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Impacts of land use change scenarios on hydrology and land use patterns in the Wu-Tu watershed in Northern Taiwan

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Abstract

Developing an approach for simulating and assessing land use changes and their effects on land use patterns and hydrological processes at the watershed level is essential in land use and water resource planning and management. This study provided a novel approach that combines a land use change model, landscape metrics and a watershed hydrological model with an analysis of impacts of future land use scenarios on land use pattern and hydrology. The proposed models were applied to assess the impacts of different land use scenarios that include various spatial and non-spatial policies in the Wu-Tu watershed in northern Taiwan. Analysis results revealed that future land use patterns differed between spatial policies. Scenarios with low land use demand for land use conversion policies did not lead to significantly different land use patterns. Moreover, patterns of future agricultural land patches obviously differed among agricultural land conversion policies. The streamflow, runoff and groundwater discharge were successfully simulated using a lumped hydrological model that can assess the impact of land use change in the watershed. The variability and magnitude of future hydrological components were significantly and cumulatively influenced by land use changes during the simulation period, particularly runoff and groundwater discharge. However, the proposed approach is an effective tool contributes to watershed land use planning, management and policy.

Keywords: Land use change modeling; Landscape metrics; Hydrological modeling; Watershed planning; Assessment; Landscape ecology

1. Introduction

Land use change can be characterized by the complex interaction of behavioral and structural factors associated with demand, technological capacity, and social relations, which affect both demand and environmental capacity, as well as the nature of the environment in question (Verburg et al., 2004). The impacts of land use changes have received considerable attention from ecologists, particularly with respect to effects on aquatic ecosystems and biodiversity (Turner et al., 2001). Land use changes in a watershed can impact water supply by altering hydrological processes such as infiltration, groundwater recharge, base flow and runoff. For instance, covering large watershed areas with impervious surfaces frequently results in increased surface runoff and reduced local surface erosion rates. Moreover, watershed development changes land use patterns and reduces base flow by changing groundwater flow pathways to surface-water bodies. An integrated landscape model can potentially extrapolate from management practices and land use pattern to determine potential environmental impacts (Turner et al., 2001). Thus, the development of an integrated approach that can simulate and assess land use changes, land use patterns and their effects on hydrological processes at the watershed level is crucial to land use and water resource planning and management.

Numerous studies have developed modeling approaches to simulate the pattern and consequences of land use changes. Different types of models are used to explore land use changes, such as stochastic models, optimization models, dynamic process-based simulation models and empirical models. Recent studies include those conducted by Agarwal et al. (2002), Parker et al. (2002), Luijten (2003), Rounsevell et al. (2003), and Parker and Meretsky (2004), Wang et al. (2004), Stewart et al. (2004),

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Brown et al. (2005), Caruso et al. (2005), Dietzel et al. (2005), Jantz and Goetz (2005), Manson (2005), Pontius and Malason (2005). One such land use model is the conversion of land use and its effects model (CLUE-s) that was developed to simulate land use change by using empirical quantified relationships between land use and its driving factors in combination with dynamic modeling (Verburg et al., 2002; Verburg and Veldkamp, 2004). The non-spatial module in the CLUE-s model calculates the aggregate area of change for all land use types, and the spatial module translates these demands into land use changes at various locations within a study region (Verburg et al., 2002). Allocation of each land use type is based on a combination of empirical and spatial analyses, and dynamic modeling (Verburg et al., 2002). Empirical analysis is applied to determine the relationships between land use spatial distribution and a number of factors that are the drivers and constraints of land use. Based on the competitive advantage of each land use at a location the competition among land uses for a particular location is simulated (Verburg et al., 2002).

Often, the assessment of land use change results in changes in landscape pattern. Landscape composition, configuration, and connectivity are primary descriptors of the landscape patterns (Turner et al., 2001). Landscape patterns can be quantified using spatial landscape indices or metrics to characterize and quantify landscape composition and configuration. The composition of a landscape denotes the features associated with the variety and abundance of patch types within a landscape. The spatial configuration of a landscape denotes the spatial character and arrangement, position, or orientation of patches within class or landscape (McGarigal and Marks, 1995). These metrics may include the number of patches, area, patch shape, total edge of patches, nearest neighbor distance, landscape diversity, interspersion and contagion metrics to represent landscape patterns, including compositions and configurations. Recent studies have applied landscape metrics to quantify landscape patterns (Cushman and Wallin, 2000; Weinstoerffer and Girardin, 2000; Lin et al., 2002; Remmel and Csillag, 2003; Fortin et al., 2003; Berling-Wolff and Wu, 2004; Li and Wu, 2004; Kearns et al., 2005). Moreover, landscape metrics may also be useful as a first approximation of broad-level landscape patterns and processes, and for characterizing differences among planned and design alternatives, and have been suggested as an appropriate tool for land use planning and design (Jongman, 1999; Botequilha Leitao and Ahern, 2002; Corry and Nassauer, 2005).

Hydrological models provide a framework to conceptualize and investigate the relationships between climate, human activities (e.g., land use change) and water resources (Legesse et al., 2003). Distributed hydrological models on a watershed scale are frequently used for quantifying the impact of land use change on hydrologic components (Haverkamp et al., 2005). The generalized watershed loading functions model developed by Haith and Shoemaker (1987) is a combined distributed/lumped parameter watershed model that can simulate runoff, sediment, and nutrient loadings in watersheds given source areas of variable sizes (e.g., agricultural, forested, and developed land). Surface loading is distributed in the sense that it allows multiple land use and land cover scenarios in which each area is assumed to have homogeneous attributes when addressed by the model (Haith and Shoemaker, 1987). Furthermore, the model does not spatially distribute source areas, but it simply aggregates the loads for each area to determine a watershed total. For subsurface loading, the model functions as a lumped parameter model utilizing a water-balance approach. Daily water balances are computed for unsaturated and saturated subsurface zones, in which infiltration is computed as the difference between precipitation and snowmelt minus surface runoff plus evapotranspiration (Haith and Shoemaker, 1987).

In this study, an integrated approach is used that combines land use, landscape metrics and hydrological models. Land use scenarios that differ with respect to planning policies and land use requirements are analyzed for their effects on landscape pattern, surface runoff, groundwater discharge and stream flow of the study watershed.

2. Methods and materials

In this study, a land use change model (CLUE-s) is used to simulate various land use scenarios based on driving factors with spatial and non-spatial policies for the Wu-Tu watershed in northern Taiwan. Landscape metrics at both the landscape and class level are calculated using the landscape pattern analysis package FRAGSTATS in GIS software Arcview 3.0 a. A two-way ANOVA is used to test the hypotheses that land use policies impact patterns of land use scenarios. Finally, the hydrological components under various land use scenarios are simulated by the generalized watershed loading function model with various land use demands. Then, a non-parametric-paired test is applied to test the hypotheses that land use changes impact surface runoff, groundwater discharge and streamflow.

2.1. Study watershed and data

The Wu-Tu watershed is an urbanizing watershed in the Keelung River Basin, bordered by the Taipei metropolitan area in northern Taiwan (Fig. 1). The Wu-Tu watershed is about 204 km^2 with a mean elevation of 242 m. Cheng and Wang (2002) noted that population density has gradually increased over the last three decades. Under an increasing population, the watershed has become intensively urbanized with an annual average population increase of approximately 2.70% during 1987–1997, especially in the down-stream area of the watershed. Therefore, land use and its patterns in the Wu-Tu watershed have changed by human uses in the last decade. Recently, the average annual population growth rate has decreased to approximately 1.05% (Cheng and Wang, 2002).

