degradation risk at some locals.

A GWML-CA model was established to forecast the impact of land-use changes on ES by 2020. Traditional CA models for land-use analysis, such as CLUE-S and Markov_CA, were built on the assumption of spatial homogeneity and the predefined transition rules of land-use change at the global scale (Lau and Kam, 2005). These models usually ignore the spatial variations in the relationship between driving forces and land-use change. Our study adapts GWML to the CA model to improve the model's accuracy by identifying the local transition rules of land-use change (Yu et al., 2013). Firstly, 5000 grid cells were randomly sampled to validate the model by deriving six significant variables for each land-use type. These variables include regional gross domestic product (RGDP), elevation, distance to the nearest national highway, distance to the closest provincial highway, distance to the nearest railway and distance to a local township seat. Secondly, the validated model was applied to simulation at the regional scale. The accuracy of simulation for land use in 2010 was as high as 92.8%. Land use in 2020 was projected under the scenario assuming that current land-use conditions in 2000–2010 will remain unchanged by 2020.

Deteriorating water quality has been a vital issue in the TLB as this has deeply influenced biodiversity as well as residents' living and wellbeing (Guo, 2007; Yang and Liu, 2010). Nitrogen (N) and phosphorus (P) are the primary limiting factors to algal growth (Xu et al., 2010), and the N emissions from the terrestrial ecosystems is the main source for the rivers or lakes. Thus, N emissions from the terrestrial ecosystems (including surface runoff and soil interflow) was selected as the key substituted indicator reflecting water purification of the ES. To improve the efficiency of modeling simulation, cropland in the basin was purposefully divided into 49 sub-zones according to soil texture, soil types, and meteorological variables (e.g. temperature and precipitation). N emissions of the cropland with the wheat-rice rotating system were obtained from a monthly field experiment (Nov. 2012–Oct. 2014) located at the Changshu Agroecological Experimental Station, Chinese Academy of Sciences (31°32′45″N, 120°41′57″E) (Li et al., 2015). The DNDC model was calibrated with the observed N emissions before it was applied to simulate the N emissions in the 49 sub-zones (Li et al., 1992; Li et al., 2005). For N emissions from the forest, we used observation data collected from the catchment of Lake Tianmu within the TLB in 2012–2014. We have particular interest in two dominant forest types: masson pine and moso bamboo (Nie et al., 2015). Since the spatial distribution of the two forest types cannot be precisely separated due to the coarse resolution of land-use data from Landsat images, their average N emissions (7.46 kg ha^{-1} yr^{-1}) was used to estimate N emissions of the forest land in the TLB. Due to the lack of projected meteorological data of 2020 with high resolution, the meteorological input data of 2010 and projected land use in 2020 were used to predict N emissions in 2020.

Flooding is the second vital threat to people's lives and property, and sustainable development in the TLB (Yang et al., 2011a; Yin et al., 2009). Recent years have witnessed increasing risk of flooding in the basin. Flooding in the region is characterized by the fact that short-term rainstorms lead to catastrophic events (Yang et al., 2011a; Yin et al., 2009). Many studies have noted that land-use change significantly intervenes water regulation in the TLB (e.g., runoff volumes and peak discharges) (Chen et al., 2009; Zhou et al., 2013). Thus, the WQAC, defined as the ratio of annual evapotranspiration and annual precipitation, indicates that a higher coefficient will generate less runoff and a lower flooding risk under the same precipitation. Thus, this coefficient was used to indicate the capability of ecosystems in adjusting water quantity. The SWAP model was calibrated and validated with observed H_2O flux data, with a covariance technique for croplands, evergreen coniferous forests and mixed forests (Kroes et al., 2008; van Dam et al., 2008). The calibrated SWAP model was subsequently applied to simulate daily evapotranspiration at the regional scale with 250 m resolution. Again, the WQAC in 2020 was simulated with the meteorological input data for 2010 and projected land use in 2020.

Carbon sequestration is another important regulating ES for the terrestrial ecosystems. It has played a vital role in mitigating climate change and tackling global warming (Piao et al., 2009; Shaffer, 2010). NEP, defined as the difference between gross primary production and total ecosystem respiration, was selected to represent the carbon sequestration capacity of terrestrial ecosystems. A modified Biome-BGC model was applied to simulate NEP of 1980–2020 (Ueyama et al., 2010; Wang et al., 2005; Xu et al., 2016). We made three modifications to the model. Firstly, a 'relative soil moisture content', defined as the ratio of the actual moisture content against the soil moisture content at field capacity, is used to replace the default limiting stress functions (SF) of soil/water potential. Note that the default SF was based on minimum temperature (Tmin), vapor pressure deficit (VPD), and soil water potential (SWP) (Hidy et al., 2012). Our study area is situated in the subtropical monsoon zone which has dramatic climate variations during summer months due to frequent and huge shifts between dry and wet weather conditions. This modification can improve the sensitivity of stomatal conductance to soil moisture, to better capture the distinctive features of our study area. Secondly, factors of fertilization and irrigation are added into the model as they are normal practices in utilizing cropland in the TLB. Thirdly, the modified BIOME-BGC model was calibrated to derive specific eco-physiological parameters for croplands, evergreen coniferous forests and mixed forests with observed NEP data. The default eco-physiological parameters for evergreen broadleaf forests, deciduous coniferous/broadleaf forests and shrubs are simply applied to the model as their areas are small and flux observation sites in the study area are very limited. The validated BIOME-BGC model is then applied to simulate NEP at the regional scale (Xu et al., 2016). NEP in 2020 is simulated with the projected land use in 2020 and meteorological input data of 2010, assuming no significant change in climactic conditions in next 10 years.

Taihu Lake Basin was one of China's major cropping areas before 1985. Yet GP has decreased dramatically since 1985 and cannot meet the demand of residents living in the region since 2010 (Pan et al., 2013). Total GP decreased by 4.5 million tonnes (or 36%) during the

