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Multivariate analysis of soil heavy metal pollution and landscape pattern in Changhua county in Taiwan

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Abstract

This study applied factor analysis and landscape indices of 55 sampling sites in Changhua county in Taiwan to characterize the factor patterns of eight soil heavy metals (As, Cd, Cr, Cu, Hg, Ni, Pb and Zn) and the interrelation patterns of these soil heavy metals, landscape and human activities. The landscape analysis results indicated that landscape indices can elucidate spatial landscape patterns, urbanization and industrialization, demonstrating that higher landscape diversity corresponded to a higher ratio of urban planning area to the number of industrial plants. Factor analyses revealed that soil heavy metals and data concerning landscape data could be grouped into a six-factor model that accounts for 82% of all the variation of data. Moreover, the first factor included the concentration of Cd, Cr, Cu, Ni and Zn, and urbanization and industrialization landscape indices. These variables together explained 34.5% of the variation in the concentration of the soil heavy metals and landscape indices data of this study area. Local urbanization and industrialization caused local soil pollution by heavy metals on the selected sampling sites in Changhua county in Taiwan. Geographic information system can fully display the spatial patterns and relationships among landscape indices and concentration of soil heavy metals in this study area.

Keywords: Landscape patterns; Landscape indices; Soil pollution; Urbanization; Geographic information system

1. Introduction

A landscape pattern is a mixture of natural and human-managed patches that vary in size, shape, and arrangement, and result from complex interactions of physical, biological, and social forces (Burgess and Sharpe, 1981; Forman and Godron, 1986; Krummel et al., 1987; Turner, 1987, 1990; Hulshoff, 1995). Agricultural landscapes reflect not only natural constraints, but also financial resources and social conditions (Forman and Godron, 1986; Urban et al., 1987; Fu and Chen, 2000). Human activities greatly shape landscapes, creating a mosaic of natural and human-managed patches that vary in size, shape, and arrangement (Burgess and Sharpe, 1981; Forman and Godron, 1986; Krummel et al., 1987; Leduc et al., 1994). Such activities also cause pollution. For instance, urban areas disperse pollution, humans, information, products, and in some cases heat, throughout suburbia (Forman, 1995). Moreover, urban, suburban and agricultural areas may interact with each other. Control of the diffusion of pollution (Haycock and Muscutt, 1995), and characterizing, understanding and managing landscape patterns and structures are

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major issues that affect agricultural landscapes and suburban areas. Accordingly, a full delineation of landscape and pollution patterns may improve the efficiency of environmental management and agricultural, suburban and urban planning.

Landscape indices such as patch size, patch shape index (curvature), landscape diversity (*H*), dominance (*D*), and fractal dimension (FD), have been widely used to elucidate landscape patterns and interactions. See, for example, Hulshoff (1995), Haines-Young and Chopping (1996), Li and Archer (1997), Johnson and Gage (1997), Obeysekera and Rutchey (1997), Bastian and Roder (1998), Aguiar and Sala (1999), Hietala-Koivu (1999), Hokit et al. (1999), Nikora et al. (1999), Stadler (1999), Baudry et al. (2000), Klenner et al. (2000) and Weinstoerffer and Girardin (2000). Patch size directly describes the landscape pattern. Dominance measures the extent to which one or a few legend types dominate the landscape (O'Neill et al., 1988; Hulshoff, 1995). Fractal dimension can be used to estimate the complexity of the geometry of land use (Kienast, 1993).

Multivariate analysis offers techniques for classifying relationships among measured variables. The two most common multivariate analyses are principal components analysis and factor analysis. Notable examples of their use in environmental chemistry are found in the work of Briz-Kishore and Murali (1992), Subbarao et al. (1996), Jayakumar and Siraz (1997), Meng and Suffet (1997), Brejda (1998) and Carlon et al. (2001). Factor analysis is based on the fundamental assumption that some underlying factors, fewer than the number of observed variables, are responsible for the covariation of the observed variables (Lewis-Beck, 1994). Principal component analysis, a statistical technique, linearly transforms an original set of variables into a substantially smaller set of uncorrelated new variables that represent most of the information of the original data set (Lewis-Beck, 1994). A small set of uncorrelated variables is much easier to understand and use in further analysis than a larger set of correlated variables (Lewis-Beck, 1994).