For land use simulation, data are required for the land use distribution and a number of biophysical and socio-economic parameters considered as potential factors driving the land use pattern. This study obtained land use data in 1999 from the Soil and Water Conservation Bureau of Council of Agriculture, Taiwan. Land use maps, which were generated and digitized by the Soil and Water Conservation Bureau based on 1:5000 aerial photographs taken in 1999, distinguish among 33 land use types in a vector format. According to the definitions of land use types by

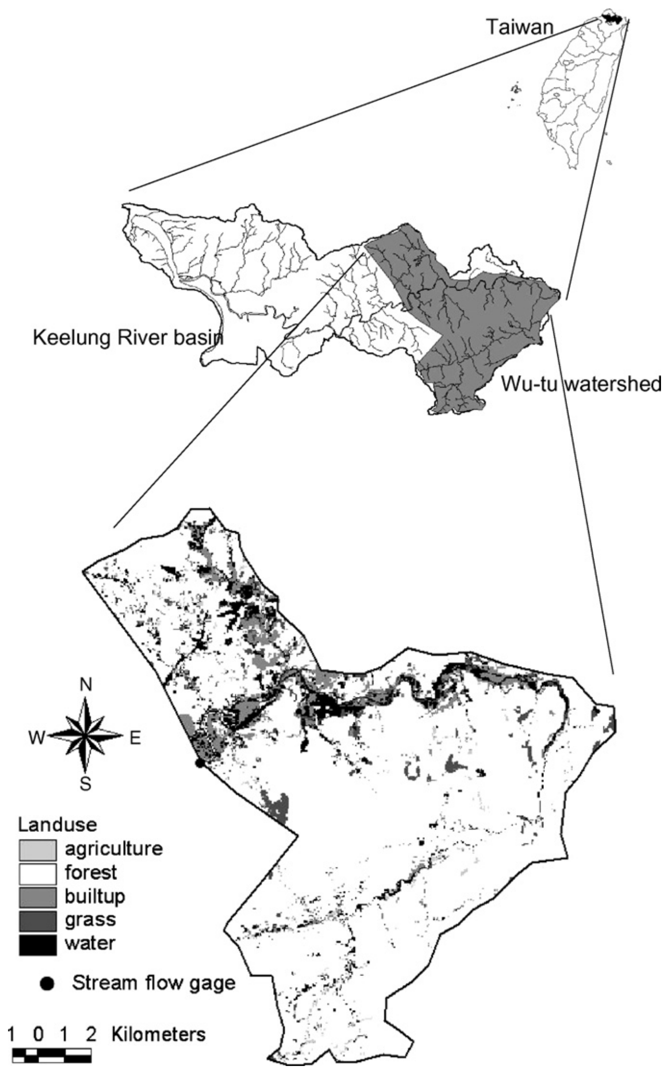

Fig. 1. Land uses in 1999 and locations of the study watershed.

the Construction and Planning Agency of the Ministry of Interior Taiwan, the land use types were converted into five types including agricultural land, forest, built up area, grassland, and water body. The proportions of agricultural land, forest, built up area, grassland, and water body in 1999 were 1%, 83%, 6%, 3% and 7%, respectively. In this study, it was assumed that the driving factors of land use changes were demography, infrastructure, geomorphology and soil-related and other variables including altitude (m), slope, distance to river, soil erosion coefficient, soil drainage, distance to major road, distance to built up area, distance to urban planning area, and population density. All of these factors and land use data were converted into a grid with the same resolution of 50 m.

2.2. Land use change model

The conversion of land use and its effects (CLUE-s) model comprises two parts: a non-spatial demand module; and, a spatially explicit allocation procedure. The non-spatial module calculates the area change for all land uses at the aggregate level (Verburg et al., 2002). In the spatial explicit allocation procedure, non-spatial demands are converted into land use changes at various locations in the study area. Yearly land use demands, which have to be defined prior to the allocation procedure, can be set by various approaches, such as economic models. The allocation procedure is based on a combination of empirical and spatial analyses and dynamic modeling (Verburg et al., 2002).

The empirical analysis of location suitability starts with the collection of relevant data. In addition to land use, data were collected that represent the assumed factors driving land use changes (Turner et al., 1993; Kaimowitz and Angelsen, 1998; Lambin et al., 2001). The relationships between land uses and its driving factors were evaluated by following stepwise logistic regression (Verburg et al., 2002)

$$\log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \cdots + \beta_n X_{n,i} \tag{1}$$

where P_i is the probability of a grid cell for the occurrence of the considered land use type and the X's are driving factors and β_i is the coefficient of each driving factor in the logistic model. The relative operating characteristic was used to evaluate the goodness of fit of the regression models. The relative operating characteristic statistic is defined as the area under the curve linking the relationship between the proportion of true positives versus the proportion of false positives for an infinite number of cut-off values (Overmars and Verburg, 2005). Consequently, the values of relative operating characteristic vary between 0.5 (completely random) and 1 (perfect discrimination). In this study, the forward stepwise logistic regression and relative operating characteristic analyses are conducted with the help of the Statistical Package for the Social Sciences (SPSS) for Windows (SPSS Inc., Il, USA). Probability maps for all the land use types were prepared based on the logistic regression results.

Next, spatial policies (such as the nature reserve area) and decision rules (including a land use transition matrix) were specified for the study watershed. For each type of the land uses, its specific conversion elasticity was specified to account for the typical conversion conditions of the different land uses (Verburg et al., 2002). The model allocated land use change in an iterative procedure using probability maps, the decision rules in combination with the actual land use maps, and the demand for the different land uses (Verburg et al., 2002). For each grid cell, the total probability is calculated for each of the land use types based on the logistic model results, elasticity of land use change and the iteration variable. Each cell is assigned to the land use with the highest probability. For land use types where the allocated area is smaller than the demanded area the value of the iteration variable is increased. The iteration continued until the aggregated cover of all grid cells equals the land use demand. The model procedure has been described in more details by Verburg et al. (2002) and Verburg and Veldkamp (2004).

2.3. Landscape metrics

To assess changes of land use paterns for the different land use scenarios, landscape metrics are calculated using FRAGSTATS in GIS software ArcView (McGarigal and Marks, 1995). In order to eliminate redundant information of land use patterns, seven landscape indices including number of patches, mean patch size, total edge, mean shape index, mean nearest neighbor and interspersion and juxtaposition index, were used to present land use composition and configuration (size, edge, shape, isolation and interspersion of patches).

Depending on the landscape context, number of patches for a particular habitat may affect a variety of ecological processes. Each patch's area is likely the most important and useful item of information contained within a landscape. Mean patch size is used to measure patch size for landscape and class levels. Total edge is an absolute measure of total edge length for a particular patch type (class level) or for all patch types (landscape level) (McGarigal and Marks, 1995). Mean shape index is a measure of average patch shape, or average perimeter-to-area ratio, for a particular patch type or for all patches in a landscape and class. Mean shape index equals 1 when all patches in a landscape are square. Thus, mean shape index increases without limits as the irregularity of patches increases. At a class level, mean nearest neighbor can be computed only when two patches of a particular type occur. At a landscape level, mean nearest neighbor considers only those patches with neighboring patches. The interspersion and juxtaposition index measure the degree to which patch types are interspersed (not necessarily dispersed); high values result from landscapes in which the patch types are well interspersed (equally adjacent to each other), whereas low values characterize landscapes in which the patch types are poorly interspersed (disproportionate distribution of patch type adjacencies) (McGarigal and Marks, 1995). The interspersion and juxtaposition index approaches 0 when the distribution of patch adjacencies among unique patch types becomes increasingly uneven. The interspersion and juxtaposition index is 100 when all patch types are equally adjacent to all other patch types.

2.4. Hydrological model

In the generalized watershed loading functions model, streamflow comprises surface runoff (Q_t) calculated by soil conservation service curve number and groundwater discharge (G_t) estimated by modeling a shallow groundwater aquifer as a linear reservoir. Storage of a shallow saturated zone is calculated by the following water balance equation (Tung, 2001):

$$S_{t+1} = S_t + \mathrm{PC}_t - G_t - D_t \tag{2}$$

$$G_t = rS_t \tag{3}$$

where S_t (cm) is the water content of a shallow ground water aquifer at the beginning of day t, PC_t is the percolation (cm) and D_t is the deep seepage (cm) during day t, r is the recession coefficient. Percolation proceeds when soil moisture of an unsaturated zone exceeds field capacity, and is calculated by

$$\mathrm{PC}_t = \max[0, U_t + I_t - \mathrm{ET}_t - U^*] \tag{4}$$

where U_t is the soil moisture content of a root zone (cm) at the beginning of day t, I_t is the infiltration (cm), ET_t is the evapotranspiration (cm) during day t, and U^* is the maximum soil water capacity (cm). Infiltration can be calculated by

$$I_t = R_t - Q_t \tag{5}$$

where R_t is rainfall. Evapotranspiration is affected by atmospheric conditions and use and soil moisture content, whose relationship is described as follows (Tung, 2001):

$$\mathrm{ET}_t = \min[k_{\mathrm{st}} \times k_{\mathrm{ct}} \times \mathrm{PET}_t, U_t + I_t] \tag{6}$$

where k_{st} and k_{ct} are the coefficients of soil moisture stress and land cover, respectively, and PET_t is the potential evapotranspiration calculated with the Hamon equation (Hamon, 1961; Tung, 2001). Water content in the unsaturated zone is traced by

$$U_{t+1} = U_t + I_t - \mathrm{ET}_t - \mathrm{PC}_t \tag{7}$$

2.5. Land use scenarios

Land use demands were based on an annual birth rate of 1.05% for simulating land use scenarios from 2000 to 2020 (Table 1). The area of water body is assumed to be constant during the simulation period. Two different spatial policies are set based on governmental regulations in Taiwan's Water Resources Protection Act and the Hillside Protection Act (Fig. 2(a)). The baseline policy is a regular baseline plan to protect water supply resources and sections of forested areas. The conservation policy is a conservation plan for protecting hillsides, water supply sources and large forested areas (Fig. 2(b)). For each land use type, conversion rules were used determine the conditions under which a land use is allowed to change in the next time step. These rules are based on the 1995 agricultural land release policy instituted by the Council of Agriculture, Executive Yuan, Taiwan. The first rule (free conversion) specifies that agricul-

Table 1
Demand area of land use from 1999 to 2020

Year	Agriculture	Forest	Buildup	Grass	Water
1999	221	15160	1187	538	1293
2000	219	15146	1206	535	1293
2001	217	15132	1225	533	1293
2002	215	15117	1244	530	1293
2003	213	15103	1263	527	1293
2004	211	15088	1283	524	1293
2005	209	15073	1303	521	1293
2006	207	15059	1323	518	1293
2007	205	15043	1343	515	1293
2008	203	15028	1363	512	1293
2009	201	15013	1384	509	1293
2010	199	14997	1404	506	1293
2011	197	14982	1425	503	1293
2012	195	14966	1446	500	1293
2013	192	14950	1468	496	1293
2014	191	14934	1489	493	1293
2015	190	14924	1502	491	1293
2016	186	14901	1533	486	1293
2017	184	14884	1555	483	1293
2018	182	14867	1578	480	1293
2019	180	14850	1600	476	1293
2020	177	14833	1623	473	1293

Unit: acre (ha).