1985–2010, and its share in national production decreased from 3.4% in 1985–1.4% in 2010 (Pan et al., 2013). Cropland productivity (i.e. output per unit of land area) is one of the important indicators used to reflect GP. Increasing cropland productivity can provide more grain products when other factors remained unchanged and vice versa. Thus, cropland productivity was selected as a key indicator to measure GP of the provisioning ES for the cropland. A modified AEZ model was employed to estimate cropland productivity, which is a function of climate potential productivity and soil effective coefficient as expressed in Eq. (2) (Pan et al., 2015; Tian et al., 2014):

$$CP_{ij} = \mathrm{CPP}_{ij} * SE_{ij} \tag{2}$$

where CP_{ij} is the cropland productivity at the cell ij; CPP_{ij} is the climate potential productivity, which can be estimated by the multiplier of photosynthetic potential productivity, temperature correction coefficient and water correction coefficient (Deng et al., 2006; Pan et al., 2015); SE_{ij} is the coefficient for soil efficiency, which can be estimated by using an analytic hierarchy process (AHP) that involves three aspects and eight factors (Pan et al., 2015), as expressed in Eq. (3):

$$\begin{aligned} SE_{ij} = {} & \alpha_1 * ST_{ij} + \alpha_2 * pH_{ij} + \alpha_3 * SD_{ij} + \alpha_4 * SO_{ij} + \alpha_5 * TN_{ij} + \alpha_6 \\ & * EP_{ij} + \alpha_7 * EL_{ij} + \alpha_8 * IGR_{ij} \end{aligned} \tag{3}$$

where SE is the coefficient for soil efficiency; ST, pH and SD are the soil texture, soil pH and soil density, indicating the physical and chemical properties of top soil layer, respectively; TN, EP and SO are the content of total nitrogen, effective phosphorus and soil organic matter in the top tilled soil layer (0–20 cm), indicating the nutrient status of the top soil layer, respectively; EL and IGR are the elevation and irrigation guarantee rate, respectively, indicating the physical and farming conditions in every locality. α_1–α_8 are coefficients for corresponding variables, which are derived from a questionnaire survey of 100 scientists working in the field of soil, ecology and geography in Jiangsu Province. GP in 2020 is simulated using the meteorological input data in 2010 and projected land use in 2020.

2.4. Data sources and processing

Historical data sets include remote sensing data, field experiments and observed flux data, meteorological data, geo-spatial data and statistics. Remote sensing data involves land-use data in 1985, 1995, 2000, 2005 and 2010 at the scale of 1:100,000 derived from Landsat TM images at the lead author's Institute. The land-use datasets 1985–2010 were classified into four categories: cropland, forest, water, urban and built-up. Grassland was classified as the forest due to its very small area, which will bring some uncertainty. As the land-use data was derived from Landsat TM images, urban and built-up areas are lumped together as one land-use type and analysed together, due to low spatial resolution of 30 m of Landsat TM images that hinder high accuracy in separation. To accurately estimate NEP and WQAC, the forest category was further subdivided into six sub-categories: evergreen coniferous forest, evergreen broadleaf forest, deciduous coniferous forest, deciduous broadleaf forest, mixed forest and shrub. To ensure reliable calibration and validation of the Biome-BGC and SWAP models, three open-path eddy covariance systems were established for three dominant land use/cover types – cropland (N31°39′14″, E120°32′43″, elevation of 6 m above sea-level, began in Dec. 2011), evergreen coniferous forest (N30°28′34.5″, E119°40′25.7″, elevation of 380 m above sea-level, began in Jan. 2011) and mixed forest (N30°20′59″, E119°26′13″, elevation of 1140 m above sea-level, began in Jan. 2013) – to observe the CO_2 and H_2O fluxes in the region. To calibrate DNDC, runoff field experiments and water quality monitoring were conducted in the city of Changshu (2012–2014). To derive the N emissions coefficient of the forest, runoff field experiments and water quality monitoring for two dominant forest types (masson pine and moso bamboo) was monitored in the sub-catchment of the Taihu Lake Basin (2012–2014). CO_2/H_2O flux data was collected from three flux sites for cropland over a two-year period (Jan. 2012–Dec. 2013), for evergreen coniferous forest over a two-year period (Jan. 2011–Jun. 2012, Jan.–Nov. 2013), and for mixed forest over a one-year period (Jan.–Dec. 2013). These observed CO_2 and H_2O flux data were used to calibrate the Biome-BGC and SWAP models, respectively.

Daily meteorological data on precipitation, maximum and minimum temperature, average temperature, day length and radiation from 1985 to 2013 were derived from the National Meteorological Center (NMC) of China. Such data was collected from 22 field observation stations in the basin and its adjacent areas, and were interpolated to the whole basin by using the inverse distance weighted (IDW) interpolation method. The interpolated maximum, minimum and average daily temperatures were calibrated with the DEM. These meteorological datasets were used as a part of input data of four ecological models. Other information includes 1:250,000 administrative district maps, DEM and soil datasets maintained at the lead author's Institute. Population, economic and GP statistical data were sourced from statistical yearbooks. All the geospatial datasets were projected to Albers Conical Equal Area projection and transformed into a binary format with a spatial resolution of 250 m.

3. Results

3.1. Degradation risk of ES in 1985–2010

As shown in Fig. 3(e1) and Fig. 4(a), slightly less than two-thirds (63.6%) of the region experienced integrated degradation risk in ES during the period of 1985–2010. Nearly 10.7% (or 3961.2 km^2) of land experienced severe deterioration, while 11.6% (4319.6 km^2) and 41.3% (15371.2 km^2) experienced moderate and slight deterioration, respectively. Epicenters of land with ‘severe deterioration’ are located in Shanghai and Jiangsu province, mainly involving the cities of Suzhou, Changzhou, Wuxi, Jiangyin, Zhangjiagang, Changshu and Kunshan. A vital reason for the deterioration is a dramatic increase in demand for land fueled by rapid industrialization. Land with ‘moderate deterioration’ was concentrated in Shanghai, Suzhou, Hangzhou, Wuxi and Changzhou, accounting for 44.4% (or 1919.1 km^2) of the total area of moderate deterioration. Strikingly, over 80% of the total area in Taicang, Zhangjiagang, Changshu, Jiangyin and Tongxiang run a degradation risk. By contrast, only a small fraction of land (29%) in the cities of Anji and Lin'an experienced degradation risk of ES. Deterioration of ES has reduced the ecological security in some localities. The dramatic degradation of water quality and extensive algal blooms in the Taihu Lake and increasing flood disasters in the whole Taihu Lake Basin are some examples in point.

There is great spatial heterogeneity in the specific risk of these four key ES, as shown in Fig. 3(a1), (b1), (c1) and (d1). Areas with ‘severe deterioration’ for water purification, water quantity adjustment, carbon sequestration, and GP accounted for 14.4%, 16.5%, 19.9% and 24.9% of the total area of the basin in 1985–2010, respectively. Land with ‘moderate deterioration’ and ‘slight deterioration’ for water purification is larger than the other three key ES, accounting for 20.9% and 7.8% of the total basin area, respectively. While those of the other three key ES were all small, ranging between 0.2%–2.2%. Areas with ‘severe deterioration’ for each specific ES account for 7.4% of total area with integrated degradation risk of ‘severe deterioration’, which suggests that there are remarkable spatial interdependencies between these four specific ES. Spatial patterns of the degradation risk for water quantity adjustment and carbon sequestration are generally similar, land with ‘severe deterioration’ both for water quantity adjustment and carbon sequestration accounts for 72.8% of total area with degradation risk. Moreover, the epicenters of land with ‘severe deterioration’ both for water quantity adjustment and carbon sequestration are also similar with those of the integrated degradation risk of ES, overlapping by 66.8%. Spatial patterns of degradation risk in water purification and GP both mainly involve the