Industrialization and urbanization in Taiwan have polluted some agricultural soils by discharging wastewater into irrigation ditches. In 1983, the Environmental Protection Administration (EPA) of Taiwan began a collaborative research program to identify the presence of As, Cd, Cu, Cr, Hg, Ni, Pb and Zn in soils. The program also aimed to detect additional soil properties, such as cation-exchange capacity and pH. These studies sampled soils from 878 sites that were representative of agricultural areas in Taiwan.

Our study applied factor analysis and landscape indices (including landscape diversity, landscape dominance, fractal dimension, the density of irrigation ditches and the number of industrial plants) of 55 sampling sites in Taiwan's Changhua county, to characterize both factor patterns of eight soil heavy metals (As, Cd, Cr, Cu, Hg, Ni, Pb and Zn) and the landscape. Correlations between the factor patterns and the landscape indices were analyzed to elucidate the characteristics of both the heavy metal pollution of the soil, and the urbanization at these 55 sampling sites. Factor analysis was also applied to group soil heavy metals and landscape indices and thereby delineate the interrelationships between soil heavy metals, landscape and anthropogenic activities.

2. Materials and methods

Our study uses data obtained by the EPA between 1981 and 1997. Samples were taken from geographically distributed sites in a network formation. Topsoil was sampled at depths of 0–15 cm. The EPA classifies the concentrations of soil heavy metals into five classes (Table 1). Table 1 shows that the concentrations of soil heavy metal samples in the first and second classes are considered to represent no soil heavy metal pollution. The concentrations of soil heavy metals in the third class are defined as background values. The

Table 1
Soil heavy metal class in Taiwan

Soil heavy metals	1	2	3	4	5
As**		<4	4–9	10–60	>60
Cd*		<0.05	0.05–0.39	0.40–10	>10
Cr*		<0.10	0.10–10	11–16	>16
Cu*	<1	1–11	12–20	21–100	>100
Hg**		<0.10	0.10–0.39	0.40–20	>20
Ni*		<2	2–10	11–100	>100
Pb*		<1	1–15	16–120	>120
Zn*	<1.5	1.5–10	11–25	26–80	>80

Unit: mg/kg.
* 0.1N HCl extractable content.
** Total content.

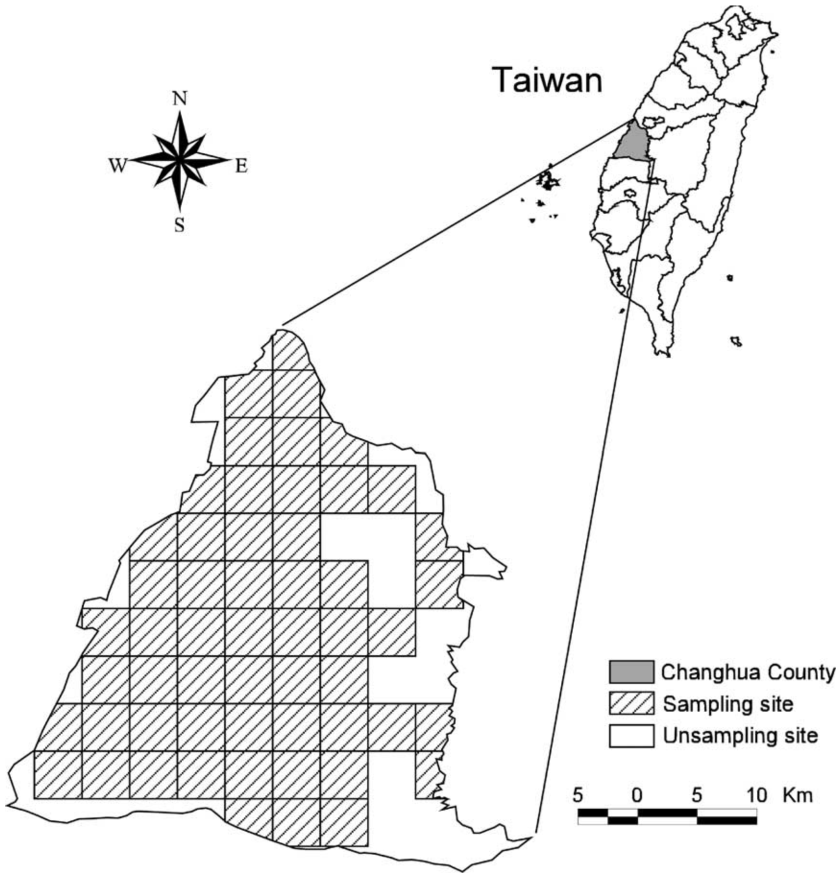

Fig. 1. Study area and sampling sites.