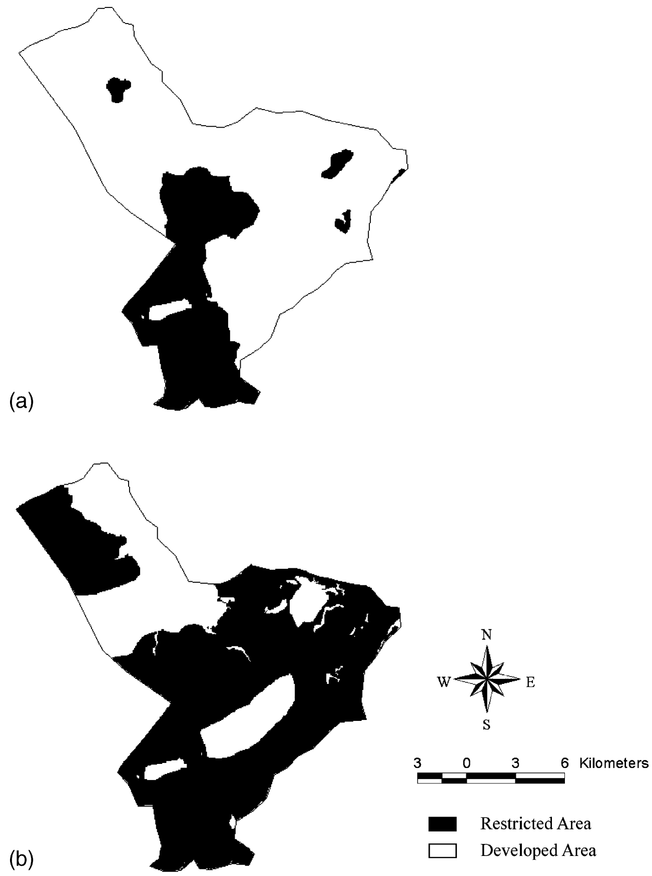

Fig. 2. Spatial policies (a) the baseline policy and (b) the conservation policy within the study watershed.

tural, forest and grasslands can be converted into any of these three land uses, and built up area and water bodies cannot be converted into other land uses. The second rule (agricultural protection) does not allow agricultural land to be converted into built up area and forest. These two rules allow us to compare the release and unreleased agricultural land policies. Based on these different spatial policies and conversion rules four different scenarios were constructed: scenario A (based on the baseline policy and the free conversion), scenario B (based on the conservation policy and the free conversion), scenario C (based on the baseline policy and the agricultural protection conversion) and scenarios D (based on the conservation policy and agricultural protection conversion).

3. Results

3.1. Land use change

Table 2 lists the estimated coefficients and relative operating characteristic values of the forward stepwise logistic regression models for all land uses. The fitted logistic models are used to calculate probabilities of occurrence for all land use types. The relative operating characteristic values for the models range from 0.74 to 0.98, suggesting that the models are capable of explaining the spatial variation of land use patterns. Driving factors include altitude, distance to urban planning area, population density and the soil erosion coefficient, each of which contributes positively to explaining the spatial distribution of agricultural land in the study area. Distance to major roads, slope and distance to built up areas have negative contributions on predicting the presence of agricultural land. Moreover, the factors distance to river, elevation, slope, distance to built up area, and soil erosion contribute positively to the probability of forest in the study watershed. Additionally, factors distance to major roads and population density negatively impact the occurrence of forest. The logistic regression model for predicting built up area includes three negative coefficients of driving factors (slope, distance to built up area and soil erosion coefficient) and one minor positive factor (population density). Finally, the model for grassland has two positive factors (distance to major roads, soil drainage) and five negative factors (distance to river, elevation, slope, distance to built up area and distance to urban planning area).

Table 2
Logistics regression model for land use types

Variable	Agriculture	Forest	Built up	Grass
Dtm	0.0015	0.0016	–	−0.0043
Slope	−0.041	0.0653	−0.0203	−0.0278
Popd	0.0002	−0.0001	3.17E−05	–
Droad	−0.0012	−0.0002	–	0.0011
Driver	–	0.0001	–	−0.0002
Dbuild	−0.0019	0.0069	−0.0627	−0.0025
Dzone	0.0003	–	–	−9.34E−05
Odr	–	–	–	0.467
Soilk	2.1461	4.6479	−1.8691	–
Constant	−3.1464	−1.4859	1.5537	−2.3934
ROC	0.735	0.88	0.983	0.757

–: Not significant and not included in model at 0.05 significant level. Dtm: altitude; Slope: slope; Popd: population density; Droad: distance to major road; Driver: distance to river; Dbuild: distance to buildup area; Dzone: distance to urban planning area; Odr: soil drainage; Soilk: soil erosion coefficient.

Based on the logistic regression models, land use demand, spatial policies and land use conversion rules, the CLUE-s model was applied to simulate the four land use scenarios for the period 2000–2020. Fig. 3 shows the resulting maps of each land use change between 1999 and 2020 for each scenario. The land use changes between 1999 and 2020 demonstrate that the most frequently changed areas are located in the northern part (the downstream area) of the Wu-Tu watershed, especially in areas with high population and low elevation (Fig. 3).

3.2. Landscape metrics

Fig. 4 illustrates the proportions of each land use type during the simulated periods in the study watershed. The change between 1999 and 2020 for agricultural land, forest, built up area and grassland was −0.36%, −1.77%, 2.37%, and 0.24%. The results of the land use model were used to calculate various landscape metrics. Fig. 5 shows the metrics number of patches, mean patch size, total edge, mean shape index and mean nearest neighbor at the landscape level. All landscape metrics display similar values for scenarios A and C (the baseline policy) as well as for scenarios B and D (the conservation policy). Fig. 6 shows the values of the other landscape metrics at the landscape level.

Fig. 3. Land use changes between land use in 1999 and (a) land use scenario A, (b) land use scenario B, (c) land use scenario C and (d) land use scenario D in 2020.

The values of patch number, total edge, and interspersion and juxtaposition index decreased from 2000 to 2020 for all scenarios (Figs. 6(a), (c) and (f)). Fig. 6(b) and (e) shows that the values of mean patch size and mean nearest neighbor of all land use scenarios increased during the period 2000–2020. The values of patch number, and interspersion and juxtaposition index of land use scenarios A and C (the baseline policy) are greater than those for scenarios B and D (the conservation policy) (Fig. 6(a) and (f)). Moreover, the values of mean patch size and mean nearest neighbor for scenarios B and D (the conservation policy) are larger than those for scenarios A and C (the baseline policy) (Fig. 6(b) and (e)). Finally, the values of total edge in scenarios B and D (the conservation policy) are greater than those in scenarios A and C (the baseline policy) in 2000–2006 and less than those in scenarios A and C during 2006–2020. the mean shape index values of A, C and D scenarios remain constant while that of scenario B remained constant (Fig. 6(d)).

Figs. 7–10 show the values of landscape metrics for the forest, agricultural land, built up and grassland patches. The values of number of patches, total edge, interspersion and juxtaposition index of forest patches in all land use scenarios gradually decreased from 2000 to 2020 (Fig. 7(a), (c) and (f)). The total edge and interspersion and juxtaposition index of forest patches in scenarios D and B (the conservation policy) are greater than those in scenarios A and C (the baseline policy) (Fig. 7(c) and (f)). Moreover, the mean patch size, mean shape index and mean nearest neighbor values of forest patches in all land use scenarios gradually increase and display similar tendencies during the simulation period, and these values remain relatively stable during 2000–2008 and 2014–2020 (Fig. 7(b), (d) and (e)).