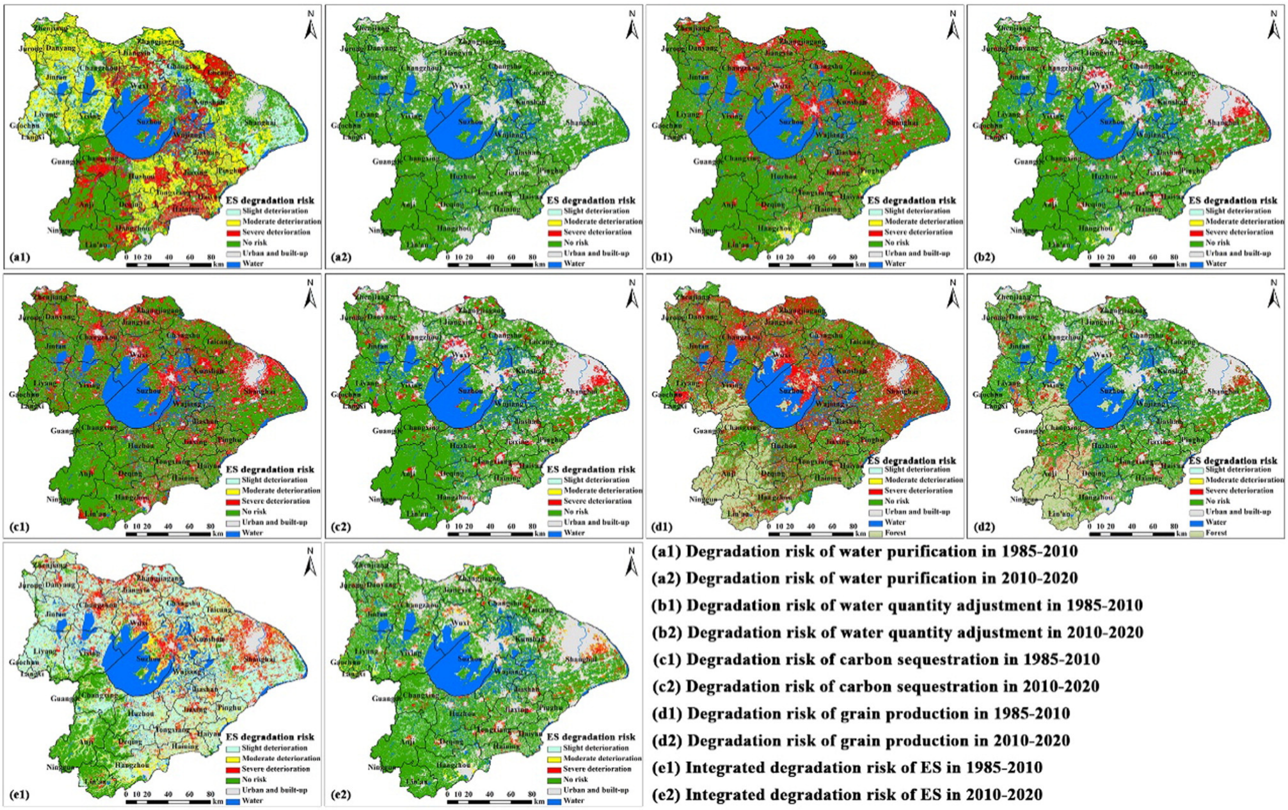


Fig. 3. Degradation risk of ES in the TLB in 1985–2020.

agroecosystems (or cropland), while their spatial patterns of degradation risk are dramatically different. Epicenters of land with 'severe deterioration' for water purification mainly centered in Taicang, Haining, Haiyan, Changxing and Jiaxing, where the percentage accounting for total area of each county ranged from 28.9% to 60.8%. While epicenters of land with 'severe deterioration' for GP mainly centralized in Jiangyin, Changzhou, Shanghai, Wuxi, Kunshan and Liyang, ranging from 30%-38%. There are dramatic inverse trends in degradation risk between GP and water purification, especially for Shanghai, Taicang, Haining and Changxing, as shown in Fig. 3(a1) and (d1). Areas with such inverse trends account for 73.8% of total area with degradation risk. It can be concluded that there are great spatial discrepancies between the specific degradation risks of four key ES and the integrated degradation risk in this basin. Degradation risks of water quantity adjustment and carbon sequestration are basically positive conjugate, while those of water purification and GP are generally reversed.

3.2. Degradation risk of ES in 2010–2020

ES in the Taihu Lake Basin will continue to decline under the projected land-use change of 2020 if there is no intervention (Fig. 3(e2), Fig. 4(b)). Approximately 12% (or 4509.2 km^2) of the land is likely to continue degrading, among which the proportion of land under severe deterioration and moderate deterioration is estimated to be 3.4% and 2.8%, respectively. Areas prone to 'severe deterioration' are centered around Shanghai, Yixing, Tongxiang, Danyang, Changshu and Wuxi, accounting for 51% of their total land. In 2020, Liyang, Tongxiang, Haining, Danyang, Jintang and Changxing would have a greater degradation risk in ES, where more than 15% of their total land area will undergo degradation compared to their 2010 level. The predicted area at degradation risk in Suzhou and Lin'an is small, taking 5.1% and 5.7% of their current land area, respectively. Areas with 'severe deterioration' for each specific ES only account for 5.3% of total area with integrated degradation risk of 'severe deterioration'. These figures suggest that spatial interdependencies between these four specific ES will continue in the future. The inverse trends in degradation risk between water purification and GP will be further intensified, totaling up 97.9% of total area with degradation risk in this basin. While spatial patterns of the degradation risk for water quantity adjustment and carbon sequestration are mostly similar, the overlapping area with 'severe deterioration' accounts for 82.9% of total area with degradation risk.

Predicted hot spots at risk of 'severe deterioration' in 2010–2020 have a distinctive feature compared to changes in 1985–2010. ES exhibiting a greater risk of severe deterioration is concentrated not only in Shanghai (the largest mega-city in China), but also in a few large- and medium-scale cities (Suzhou, Changzhou and Wuxi) as well as in some small cities (Yixing, Tongxiang, Danyang, Jitan and Changshu). Also, there is great spatial heterogeneity in degradation risk of four key specific ES, as shown in Fig. 3(a2), (b2), (c2) and (d2). Water quantity adjustment, carbon sequestration and GP would face further degradation risk, while water purification would have lower risk. The projected risk likelihood is highly related to the projected land-use change, suggesting that any change in land-use type will lead to change in ES. China's *National New-type Urbanization Plan* (2014–2020) aims to accelerate further expansions of medium- and small-scale cities, while urban growth in the mega- and large-scale cites will be controlled strictly. Spatial sprawl of urban areas will undoubtedly take up more cropland, water bodies and forest, and this process will consequently trigger further degradation of ES.