fourth and fifth soil heavy metal classes require intensive monitoring and consideration of remedial action. Taiwan EPA has also supported investigation projects for detail monitoring and remediation of soil heavy metals in 2002.

Fifty-five sampling sites within Changhua county (Fig. 1), located in the center of Taiwan were selected from the original 878 sampling sites across Taiwan, and considered in this study. Changhua county is one of the most important agricultural counties in Taiwan. In this county, some local sites might be polluted by wastewater of industrial plants that has been distributed through irrigation systems. Lin and Chang (2000a,b) and Lin et al. (2001) indicated that the local spatial patterns of soil heavy metal pollution were significantly related to the locations of industrial plants and irrigation systems, in a 2.69 km^2 site in northern Changhua county. Table 2 lists heavy metals that might be discharged with wastewater from different industrial plants.

The following landscape indices for each sampling site were used to characterize landscape patterns; landscape diversity (H), dominance (D), area-perimeter fractal dimension (FD), density of irrigation ditches (DL), number of electroplating plants (NE), number of textile plants (NT), number of livestock plants (NL), number of metal surface treatment plants (NMs) and number of metal plants (NM), total number of industrial plants (Np) and the ratio of urban planning area (RAup). Fig. 2 shows land use data, as digitized and developed by the Food and Agriculture Department of the Council of Agriculture and the Department of Land Administration of the Ministry of the Interior in 1994. The land use data of the 55 sampling sites

Table 2
Industrial plants and heavy metals

Element	Description of use
As	Pesticides, pigments, glass, textiles, wood preservatives, fireworks, printing, tanning, enamels, ceramics, lubricating oil, alloys, oil cloth, linoleum, semiconductors, photo-conductors.
Cd	Electroplating, pigments, alloys, enamels, batteries, rubber, plastics, fungicides, motor oil, textiles.
Cr	Pigments, chrome tanning, electroplating, chrome-plating, corrosion inhibitor, varnishes, dye fixers, photography emulsion, defoliant.
Cu	Brass, dyes, wires, fungicides, alloys, plating, pipes, roofing, paints.
Pb	Batteries, paints, glass, insecticides, gasoline additive, ammunition, solder, brass and bronze, pigments.
Hg	Paints, catalyst, fungicides, pharmaceutical, plastics, paper products, batteries, electrical apparatus manufacturing.
Ni	Steel and alloys, pigments, cosmetics, batteries, electroplating.
Zn	Alloys, metal coating, ink, copying paper, cosmetics, paints, rubber, linoleum, glass

were clipped using Arcview 3.0a, to calculate landscape indices. The landscape diversity index (H) was the Shannon–Weaver Diversity,

$$H = -\sum_{i=1}^{m} P_i \log_2 P_i \qquad (1)$$

where P_i is the proportion of landscape type i in a site, and m is the number of observed landscape types.

Dominance (D) is given by,

$$D = \ln c + \sum_{k=1}^{c} P_k \ln P_k \qquad (2)$$

where c is the number of land use types and P_k is the proportion of area in type k.

For all landscape types at each sampling site, the FD were estimated by linear regression using,

$$P = CA^{\mathrm{FD}/2} \qquad (3)$$

where P is the perimeter of a patch; A is the area of a patch, and C is a constant.

The DL was defined as,

$$\mathrm{DL} = \frac{\mathrm{TL}}{S} \qquad (4)$$

where TL is the total length of irrigation ditches at each sampling site, and S is the area of the sampling site. TL was extracted and calculated using the geographic information system, ArcView 3.0.

The ratio of the urban planning area to the area of the sampling site is defined as,

$$\mathrm{RAup} = \frac{\mathrm{Aup}}{S} \qquad (5)$$

where Aup is the urban planning area at each sampling site.