The values of patch number and total edge of agricultural land patches in all land use scenarios decreased during the simulation period (Fig. 8(a) and (c)). Moreover, the mean patch size values of agricultural land in all scenarios fluctuated during the simulation period, but all reached similar values in 2020 (Fig. 8(b)). The mean shape index of agricultural land in scenarios A, B and D changed significantly during 2005–2010, whereas in scenario C it remained almost constant (Fig. 8(d)). Moreover, the mean nearest neighbor values of agricultural land in scenarios A, B and D gradually increased from 2000 to 2020, whereas in scenario

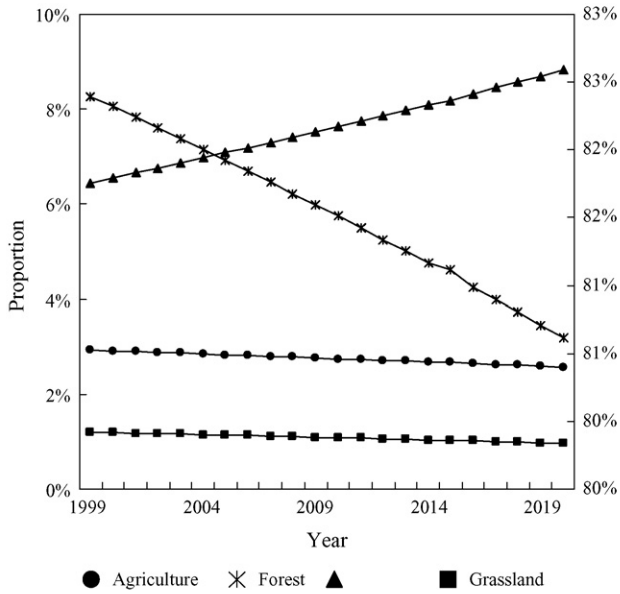

Fig. 4. Proportions of each land use type for land use demand.

C they changed significantly (Fig. 8(e)). During the simulation period, the interspersion and juxtaposition index value of agricultural land remained almost constant in each scenario. For scenarios A and C (the baseline policy), the interspersion and juxtaposition index values are greater than those in scenarios B and D (the conservation policy) in the agricultural land class level.

Values for all landscape metrics of built up patches other than interspersion and juxtaposition index values for all land use scenarios demonstrate the same tendencies (increasing or decreasing) and similar to each other in 2000–2006 (Fig. 9). Following 2006, differences in landscape metric values of built up area patches gradually become larger through time, except for the mean nearest neighbor of built up area. The values of interspersion and juxtaposition index of built up area patches in scenarios A and C (the baseline policy) are greater than those in scenarios B and D (the conservation policy) during the simulation period (Fig. 9(f)).

The landscape metrics for four land use scenarios at the grassland class level decreased or increased at similar rates and have different values for various spatial policies during the same period (Fig. 10). Moreover, the values of patch number, total edge, and interspersion and juxtaposition index of grassland patches in scenarios A and C (the baseline policy) are greater

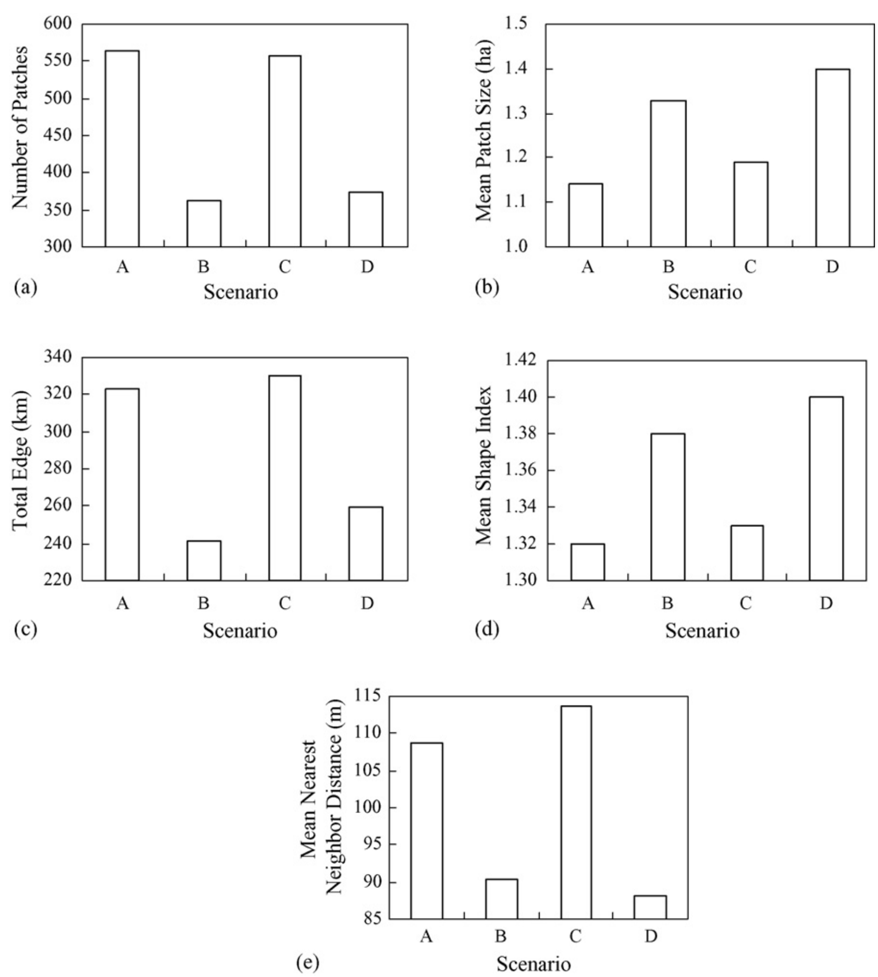

Fig. 5. Landscape metrics for land use change patches (a) number of patches, (b) mean patch size, (c) total edge, (d) mean shape index and (e) mean nearest neighbor.

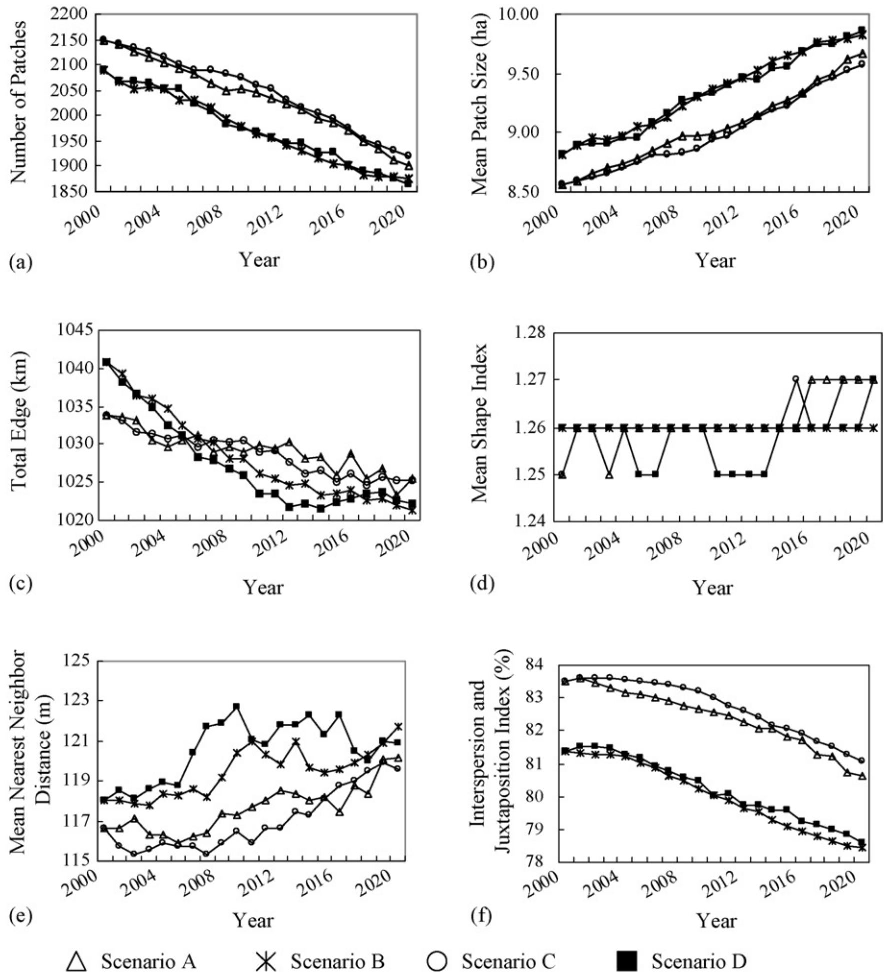

Fig. 6. Landscape metrics of land use scenarios at landscape level (a) number of patches, (b) mean patch size, (c) total edge, (d) mean shape index, (e) mean nearest neighbor and (f) interspersion and juxtaposition index of land use scenarios at landscape level.

than those in scenarios B and D (the conservation policy) during the simulation period (Fig. 10(a), (c) and (f)). During the simulation period, the mean patch size and mean nearest neighbor of grassland patches in scenarios B and D are greater than those in scenarios A and C (Fig. 10(b) and (e)).