4. Discussion

4.1. Impacts of land-use change

Rapid growth of economy and population in 1985–2010 has dramatically changed land use and land cover in the basin (Fig. 5, Table 2). This change was characterized by fast urban expansion (by 1.5 times over the 25 year period) at the cost of massive loss of cropland

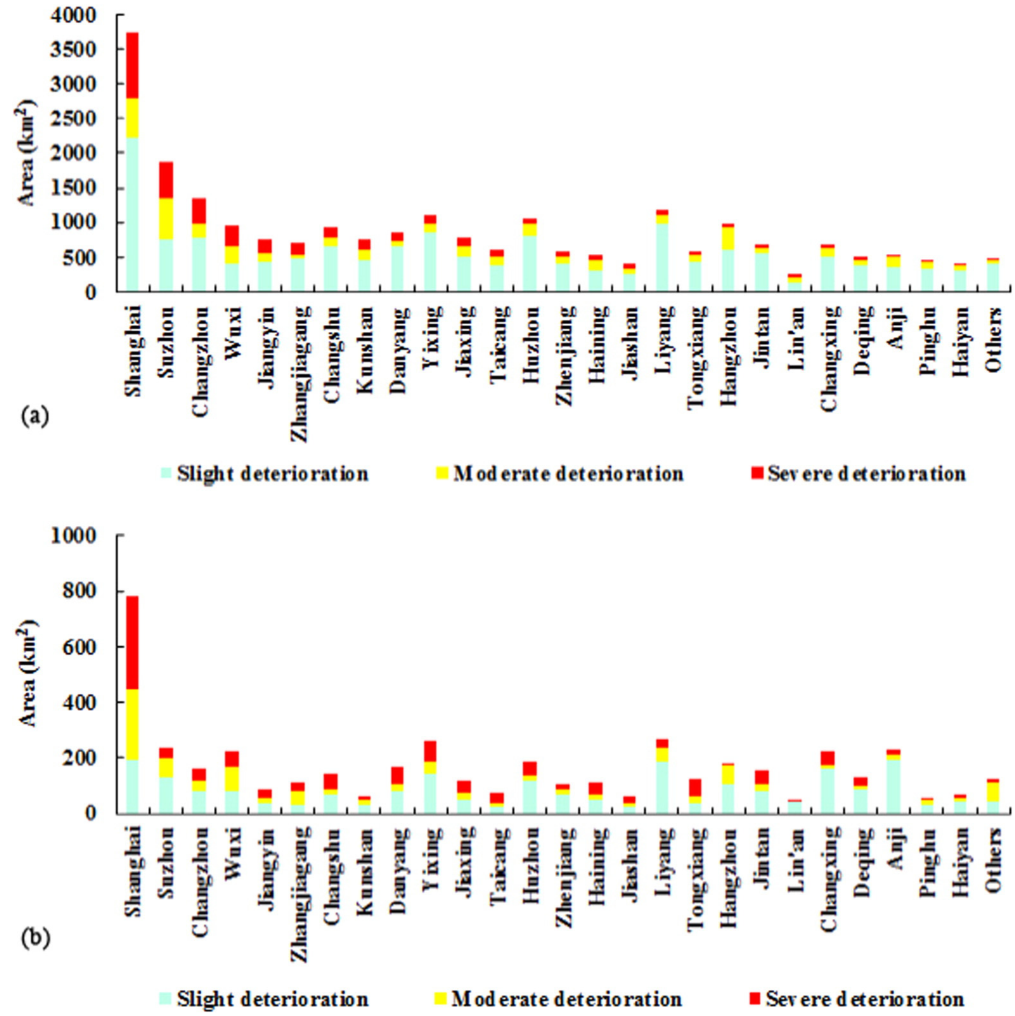


Fig. 4. Areas of different degradation risk scales in 1985–2020. Note: (a) and (b) indicate the areas of different degradation risk scales in 1985–2010 and 2010–2020, respectively; 'Others' indicates the counties with very small area located in the LTB (Jurong, Gaochun, Lanxi, Guangde and Ningguo).

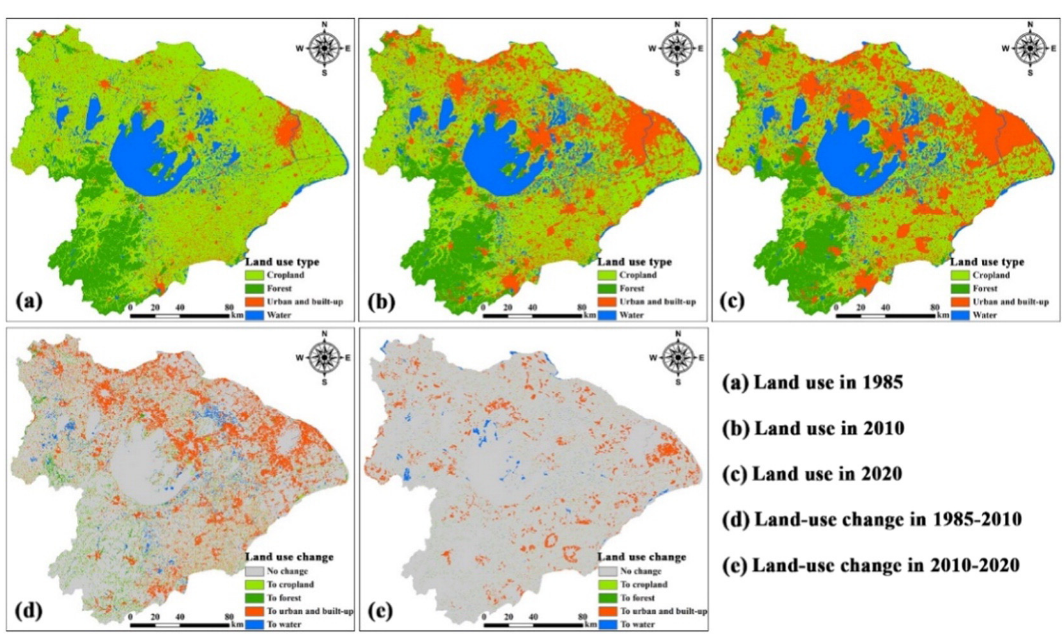


Fig. 5. Land-use change in the Taihu Lake Basin, 1985–2020.

Table 2
Matrix of land-use conversion (km^2) in the Taihu Lake Basin, 1985–2020.

		Land-use type in 2010						Land-use type in 2020			
		Cropland	Forest	Water	Urban and built-up			Cropland	Forest	Water	Urban and built-up
Land-use type in 1985	Cropland	16,251.8	615.2	846.6	5939.3	Land-use type in 2010	Cropland	15,462.9	66.3	178.4	2098.1
	Forest	342.0	4623.5	53.6	150.8		Forest	50.6	5093.7	115.8	52.2
	Water	447.4	35.5	4101.3	161.9		Water	86.8	2.9	4935.5	17.2
	Urban and built-up	764.6	38.1	40.8	2766.4		Urban and built-up	335.1	16.8	19.1	8647.4

Source: authors' estimation based on the analysis of land-use data in1985, 2010 and 2020.