NE, NT, NL, NMs, NM and Np are the number of electroplating, textile, livestock, metal surface treatment, metal, and all industrial plants at each sampling site, respectively.

Landscape indices, including landscape diversity (H), landscape dominance (D), area-perimeter fractal dimension (FD), density of irrigation ditches (DL), urban planning area ratio (Raup) and the number of industrial plants (electroplating industry (NE), textile industry (NT), livestock industry (NL), metal surface treatment industry (NMs) and metal industry (NM)), the total number of industrial plants (Np), were extracted and calculated using the geographic information system, ArcView 3.0a.

Fig. 3(a) shows the urban planning area in the study area, as digitized by the Construction and Planning Administration of Ministry of the Interior. Fig. 3(b) and (c) depict the irrigation system and location of industrial plants. The nine land-use types—agricultural (75.4%), built-up (10.4%), hydraulic (9.7%), industrial (2.1%), recreational (0.3%), traffic (0.3%), mining (<0.1%), military land-use (<0.1%), and others (2.1%) were defined by the Department of Land Administration of the Ministry of the Interior and were used to calculate landscape diversity.

The factor analyses were performed by computing eigenvalues and eigenvectors of the data, using principal components methods and the statistical software, SPSS (Norusis, 1993). Factors with eigenvalues higher than one were retained. The first factor explains the most variation in interesting variables, the second factor the next highest variance, and so on (Carlon et al.,

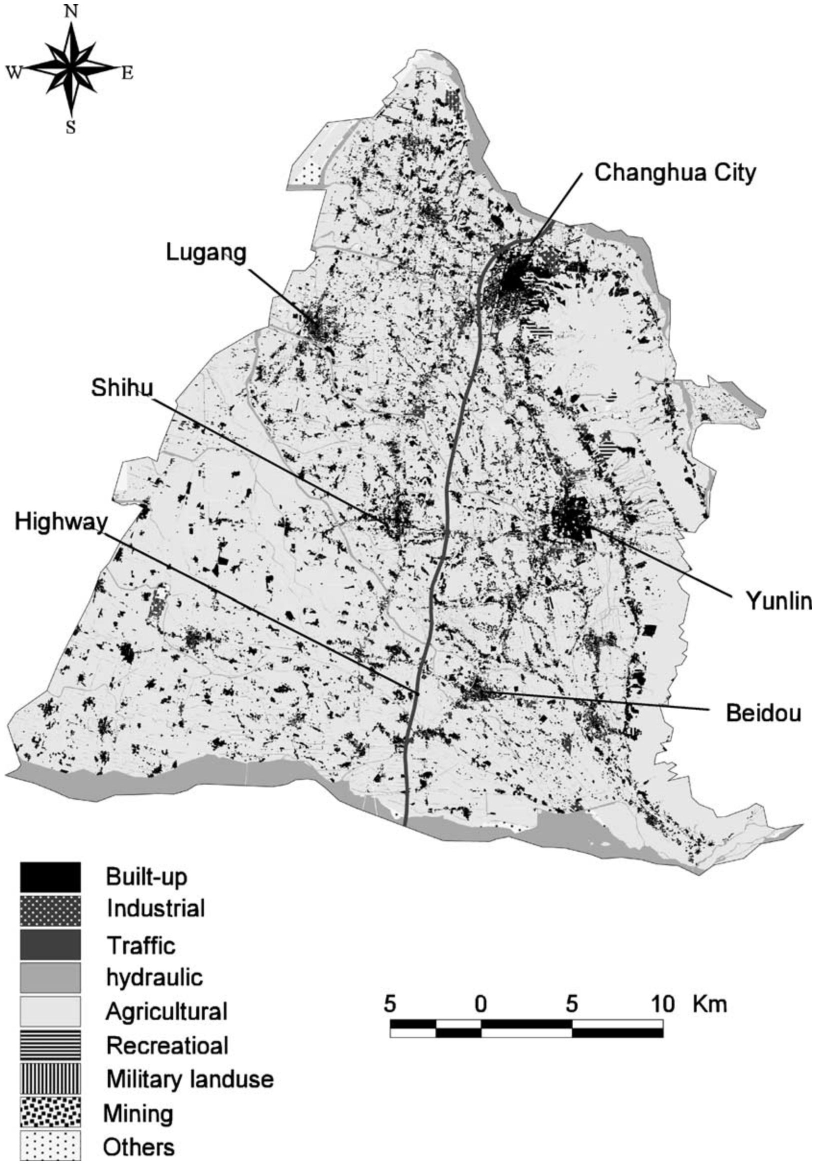

Fig. 2. Land use of Changhua county.