3.3. ANOVA analysis of landscape metrics of land use scenarios

Table 3 shows the two-way ANOVA results for all landscape metrics and four land use scenarios at the landscape and class levels in the study watershed. Analytical results for landscape metrics indicate that the landscape metrics for patch number, mean patch size, total edge, mean shape index, mean nearest neighbor and interspersion and juxtaposition index for land use scenarios at the landscape level did not significantly differ for the two different conversion policies. The landscape metrics patch number, mean patch size, mean shape index, mean nearest neighbor and interspersion and juxtaposition for land use scenarios at the landscape level in the study watershed differed significantly for the different spatial policies during the simulation period. The interaction effects of the conversion and spatial policies are significant only for mean nearest neighbor.

Landscape metrics patch number, total edge, mean nearest neighbor and interspersion and juxtaposition for land use scenarios at the forest class level differed significantly by spatial policies during the simulation period (Table 3). At the forest class level, the landscape metrics for land use scenarios did not differ significantly by conversion policies or the interaction of conversion and spatial policies. At the agricultural land class level, the landscape metrics mean shape index, mean nearest neighbor and interspersion and juxtaposition Index for land use scenarios differed significantly by both spatial polices and the interaction of spatial and conversion policies during the simulation period. The landscape metrics mean patch size, mean shape index, and interspersion and juxtaposition index for land use scenarios at the agricultural land class level differed significantly by conversion policies during the simulation period. At the built up area class level, the landscape metrics mean shape index, mean nearest neighbor and interspersion and juxtaposition for land use scenarios differed significantly by spatial polices during the simulation period. Meanwhile, no landscape metrics except mean shape index for land use scenarios at the built up area class level differed significantly by conversion policies during the simulation period. Only mean nearest neighbor for land use scenarios differed significantly by the interaction

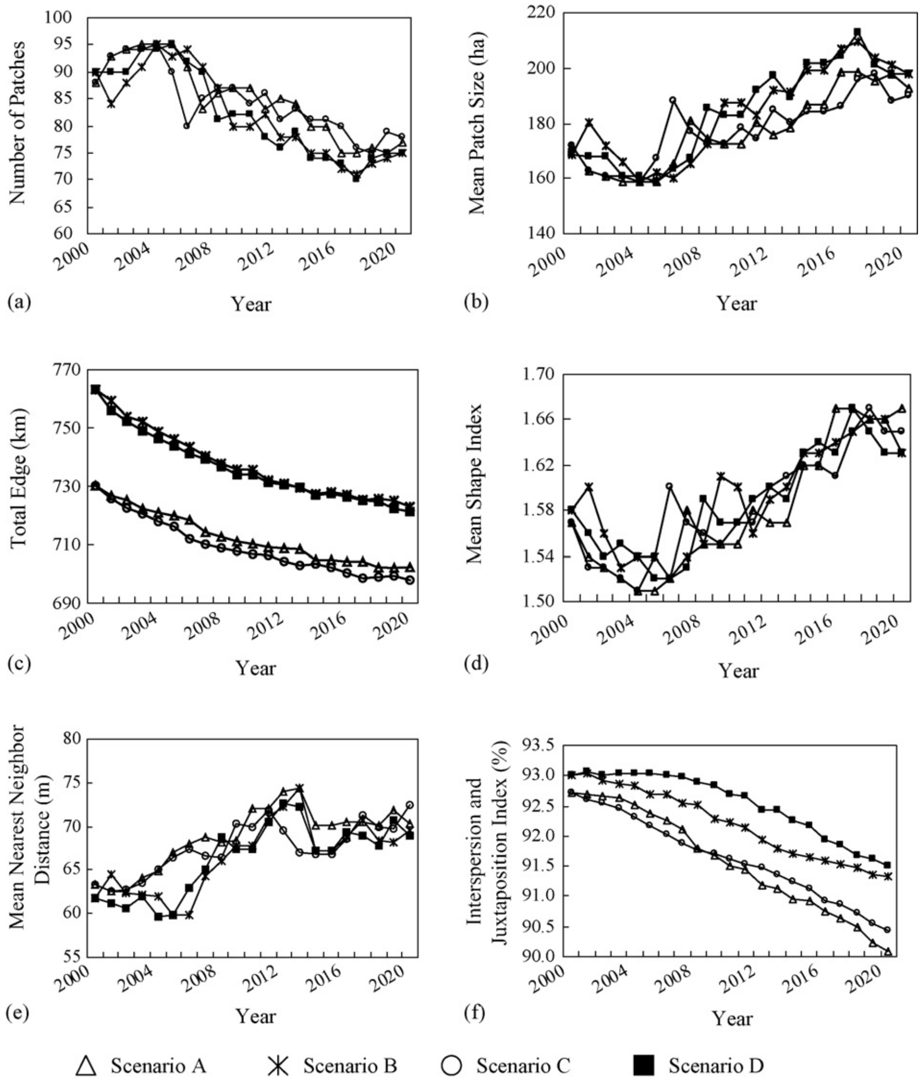

Fig. 7. Landscape metrics of land use scenarios at forest class level (a) number of patches, (b) mean patch size, (c) total edge, (d) mean shape index, (e) mean nearest neighbor and (f) interspersion and juxtaposition index of land-use scenarios at forest class level.

between conversion and spatial policies in built up area patches. At the grassland class level, all landscape metrics for all scenarios differed significantly by spatial policies, and did not differ significantly by conversion policies (Table 3). Mean patch size and interspersion and juxtaposition index for land use scenarios at the grassland class level differed significantly by the interaction of conversion and spatial polices during the simulation period.

3.4. *Stream flow under land use change demands*

Ten-year (1993–2002) streamflow data were used to validate the simulated streamflow modeled by the generalized watershed loading function using historical weather data and parameters that include the recession coefficient, evapotranspiration coefficient and the curve number for the study watershed. Fig. 11 shows the monthly observed streamflow versus the simulated monthly streamflow, and the mean measured monthly streamflow versus the mean predicted monthly streamflows. The R^2 value of the linear regression model for the monthly observed streamflows and simulated streamflows during the 10-year period is 0.79. Moreover, the R^2 value of the linear regression model of the monthly mean observed streamflows and the mean simulated streamflows during the 10-year period is almost 1.0. Both linear regression models are significant at a 0.01 significance level.

Based on historical weather data, hydrological components are simulated using the generalized watershed loading function model with the above parameters (the recession coefficient, evapotranspiration coefficient and the curve number) and future land use changes from 2000 to 2020. The differences in the annual streamflow, surface runoff and groundwater discharge between 1999 and the simulation period (2000–2020) are calculated from simulated monthly streamflows (Fig. 12). The differences in annual streamflow due by land use change gradually increase to 0.61% during the simulation period. Moreover, differences in annual surface runoff between the land use change and no change increase by 4.0% during the simulation period.