(5939.3 km^2), water bodies (161.9 km^2) and forest (150.8 km^2). Overall, there was a significant reduction of cropland (by 5847.1 km^2, or 24.7% of the 1985 amount). In contrast, the total area of water bodies and forests increased marginally, by 296.3 km^2 (6.2%) and 142.4 km^2 (2.8%) respectively. The expansion of water bodies was associated with two factors. First, the cultivated area within a 5-kilometer radius of the Taihu Lake was returned to water bodies under the national *Returning Cropland to Lake Project* that has been implemented in the region since 2007. This project has been one of the key ecological projects to curb the deterioration of the water environment of Taihu Lake since the water crisis caused by algae blooms in 2007. Second, some of the cropland has been converted into water bodies as the fishery industry brings farmers higher profit than grain cropping. The increase of water bodies is centralized in the cities of Kunshan, Changshu and Jintan, jointly accounting for 43.9% of the overall increase of water bodies in the region. In order to protect China's food security, the country has established a fundamental land-use policy under which 120 million hectares of arable land must be guaranteed for grain and fiber crops. A number of adaptive strategies for farmland exploitation, consolidation and reclamation have been implemented in the region since 2000. Consequently, 764.6 km^2 of urban and built-up land, 447.4 km^2 of water bodies and 342.0 km^2 of forest were converted to cropland over 1985–2010. Further, another national environmental policy on *Grain to Green* (i.e. returning cropland on steep slopes with a gradient of 25° or greater to forest or grassland) has been carried out since 2000, resulting in 615.2 km^2 of cropland on steep slopes being returned to forest in the region. In turn, four key ES in the basin decreased dramatically (Fig. 3). The degradation risks of water quantity adjustment and carbon sequestration were deeply influenced by land-use change (e.g., cropland converted to urban land, water or forest), while those of water purification and GP were doubly impacted by land-use change and agricultural management (e.g., increasing fertilizer utilization).

The scale of land-use change increased dramatically over time during the 1985–2010 period. This was especially the case after 2000. The key reasons for the change are related to industrial development and population growth. Land-use change has a significant correlation ($R^2 = 0.82$) with GDP at the county level. Assuming the current land-use change trend will remain constant, urban land-use area is projected to continue to be expanded from 2010 to 2020, increasing by 19.9% (or 1796.5 km^2) from the 2010 level. This expansion is anticipated to involve encroachment of large areas of cropland (1870.3 km^2) distributed in the areas adjacent to the major cities of Shanghai, Wuxi, Suzhou and Changzhou. Strikingly, cropland in some small cities such as Yixing, Danyang, Tongxiang, Jintan and Changxing will be greatly encroached upon as well. However, the growth rate of urban land area, compared to that of 2000–2010 (80.7%), is expected to drop slightly in 2010–2020. Forest land is likely to reduce moderately (by 132.7 km^2, or 2.5%). Water bodies will increase slightly (by 206.5 km^2, or 4.1%), and this increase mainly centers in the cities of Suzhou, Changzhou and Changshu. These changes will undoubtedly reduce the ES, including water quantity adjustment, carbon sequestration and GP, which will further aggravate degradation risk of ES in the region over the next five years. However, water purification at the regional scale would experience a small increase, due to less N emissions from the reducing cropland and forest (Fig. 3(a2)), and related ES generated by urban land and water bodies were assumed to be zero.

4.2. Adaptation strategies

Dramatic urbanization and industrialization has resulted in significant land-use changes in 1985–2010, and subsequently induced degradation of ES in the TLB since 1985. The urbanization rate in this region was 65% in 2010 and it is expected to be 82.7% by 2020, which is much higher than the national target (60%) (Li, 2013). Rapid urbanization is undoubtedly an important trigger of fast land-use change and ES degradation. The trade-off between maintaining economic development and protecting environmental sustainability is a tremendous challenge and represents a significant concern from a policy perspective. Based on the results of this study, three countermeasures are suggested as follows.

First, is regulating accelerated urban sprawl and population growth. One practical option to this end is to improve land-use intensity in the urban areas to curtail further encroachment on farmland and thus on further reduction of ES. With the implementation of China's *National New-type Urbanization Plan* (2014–2020), urban agglomeration in the TLB (and the Yangtze River Delta more broadly) is expected to accelerate (State Council of China, 2014). This policy is a key determinant of the rate at which the land encroachment process will continue in the next decade. It is imperative to take a new-style urbanization approach, shifting from a conventional to a new model, characterized by an intensive, smart, green, and low-carbon economy and limiting massive inflows of rural migrants to the mega- and large-scale cities in the region. This approach is also needed for those medium- and small-scale cities as they face an increasing degradation risk of ES.

Second, is reinforcing current environmental programs that protect cropland, forest and wetland. These programs, particularly the 'Grain to Green' and 'Returning Cropland to Lake' designated to be completed in 2015 or 2020, should be extended to 2020 and beyond. Such programs have evidently played a vital role in improving ES and could serve to do so well into the future. Simultaneously, the trade-off between specific key ES should be considered during the implementation of these environmental programs. Moreover, it is imperative to upgrade the region's industrial structure to reduce pollutants injecting into the river-lake system, thereby maintaining or even improving ES of the Taihu Lake and dozens of rivers flowing into this lake.

Third, is establishing a regional ES monitoring system. At present, there is only one Lake Ecosystem monitoring station to monitor water quality and aquatic ecosystems in the basin. It is of great significance and urgency to establish an observation system to monitor the dynamics of ES for the key ecosystems in the basin for two primary reasons: it is important to increase understanding of the interactions and interdependencies between ecosystem functions, processes and services within and between ecosystems, and to increase understanding between demand for and supply of ES. Next, it is important to provide science-grounded evidence for policy-making to achieve an equilibrium in economic and urban growth that will not cause irreversible degradation risk in ES.

4.3. Limitations

The methodology developed in this study, i.e. integrating a land-use model, four ecological models and field experiments to capture the spatial and temporal changes in degradation risk of ES at a regional scale, is applicable to other similar environments in China and throughout the world. However, several limitations of the study deserve mention.