2001). Finally, the factor scores are calculated from variables, using regression methods with a matrix of factor-score coefficients. In this study, factor analysis was first applied to determine the factor patterns of eight soil heavy metals (As, Cd, Cr, Cu, Hg, Ni, Pb and Zn) at these 55 sampling sites. Moreover, these eight soil heavy metals and landscape indices were grouped by factor analysis to delineate interrelationships between soil heavy metals and the landscape. Figs. 4 and 5 show spatial maps of the measured values for these heavy metals. Table 3 summarizes the basic statistics of the investigated heavy metals. Figs. 6 and 7 show landscape indices at the 55 sampling sites.

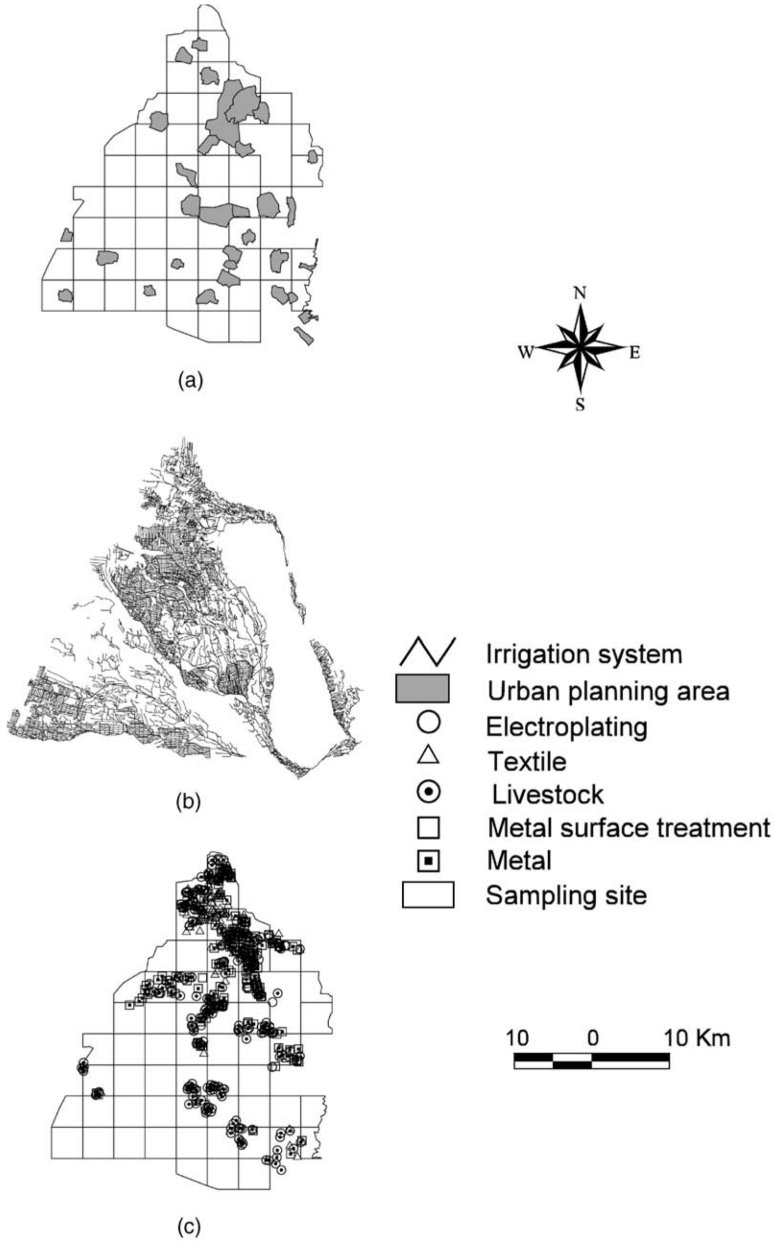

Fig. 3. Spatial distribution of: (a) irrigation system, (b) urban planning area, and (c) industrial plants.