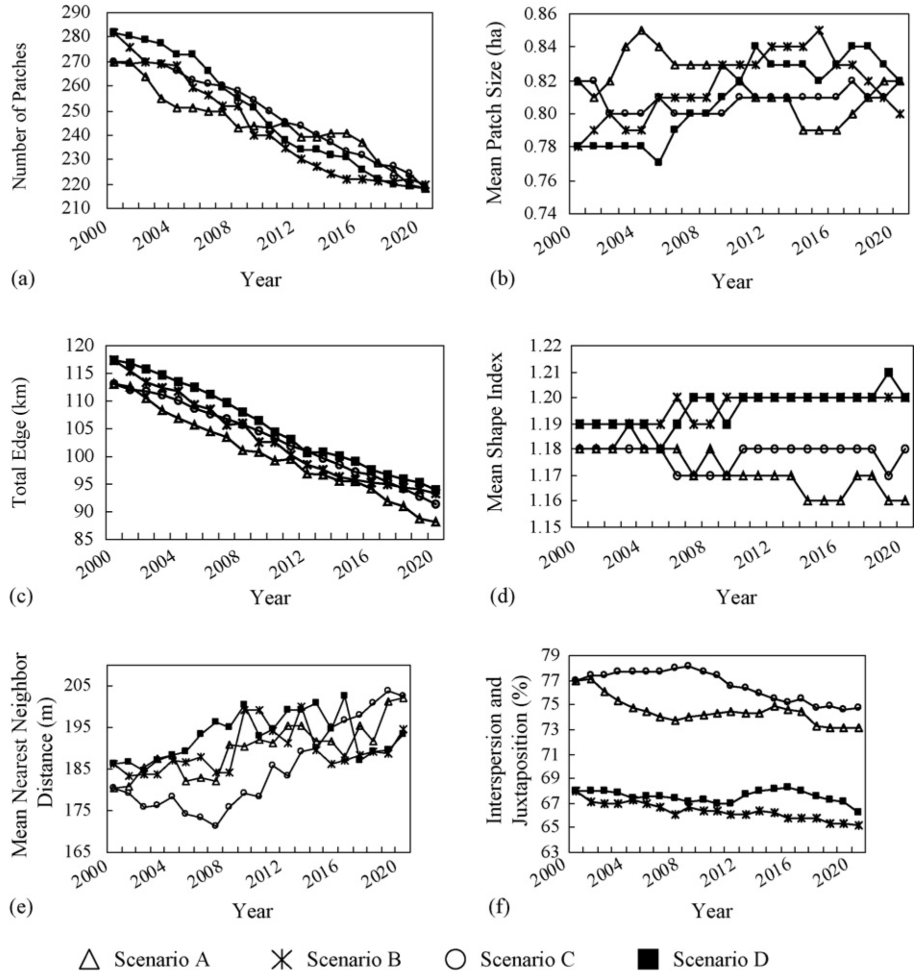

Fig. 8. . Landscape metrics of land use scenarios at agricultural land class level (a) number of patches, (b) mean patch size, (c) total edge, (d) mean shape index, (e) mean nearest neighbor and (f) interspersion and juxtaposition index of land use scenarios at agricultural land class level.

Table 3
Two-way ANOVA for the effects of conversion and spatial policy on landscape metrics

Level	Sources	*F* value					
		NP	MPS	TE	MSI	MNN	IJI
	Con.	0.217	0.214	0.566	1.404	0.646	1.691
Landscape	Spat.	18.376**	18.263**	1.116	6.798*	80.720**	140.31**
	Con. × Spat.	0.048	0.045	0.141	1.404	8.162**	0.112
	Con.	0.719	0.002	1.030	0.000	0.719	1.685
Forest	Spat.	4.640*	3.531	125.60**	0.264	4.640*	26.929**
	Con. × Spat.	0.381	0.005	0.172	0.144	0.381	0.851
	Con.	1.265	3.954**	2.426	4.162*	0.133	61.68**
Agricultural land	Spat.	0.014	0.004	2.591	234.10**	5.267*	1754**
	Con. × Spat.	0.006	0.091	0.027	4.162*	6.865*	4.319*
	Con.	0.171	0.020	0.246	5.396*	2.167	2.286
Buildup	Spat.	2.060	0.350	2.073	59.327**	16.148**	324.63**
	Con. × Spat.	1.207	0.181	0.261	0.374	76.707**	0.705
	Con.	0.040	0.480	0.019	0.850	0.300	1.128
Grassland	Spat.	777.40**	2054**	166.07**	5.312*	427.11**	495.89**
	Con. × Spat.	3.188	9.954**	0.093	1.912	1.365	4.902*

Con.: conversion, Spat.: spatial policy; NP: Number of patches; MPS: Mean patch size; TE: Total edge; MSI: Mean shape index; MNN: Mean nearest neighbor; IJI: Interspersion and juxtaposition index.
* Significant at 0.05.
** Significant at 0.01.

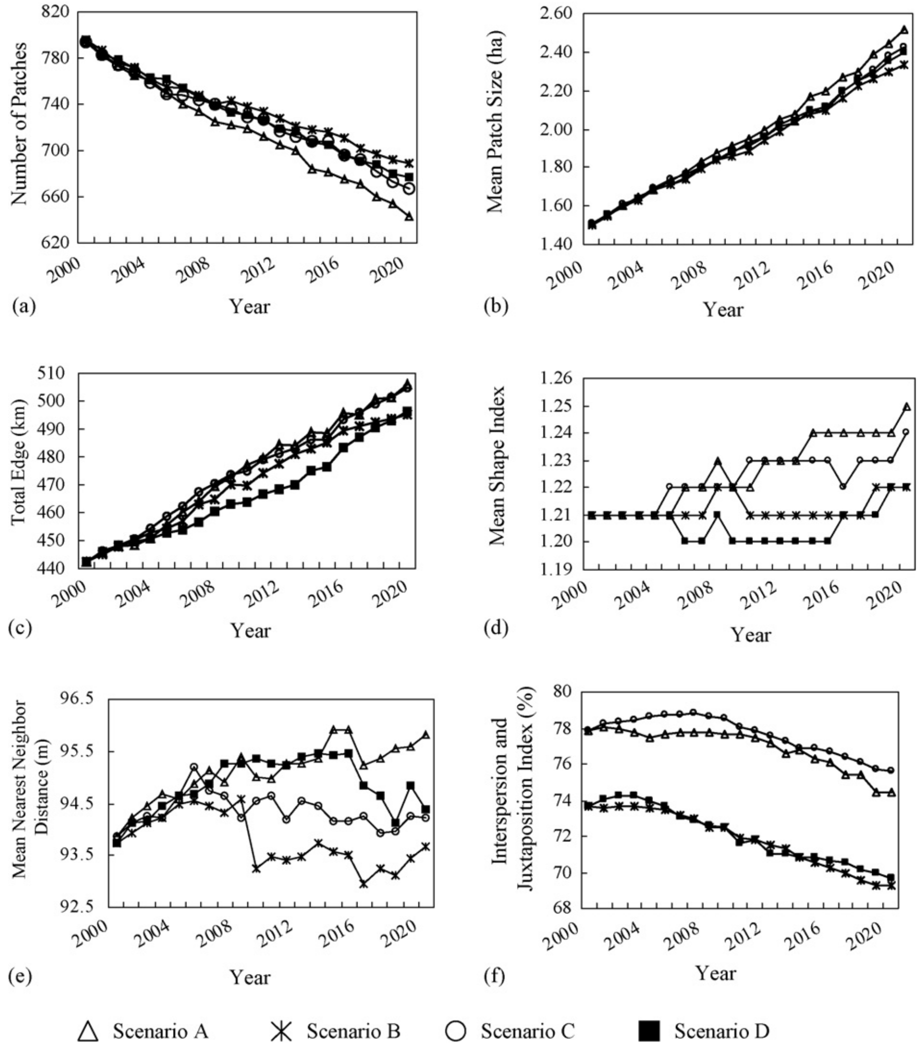

Fig. 9. Landscape metrics of land use at built up area class level (a) number of patches, (b) mean patch size, (c) total edge, (d) mean shape index, (e) mean nearest neighbor and (f) interspersion and juxtaposition index of land use scenarios at built up area class level.

Finally, differences in annual groundwater discharge decrease by 3.5% during the simulation period.

Fig. 13 shows the differences in monthly stream flow, monthly surface runoff and monthly groundwater discharge between no land use change and land use change in 2004, 2008, 2012, 2016 and 2020. The highest changes in monthly stream flows occurred during May–August in 2012, 2016, 2020, and particularly in 2020, when monthly stream flow increased by 1.2% (Fig. 13(a)). Peak differences in monthly stream flow between the land use change and no change situations occurred in May and August. Moreover, the peak differences in surface runoff between land use change and no change occurred in April (5.3%) and July (4.1%) of each year, and peak differences were highest in 2020 (Fig. 13(b)). Fig. 13(c) shows the differences in monthly groundwater discharge due to land use change. The greatest decrease (−3.2%) in groundwater discharge occurred in August 2020 (Fig. 13(c)). Differences in streamflow, surface runoff and groundwater discharge between land use in 1999 and that in each simulated year (2000–2020) were tested by using a non-parametric paired test, two related-samples Wilcoxon test (Table 4). Differences in streamflow between land use in 1999 and that in 2000 and 2001 were not significant. However, stream flow did differ significantly between land use in 1999 and that after 2006. Surface runoff and groundwater discharge differed significantly between 1999 and each simulated year, with the only exception being no difference in groundwater discharge between 1999 and 2000.