Firstly, degradation risk of ES for water bodies (lakes, rivers) and urban ecosystems was not considered in this study. Given the fact that urban areas and water bodies accounted for 24.3% and 13.6% of the total area of the basin in 2010, respectively, there is a great uncertainty in estimating regional ES by excluding those generated by such systems. For example, Taihu Lake provided 20.2 billion tonnes of fresh water and aquatic products of USD 293.7 million, and retained total nitrogen (TN) of 17,000 million tonnes and total phosphorus (TP) of 769 tonnes in 2009 (Jia et al., 2015). The green space of urban ecosystems in the Taihu Lake Basin absorbed COD of 1916.2 tonnes, TN of 946.1 tonnes, NH4-N of 25.9 tonnes and TP of 34.5 tonnes in 2008 (Yang et al., 2011b). Thus, the ES of water and urban ecosystems should be taken into account in order to have a comprehensive understanding of the impact of land-use change on ES in future research. As the area of wetland is very small in the basin, the wetland was grouped into water bodies in the current study. Wetland related issues need to be separated from bodies of water in future simulation as its ES have distinctive features. More ecological indictors, such as biodiversity, gene resources, water and soil conservation, adjusting climate, and water quality purification, need to be incorporated in the model in future studies to capture the degradation risk of ES at the regional scale more holistically.

Secondly, the ecological risk criterion used in the model to classify degradation risk of ES needs to be further improved in future study. In this study, degradation severity scales were roughly classified according to the *Technical Criterion for Eco-Environmental Status Evaluation* (HJ/T192-2006).The weights for the sensitivity and roles across the four types of ES were treated as being equally distributed. Many previous studies have indicated that different ES have different sensitivities to the degradation (Galic et al., 2012; Kroel-Dulay et al., 2015) and different resilience to recovery (Folke et al., 2004; McPhearson et al., 2015; Sasaki et al., 2015). Thus, the unique ecological risk criterion with the same weight would mask the internal discrepancy for different services of a specific ecosystem, and conceal external heterogeneity among different types of ecosystems. The spatial and temporal interdependencies of ES have not been considered in this study, which would lead to some uncertainty in the integrated risk assessment of ES. In future, a specific criterion on degradation risk of ES tailored to a specific area and a specific ecosystem needs to be constructed to reflect the heterogeneity and interdependencies among ecosystems and localities. Furthermore, the method for degradation risk assessment of ES can be further advanced by adopting more sophisticated approaches such as Bayesian network approaches (Landuyt et al., 2014; McDonald et al., 2015).

Thirdly, land-use simulations under different scenarios and the accuracies of ecological models need to be further improved. The GWML-CA model used in this study rightly simulated land use in 2020 under the trajectory trend. It will be helpful to provide more possible scenarios for risk assessments so that policy-makers can have better options. This might be done by simulating land use of 2020 under different scenarios and in long-term (e.g., by 2030) that consider ecological protection and accelerated development of small and medium-sized cities in the region. Three flux towers were used to collect monitoring data to calibrate the BIOME-BGC and SWAP models. However the effects of scaling up from a local site to the regional scale might bring some uncertainties in the simulations at the regional scale. The uncertainty issue needs to be addressed in future research. It is also important to define indicators for ES by using more accurate monitoring data. N emissions of the forest need to be improved at the grid scale with higher accuracy of land-use data and other ecological models (e.g., SWAT, STREAM) in the future. In addition, the coefficient for soil efficiency in the AZE model can robustly capture the spatial heterogeneity in the impact of soil conditions on cropland productivity with eight factors. However, the weights for these eight factors derived from expert knowledge gathered from 100 experts specializing in soil, ecology and geography still contain uncertainties due to the subjectivity and differences of those experts' knowledge during the survey.

5. Conclusion

Land-use change is a significant contributor to regional and national ES. This study developed an interdisciplinary methodology for assessing integrated degradation risk of ES on a regional scale, for the Taihu Lake Basin of China. A key contribution of this study is its novelty in incorporating remote sensing data and field monitoring data, and integrating land-use model and ecological models to derive fundamental indicators for the key ES. This study identified the current and future degradation risk of ES in the region, and provides suggestions for halting the degradation trend of ES. This ERA approach is applicable to other parts of China.

This study suggests that dramatic land-use changes caused by fast urban expansion will continue in the next decade. About 12% of the land in the basin will have a likelihood of degradation in ES. Some small-scale cities will tend to have greater degradation risk of ES over the next five years. Practical counter-measures include mediating accelerated urban sprawl and population growth, reinforcing current environmental programs and establishing regional ES monitoring systems. It's significant for policy makers to achieve a dynamic balance between growth in population and GDP and multi-dimensional ES. The mechanisms between ecological functions and ES, spatial and temporal interdependencies of ES, the trade-offs among specific key ES and between ES protection and socio-economic development in this basin need further study to capture the most dynamic processes of these forces in China, in an accurate and timely way.

Acknowledgements

This study was supported by the National Natural Science Foundation of China (41030745; 41371532), and Interdisciplinary Frontier Project of Nanjing Institute of Geography and Limnology, CAS (NIGLAS2012135019). This research is also partially supported by a NASA Land Use and Land Cover Change program project (NASA-NNX09AI26G) and the NSF Division of Information & Intelligent Systems (NSF-1028291). We would like to express our great gratitude to the National Meteorological Center (NMC) of China for sharing extensive data used in this study. We are very grateful to two anonymous reviewers for their constructive suggestions.

References

Bennett, E.M., Peterson, G.D., Gordon, L.J., 2009. Understanding relationships among multiple ecosystem services. Ecol. Lett. 12, 1394–1404.
Burton, G.A., Chapman, P.M., Smith, E.P., 2002. Weight-of-evidence approaches for assessing ecosystem impairment. Hum. Ecol. Risk. Assess. 8, 1657–1673.
Chen, Q., Liu, J., 2014. Development process and perspective on ecological risk assessment. Acta Ecol. Sin. 34, 239–245 (in Chinese).
Chen, Y., Xu, Y.P., Yin, Y.X., 2009. Impacts of land use change scenarios on storm-runoff generation in Xitiaoxi basin, China. Quat. Int. 208, 121–128.
Chen, Q.Y., Liu, J.L., Ho, K.C., Yang, Z.F., 2012. Development of a relative risk model for evaluating ecological risk of water environment in the Haihe River Basin estuary area. Sci. Total Environ. 420, 79–89.
Cormier, S.M., Smith, M., Norton, S., Neiheisel, T., 2000. Assessing ecological risk in watersheds: a case study of problem formulation in the Big Darby Creek watershed, Ohio, USA. Environ. Toxicol. Chem. 19, 1082–1096.
Daily, G.C., Matson, P.A., 2008. Ecosystem services: from theory to implementation. Proc. Natl. Acad. Sci. U. S. A. 105, 9455–9456.
Deacon, S., Norman, S., Nicolette, J., Reub, G., Greene, G., Osborn, R., et al., 2015. Integrating ecosystem services into risk management decisions: case study with Spanish citrus and the insecticide chlorpyrifos. Sci. Total Environ. 505, 732–739.
Deng, X.Z., Huang, J.K., Rozelle, S., Uchida, E., 2006. Cultivated land conversion and potential agricultural productivity in China. Land Use Policy 23, 372–384.

Doria, M.D., Pidgeon, N., Hunter, P.R., 2009. Perceptions of drinking water quality and risk and its effect on behaviour: a cross-national study. Sci. Total Environ. 407, 5455–5464.