3. Results and discussions

3.1. Landscape indices

The sampling sites with high landscape diversity were in the east of Changhua county (Fig. 6(a)). High landscape dominance sites were in the southwest of Changhua county (Fig. 6(b)). A comparison of the urban planning area and landscape diversity maps (Figs. 3(a) and 6(a)) shows that urbanization dominated the landscape diversity. Moreover, the spatial distribution of landscape diversity values seems to

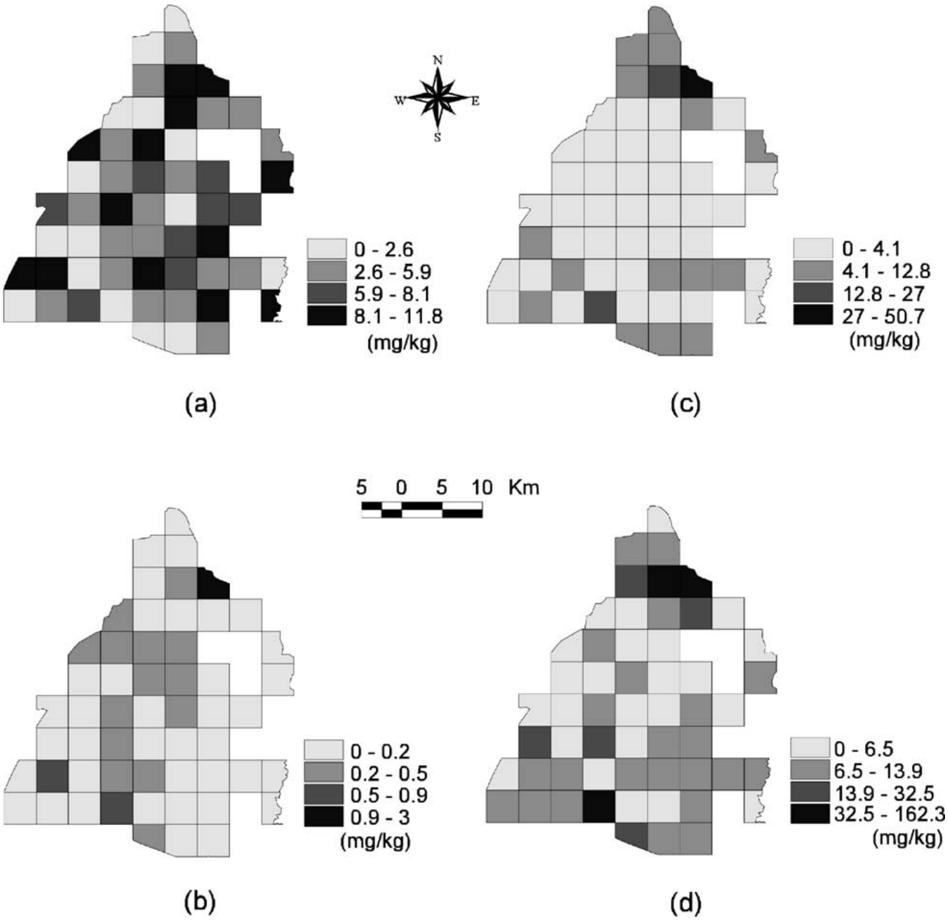

Fig. 4. Sampling maps of soil heavy metal: (a) As, (b) Cd, (c) Cr, and (d) Cu.

Table 3
Statistics of soil heavy metals

Metal	As	Cd	Cr	Cu	Hg	Ni	Pb	Zn
N	55	55	55	55	55	55	55	55
Mean	5.16	0.29	4.87	14.85	0.25	8.46	8.54	27.44
Median	5.53	0.21	3.04	7.56	0.18	6.05	8.12	12.14
Standard deviation	3.28	0.40	7.78	29.58	0.20	12.25	5.67	46.80
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.81	0.51
Maximum	11.76	2.99	50.71	162.33	0.84	88.91	31.23	281.75
25th	2.24	0.16	1.09	3.64	0.13	3.89	4.83	8.00
75th	8.07	0.28	5.16	11.77	0.33	8.07	10.83	23.03

Unit: mg/kg.