4. Discussion

4.1. Driving factors

In this study, logistic models are estimated to explain the spatial variation in occurrence of the different land use types. The logistic model results for all land uses indicate that agricultural land locations are jointly determined by biophysical parameters (altitude, slope and soil erosion coefficients) and socio-economic characteristics, such as distance to major roads, distance to built up areas, distance to urban planning areas and population density. These analytical results showed that agricultural activity is complex and affected by both physical and socio-economic characteristics in the subject watershed, partic-

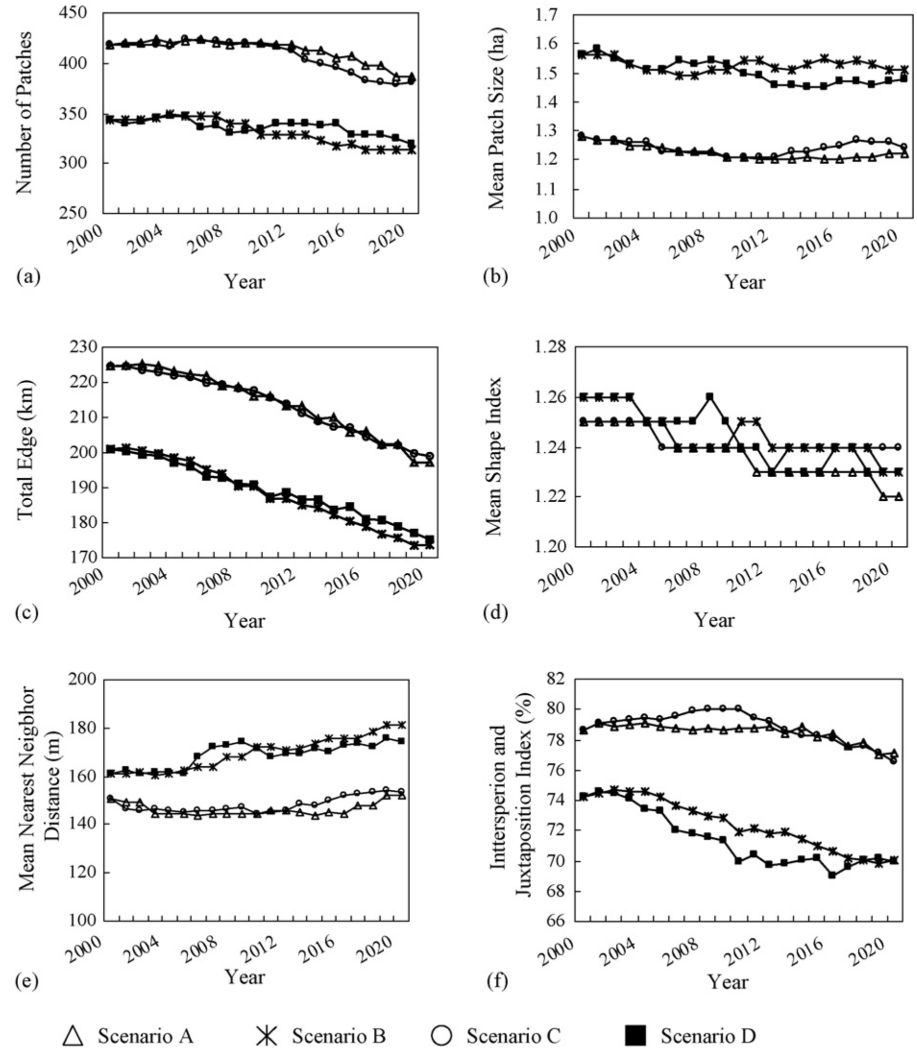

Fig. 10. Landscape metrics of land use scenarios at grass land class level (a) number of patches, (b) mean patch size, (c) total edge, (d) mean shape index, (e) mean nearest neighbor and (f) interspersion and juxtaposition index of land use scenarios at grassland level.

ularly by slope and soil conditions. The location and distribution of forests are influenced by all biophysical and socio-economic factors except distance to urban planning areas and soil drainage. This regression analysis showed that forest distribution is influenced by human activity and natural conditions in the watershed, especially the negative impact of road construction and urban sprawl resulting from population growth. However, the regression results confirm that each location possesses specific soil characteristics that influence the potential for natural and agricultural vegetation (Verburg et al., 2004) and its slope. The locations of built up areas are constrained by three socio-economic parameters and the soil erosion coefficient. The slope and distance to built up area have negative coefficients, implying that population pressure caused the expansion of built up areas into non-urban planning areas with low elevations. The locations of grasslands are influenced by all factors, except population density and the soil erosion coefficient. Only soil drainage and distance to road had positive coefficients in the logistic model for grassland. This regression result indicates that grassland distributions, including natural succession and human-made development (e.g., parks and open spaces) are controlled by natural conditions (soil drainage and slope) and human activity. The distributions of most land use types are affected by socio-economic factors, implying that urbanization influences land use in the study watershed. The logistic regression results also confirm that the biophysical characteristics determine the potential benefits that can be achieved by allocating a particular land use at a certain locations (Verburg et al., 2004), and that different factors are required to capture the different processes resulting in specific land use patterns (Lambin, 1994; Serneels and Lambin, 2001). In this study, the relative operating characteristic values vary between 0.74 and 0.98 depending on land use type, implying that the logistic regression model effectively explains land use distribution.

4.2. Impacts of land use change on patterns

Spatial models, such as an explicit model forecasting land use, can help planners to evaluate long-term effects of development patterns on landscape structures and the value derived

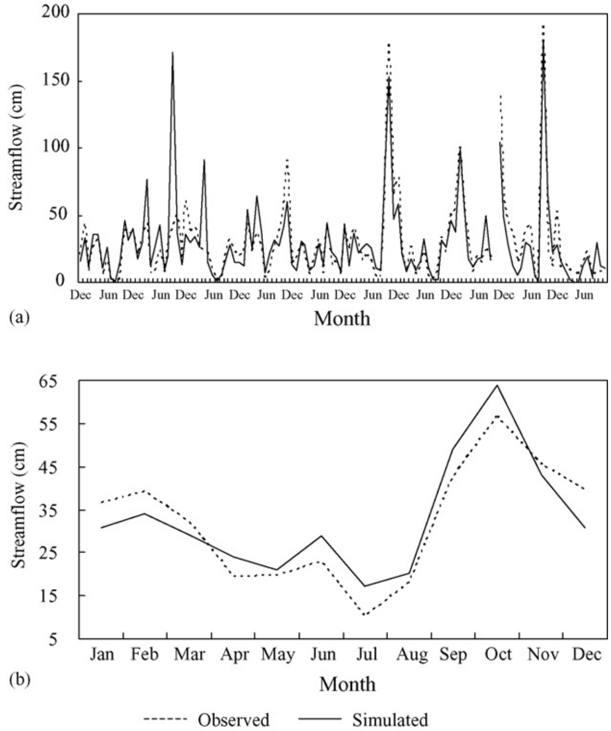

Fig. 11. (a) Monthly observed streamflow vs. simulated monthly streamflow and (b) mean monthly observed streamflow vs. mean simulated monthly streamflow.

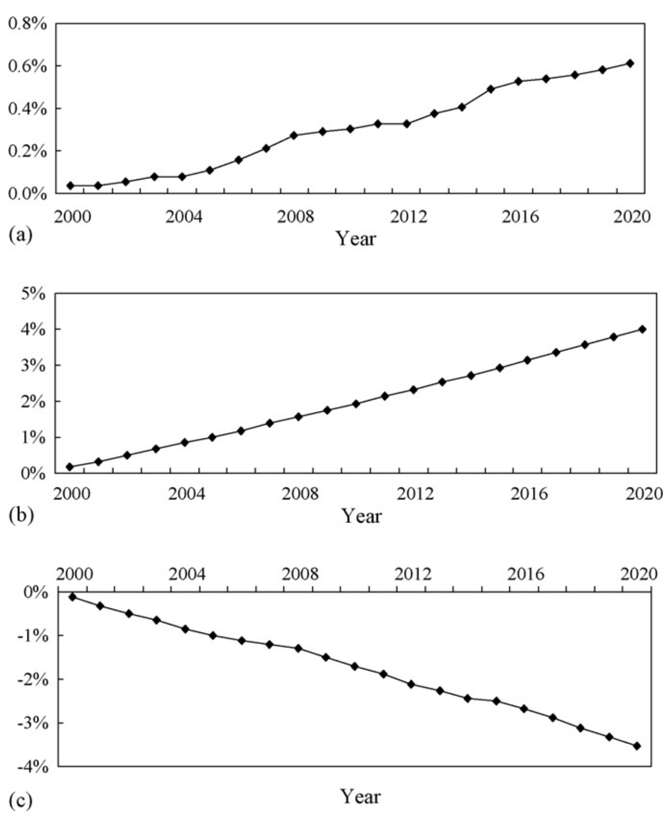

Fig. 12. Differences in annual (a) streamflow, (b) runoff and (c) groundwater discharge between land use in 1999 and land use in each simulated year.