Environmental Protection Agency E, 1998. Guidelines for Ecological Risk Assessment (EPA/630/R-95/002F). Federal Register, Washington, DC, pp. 26846–26924.

Fisher, B., Turner, K., Zylstra, M., Brouwer, R., de Groot, R., Farber, S., et al., 2008. Ecosystem services and economic theory: integration for policy-relevant research. Ecol. Appl. 18, 2050–2067.

Folke, C., Carpenter, S., Walker, B., Scheffer, M., Elmqvist, T., Gunderson, L., et al., 2004. Regime shifts, resilience, and biodiversity in ecosystem management. Annual Review Of Ecology Evolution And Systematics 35, 557–581.

Forbes, V., Hommen, U., Thorbek, P., Heimbach, F., Van den Brink, P.J., Wogram, J., Thulke, H.H., Grimm, V., 2009. Ecological models in support of regulatory risk assessments of pesticides: developing a strategy for the future. Integr. Environ. Assess. Manag. 5, 167–172.

Galic, N., Schmolke, A., Forbes, V., Baveco, H., van den Brink, P.J., 2012. The role of ecological models in linking ecological risk assessment to ecosystem services in agroecosystems. Sci. Total Environ. 415, 93–100.

Gao, J.F., Xu, Y., 2013. The Ecological Risk Assessment of Taihu Lake Watershed (in Chinese). Science press, Beijing, China.

Goldstein, J.H., Caldarone, G., Duarte, T.K., Ennaanay, D., Hannahs, N., Mendoza, G., et al., 2012. Integrating ecosystem-service tradeoffs into land-use decisions. Proc. Natl. Acad. Sci. U. S. A. 109, 7565–7570.

Guo, L., 2007. Ecology - doing battle with the green monster of Taihu Lake. Science 317, 1166.

Hidy, D., Barcza, Z., Haszpra, L., Churkina, G., Pinter, K., Nagy, Z., 2012. Development of the Biome-BGC model for simulation of managed herbaceous ecosystems. Ecol. Model. 226, 99–119.

Jia, J.M., Luo, W., Du, T.T., Li, Z.H., Lv, Y.L., 2015. Valuation of changes of ecosystem services of Tai Lake in recent 10 years. Acta Ecol. Sin. 35, 2255–2264 (in Chinese).

Jiao, Y.Y., Chen, Q.K., Chen, X., Wang, X., Liao, X.W., Jiang, L.J., et al., 2014. Occurrence and transfer of a cyanobacterial neurotoxin beta-methylamino-L-alanine within the aquatic food webs of Gonghu Bay (Lake Taihu, China) to evaluate the potential human health risk. Sci. Total Environ. 468, 457–463.

Kragt, M.E., Robertson, M.J., 2014. Quantifying ecosystem services trade-offs from agricultural practices. Ecol. Econ. 102, 147–157.

Kroel-Dulay, G., Ransijn, J., Schmidt, I.K., Beier, C., De Angelis, P., de Dato, G., et al., 2015. Increased sensitivity to climate change in disturbed ecosystems. Nat. Commun. 6. http://dx.doi.org/10.1038/ncomms7682.

Kroes, J.G., van Dam, J.C., Groenendijk, P., Hendriks, R.F.A., Jacobs, C.M.J., 2008. SWAP version 3.2. Theory Description and User Manual. Alterra, Research Institute, Wageningen, The Netherlands, p. 262.

Landis, W.G., 2003. The frontiers in ecological risk assessment at expanding spatial and temporal scales. Hum. Ecol. Risk. Assess. 9, 1415–1424.

Landis, W.G., 2004. Regional Scale Ecological Risk Assessment: Using the Relative Risk Model. CRC Press, Boca Raton, FL, USA.

Landis, W.G., Wiegers, J.K., 2007. Ten years of the relative risk model and regional scale ecological risk assessment. Hum. Ecol. Risk. Assess. 13, 25–38.

Landuyt, D., Lemmens, P., D'hondt, R., Broekx, S., Liekens, I., De Bie, T., et al., 2014. An ecosystem service approach to support integrated pond management: a case study using Bayesian belief networks - highlighting opportunities and risks. J. Environ. Manag. 145, 79–87.

Lau, K.H., Kam, B.H., 2005. A cellular automata model for urban land-use simulation. Environment And Planning B-Planning & Design 32, 247–263.

Lawler, J.J., Lewis, D.J., Nelson, E., Plantinga, A.J., Polasky, S., Withey, J.C., et al., 2014. Projected land-use change impacts on ecosystem services in the United States. Proc. Natl. Acad. Sci. U. S. A. 111, 7492–7497.

Li, W., 2013. Water resources planning and its development trend in Taihu basin. Water Resources Planning and Design 12, 7–12 (in Chinese).

Li, C.S., Frolking, S., Frolking, T.A., 1992. A model of nitrous-oxide evolution from soil driven by rainfall events. 1. Model structure and sensitivity. J. Geophys. Res.-Atmos. 97, 9759–9776.

Li, C.S., Frolking, S., Xiao, X.M., Moore, B., Boles, S., Qiu, J.J., et al., 2005. Modeling impacts of farming management alternatives on CO2, CH4, and N2O emissions: a case study for water management of rice agriculture of China. Glob. Biogeochem. Cycles 19, GB3010. http://dx.doi.org/10.1029/2004GB002341.

Li, X.Y., Li, H.P., Yang, G.S., Hudson, N., Zhang, H., Nie, X.F., 2015. Variations of farming systems and their impacts on surface water environment in past 60 years in intensive agricultural area of Taihu Region, China. Journal of Water Resource and Protection 7, 647–658.

Liu, J.L., Chen, Q.Y., Li, Y.L., 2010. Ecological risk assessment of water environment for Luanhe River Basin based on relative risk model. Ecotoxicology 19, 1400–1415.

Liu, G.L., Zhang, L.C., Zhang, Q., Musyimi, Z., 2015. The response of grain production to changes in quantity and quality of cropland in Yangtze River Delta, China. J. Sci. Food Agric. 95, 480–489.

McDonald, K.S., Ryder, D.S., Tighe, M., 2015. Developing best-practice Bayesian Belief Networks in ecological risk assessments for freshwater and estuarine ecosystems: a quantitative review. J. Environ. Manag. 154, 190–200.

McNeely, J.A., Mittermeier, R.A., Brook, T.M., Boltz, F., Ash, N., 2011. The Wealth of Nature: Ecosystem Services, Biodiversity, and Human Well-Being. Conservation International, Arlington, United States.

McPhearson, T., Andersson, E., Elmqvist, T., Frantzeskaki, N., 2015. Resilience of and through urban ecosystem services. Ecosystem Services 12, 152–156.

Millennium Ecosystem Assessment M, 2005. Ecosystems and human well-being: biodiversity synthesis. Island Press, Washington, DC.