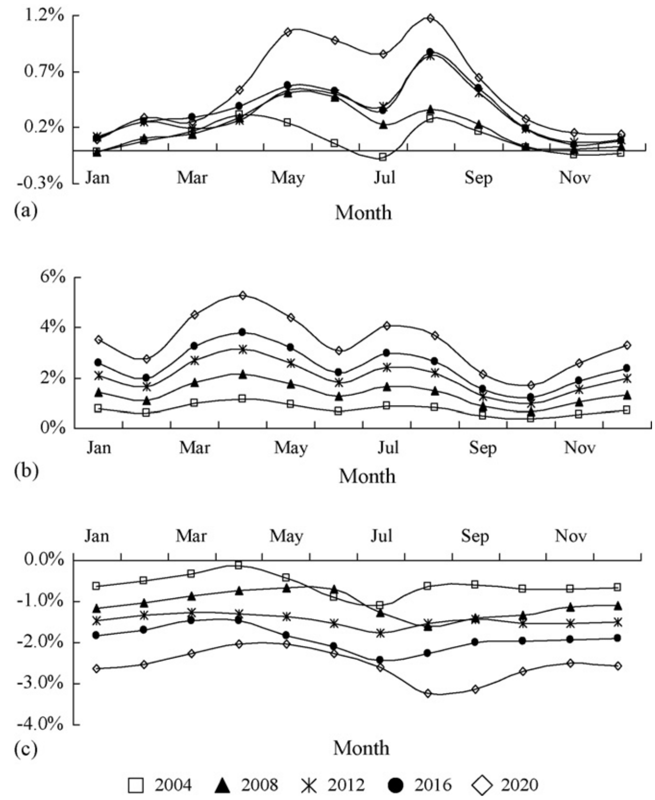

Fig. 13. Differences in monthly (a) streamflow, (b) runoff and (c) groundwater discharge between land use in 1999 and land use in each simulated year.

Table 4
Non-parametric test, two related-samples Wilcoxon test, for differences in hydrological components between land use in 1999 and land use in each simulated year

	SF	RF	GW
Y_{99}–Y_{00}	0.110	0.002**	0.012
Y_{99}–Y_{01}	0.110	0.002**	0.002**
Y_{99}–Y_{02}	0.041*	0.002**	0.002**
Y_{99}–Y_{03}	0.026*	0.002**	0.002**
Y_{99}–Y_{04}	0.026*	0.002**	0.002**
Y_{99}–Y_{05}	0.021*	0.002**	0.002**
Y_{99}–Y_{06}	0.003**	0.002**	0.002**
Y_{99}–Y_{07}	0.003**	0.002**	0.002**
Y_{99}–Y_{08}	0.003**	0.002**	0.002**
Y_{99}–Y_{09}	0.003**	0.002**	0.002**
Y_{99}–Y_{10}	0.003**	0.002**	0.002**
Y_{99}–Y_{11}	0.003**	0.002**	0.002**
Y_{99}–Y_{12}	0.003**	0.002**	0.002**
Y_{99}–Y_{13}	0.003**	0.002**	0.002**
Y_{99}–Y_{14}	0.003**	0.002**	0.002**
Y_{99}–Y_{15}	0.003**	0.002**	0.002**
Y_{99}–Y_{16}	0.003**	0.002**	0.002**
Y_{99}–Y_{17}	0.003**	0.002**	0.002**
Y_{99}–Y_{18}	0.003**	0.002**	0.002**
Y_{99}–Y_{19}	0.003**	0.002**	0.002**
Y_{99}–Y_{20}	0.003**	0.002**	0.002**

SF: Stream flow; RF: Surface runoff; GW: Groundwater discharge.
* Significant at 0.05.
** Significant at 0.01.

from such development (Wear and Bolstad, 1998; Turner et al., 2001). However, land use model results that integrate social, economic, and ecological considerations still have a high level of uncertainty, and no consensus has been reached regarding the optimal approach for this task (Dale et al., 2000; Turner et al., 2001). In this study, the CLUE-s model combining land use demands and policies successfully simulated land use scenarios in the study watershed during a specific period. Simulation results indicated that land use changes occur more frequently at low elevations and near urbanized areas, roads and the river.

Landscape metrics provide an effective means of evaluating and comparing before and after conditions in a landscape plan for a particular landscape (Gustafson, 1998; Botequilha Leitao and Ahern, 2002; Corry and Nassauer, 2005). At the landscape level, patterns of all land use scenarios have similar tendencies and different magnitudes under different spatial policies during the simulation period. The land use patterns in the baseline policy scenarios involve smaller but more closely positioned patches compared to the scenarios with the conservation policy. Moreover, the land use patterns in conservation policy scenarios are more isolated than those in baseline policy scenarios. The patterns in the land use change area with the baseline policy are more fragmented than those with the conservation policy at the landscape level.

No association was found between conversion policies and land use patterns, but different spatial policies resulted in significantly different landscape metrics at the landscape level. Interaction of the conversion and spatial policies at the landscape level only resulted in significant differences in isolation among patches. These relatively minor effects may result from the relatively small change in land use demand during 2000–2020, and the influence of initial land use patterns on future land use.

At the level of individual forest patches, forest was slightly more fragmented in the baseline policy scenarios than in conservation policy scenarios. Additionally, different patterns in land use scenarios were not detected among the conversion policies or by the interaction between conversion and spatial policies at the forest class level.

For agricultural land, size and isolation of agricultural land patches significantly differed among different conservation and spatial policy scenarios. Regarding agricultural land, the configurations of all land use patterns for all scenarios differed significantly between spatial and conservation policies in the study watershed. However, differences in the shape, isolation and interspersion of agricultural land patches were detected by interaction of agricultural land conversion and spatial policies in simulated land use scenarios throughout the simulation period, even in situations given small changes in land use demand. Pattern analyses for land use scenarios revealed that the differences in future land use patterns among spatial policies were greater than those among conversion policies given low demand for land use change. However, conversion policies and the interaction of conversion and spatial policies directly influenced agricultural land patch patterns.

For the built up area class, no differences in patterns of built up area patches were detected among conversion policies in land use scenarios, with the exception of built up area patch shape. Significant differences in shape, isolation and interspersion of built up area patches of land use scenarios were detected among spatial policies during the simulation period. The interaction between conversion and spatial policies was found to result in differences in isolation among built up patches in the watershed. Moreover, large numbers of suitable locations for built up area patches were located downstream and in highly populated areas prior to 2006. Built up area patches were then dispersed and expanded into neighboring areas that were suited to built up area patches after 2006.

For the grassland class, land use patterns in baseline policy scenarios were smaller, but were closer together than in conservation policy scenarios. In conservation policy scenarios, the land use patterns were more isolated than in baseline policy scenarios. The interspersion of available patch types was greater in land use patterns in scenarios with the baseline policy than for those in scenarios with the conservation policy at the grassland level in 2000–2020. Moreover, among grassland patch patterns no significant differences in grassland patch patterns were detected among conversion policies. However, significant differences in all land use pattern characteristics in land use scenarios were detected among spatial policies. Differences in patch size and interspersion of grassland patches were detected by the interaction of conversion and spatial policies in the watershed as grassland patches became dispersed and interacted with built up area patches, such as when grassland was replaced by built up areas.

4.3. Impacts on hydrological processes

Simulated hydrological effects for land use scenarios are fundamental to decisions aiming to optimize landscape functions (Haverkamp et al., 2005). In this study, the generalized watershed loading function model effectively simulated monthly streamflow, surface runoff and groundwater discharge in both no land use change and land use change conditions. The hydrological components were impacted by land use changes even through time and low land use change pressure. Runoff from built up areas increased and groundwater discharge decreased as infiltration reduced owing to replacement of vegetation resulting from development. Land use change increased peak differences in streamflow, surface runoff, groundwater discharge, and streamflow variability. Peak differences in surface runoff between land use in 1999 and that in each simulated year occurred in April and July, since these months typically have low precipitation. Moreover, peak differences in streamflow between land use in 1999 and that in each simulated year occured during periods of low precipitation (May–August), mainly as a result of land use change, particularly peak differences in 2020. During the simulation period, the cumulative changes of surface runoff, groundwater discharge and streamflow in the study watershed were 0.61%, 3.99% and 3.53%, respectively.

The surface loading in this model was distributed in the sense that it allows multiple land use and land cover scenarios in which each area was assumed to have homogeneous attributes when simulated using the generalized watershed loading function model. The model did not use spatially distributed source areas, but simply aggregated the loads for each area to calculate watershed total. Therefore, the lumped model distinguished the differences of simulated hydrological components based on land use demands for the entire watershed scale, but could not distinguish those between simulated land use scenarios with different spatial land allocation.

5. Conclusion

This study developed an integrated approach, comprising land use and hydrological models with statistical tests, designed to enable the simulation, evaluation and extrapolation of land use management practices and planning policies. The proposed approach enables the identification of the potential impacts of future land use changes on future land use patterns and hydrological components in the study watershed. The empirical land use model successfully simulated land use scenarios to provide basic data for calculating landscape pattern metrics and hydrological components in the study watershed. In this study, future land use patterns differ more among spatial policies than among conversion policies. This novel approach is extremely important and is suitable for use in further developing a landscape eco-hydrological decision-support system for watershed land use planning, management and policy. Future research could use the spatial distributed hydrological model to simulate hydrological components to distinguish the differences among land use scenarios involving different spatial land allocation. Furthermore, future studies can also incorporate the impacts of land use change on stream water quality.

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