Ministry of Environmental Protection of the People's Republic of China M, 2006l. Technical Criterion for Eco-Environmental Status Evaluation (HJ/T192-2006) (in Chinese). China Environmental Science Press, Beijing.

Ministry of Environmental Protection of the People's Republic of China M, Chinese Academy of Sciences C, 2015l. National Ecological Function Zones of China (Revision Version) (in Chinese) .

Moraes, R., Molander, S., 2004. A procedure for ecological tiered assessment of risks (PETAR). Hum. Ecol. Risk. Assess. 10, 349–371.

Munns, W.R., 2006. Assessing risks to wildlife populations from multiple stressors: overview of the problem and research needs. Ecol. Soc. 11, 23.

Nelson, E., Sander, H., Hawthorne, P., Conte, M., Ennaanay, D., Wolny, S., et al., 2010. Projecting global land-use change and its effect on ecosystem service provision and biodiversity with simple models. PLoS One 5, e14327.

Nie, X.F., Li, H.P., Jiang, J.F., Diao, Y.Q., Li, P.C., 2015. Spatiotemporal variation of riverine nutrients in a typical hilly watershed in southeast China using multivariate statistics tools. J. Mt. Sci. 12, 983–998.

Pan, P.P., Yang, G.S., Su, W.Z., Zhang, J., Yao, S.M., 2013. Research of cropland change and grain production in Taihu Lake Basin since 1985. Resources and Environment in the Yangtze Basin 22, 1289–1296 (in Chinese).

Pan, P.P., Wang, X.X., Yang, G.S., Su, W.Z., 2015. Research on temporal and spatial variation of cultivated land quality in the region with rapid development. Geography and Geo-Information Science 31, 65–70 (in Chinese).

Piao, S.L., Fang, J.Y., Ciais, P., Peylin, P., Huang, Y., Sitch, S., et al., 2009. The carbon balance of terrestrial ecosystems in China. Nature 458, 1009-U82.

Qu, C.S., Chen, W., Bi, J., Huang, L., Li, F.Y., 2011. Ecological risk assessment of pesticide residues in Taihu Lake wetland, China. Ecol. Model. 222, 287–292.

Sasaki, T., Furukawa, T., Iwasaki, Y., Seto, M., Mori, A.S., 2015. Perspectives for ecosystem management based on ecosystem resilience and ecological thresholds against multiple and stochastic disturbances. Ecol. Indic. 57, 395–408.

Shaffer, G., 2010. Long-term effectiveness and consequences of carbon dioxide sequestration. Nat. Geosci. 3, 464–467.

State Council of China S, 2014. National New-Type Urbanization Plan 2014–2020 (in Chinese) People's Publishing House, Beijing, China.

Tian, Z., Zhong, H.L., Sun, L.X., Fischer, G., van Velthuizen, H., Liang, Z.R., 2014. Improving performance of Agro-Ecological Zone (AEZ) modeling by cross-scale model coupling: an application to japonica rice production in Northeast China. Ecol. Model. 290, 155–164.

Ueyama, M., Ichii, K., Hirata, R., Takagi, K., Asanuma, J., Machimura, T., et al., 2010. Simulating carbon and water cycles of larch forests in East Asia by the BIOME-BGC model with AsiaFlux data. Biogeosciences 7, 959–977.

van Dam, J.C., Groenendijk, P., Hendriks, R.F.A., Kroes, J.G., 2008. Advances of modeling water flow in variably saturated soils with SWAP. Vadose Zone J. 7, 640–653.

Wang, Q.X., Masataka, W., Zhu, O.Y., 2005. Simulation of water and carbon fluxes using BIOME-BGC model over crops in China. Agric. For. Meteorol. 131, 209–224.

Wang, G., Zhang, L., Zhuang, Q., Yu, D., Shi, X., Xing, S., et al., 2016. Quantification of the soil organic carbon balance in the Tai-Lake paddy soils of China. Soil Tillage Res. 155, 95–106.

Wong, C.P., Jiang, B., Kinzig, A.P., Lee, K.N., Ouyang, Z.Y., 2015. Linking ecosystem characteristics to final ecosystem services for public policy. Ecol. Lett. 18, 108–118.

Xu, H., Paerl, H.W., Qin, B.Q., Zhu, G.W., Gao, G., 2010. Nitrogen and phosphorus inputs control phytoplankton growth in eutrophic Lake Taihu, China. Limnol. Oceanogr. 55, 420–432.

Xu, X.B., Tan, Y., Chen, S., Yang, G.S., 2014. Changing patterns and determinants of natural capital in the Yangtze River Delta of China 2000-2010. Sci. Total Environ. 466, 326–337.

Xu, X.B., Yang, G.S., Tan, Y., Tang, X.G., Jiang, H., Sun, X.X., Zhuang, Q.L., 2016. Impacts of land use change on net ecosystem production in the Taihu Lake Basin of China, 1985–2010. Remote Sens. (under review).

Yang, S.Q., Liu, P.W., 2010. Strategy of water pollution prevention in Taihu Lake and its effects analysis. J. Great Lakes Res. 36, 150–158.

Yang, L.Y., Li, W.H., Peng, K., Li, Y., 2011a. Water ecological functions of the green space in the Taihu Lake Basin. Resources Science 33, 217–222 (in Chinese).

Yang, G.S., Ma, C.D., Chang, S.Y., 2011b. Yangtze River Conservation and Development Report 2011 (in Chinese) Yangtze River Press, Wuhan, China.

Yin, Y.X., Xu, Y.P., Chen, Y., 2009. Relationship between flood/drought disasters and ENSO from 1857 to 2003 in the Taihu Lake basin, China. Quat. Int. 208, 93–101.

Yu, T., Zhang, Y., Hu, X.N., Meng, W., 2012. Distribution and bioaccumulation of heavy metals in aquatic organisms of different trophic levels and potential health risk assessment from Taihu lake, China. Ecotoxicol. Environ. Saf. 81, 55–64.

Yu, L.J., Sun, D.F., Peng, Z.R., Li, H., 2013. A cellular automata land use model based on localized transition rules. Geogr. Res. 32, 671–682 (in Chinese).

Zagonari, F., 2016. Using ecosystem services in decision-making to support sustainable development: critiques, model development, a case study, and perspectives. Sci. Total Environ. 548–549, 25–32.

Zhong, W.J., Wang, D.H., Xu, X.W., Luo, Q.A., Wang, B.Y., Shan, X.Q., et al., 2010. Screening level ecological risk assessment for phenols in surface water of the Taihu Lake. Chemosphere 80, 998–1005.

Zhou, F., Xu, Y.P., Chen, Y., Xu, C.Y., Gao, Y.Q., Du, J.K., 2013. Hydrological response to urbanization at different spatio-temporal scales simulated by coupling of CLUE-S and the SWAT model in the Yangtze River Delta region. J. Hydrol. 485, 113–125.