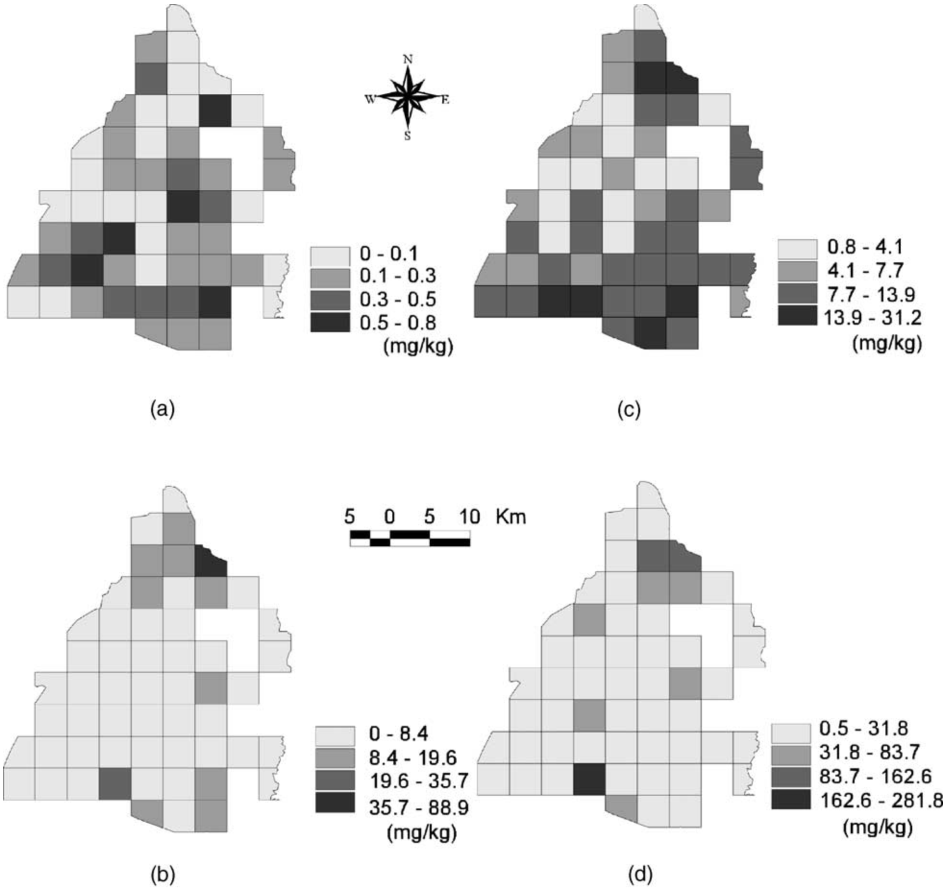

Fig. 5. Sampling maps of soil heavy metal: (a) Hg, (b) Ni, (c) Pb, and (d) Zn.

display north–south tendency that corresponds to urban planning areas and is parallel to Sun Yet-Sen freeway (Figs. 2 and 6(a)). The values show that the irrigation system covered most of the county (Figs. 3(b) and 6(d)). The higher urban planning area ratios were found in the eastern sampling sites of the study areas (Figs. 3(a) and 6(e)). Most electroplating, textile, metal surface treatment and metal industrial plants were located in the northern sampling sites (Figs. 3(c) and 7). The highly urbanized and industrialized sampling sites were in the east of the study area.

The overlaid map (Fig. 8) of the urban planning area, landscape diversity and industrial plants shows that industrial plants were located at sites with high landscape diversity and a high urban planning area ratio. Most industrial plants were located on the borders of the urban planning area. This finding shows that higher landscape diversity corresponds to a higher urban planning area ratio and more industrial plants.

The results of correlation analysis illustrate that the correlation coefficient between the landscape diversity index (H) and the urban planning area ratio (Raup) is 0.63, revealing a strong linear correlation at the 0.01 probability level (Table 4). This result confirms that greater man-made landscape diversity corresponds to more urbanization. The correlation coefficients among H, RAup, NE, NT, NMs, NM and Np are significant at the 0.01 probability level, according to the two-tailed test (Table 4). The correlations among H, NMs and NM exceed 0.6. Moreover, RAup is strongly linearly correlated with NE. However, only

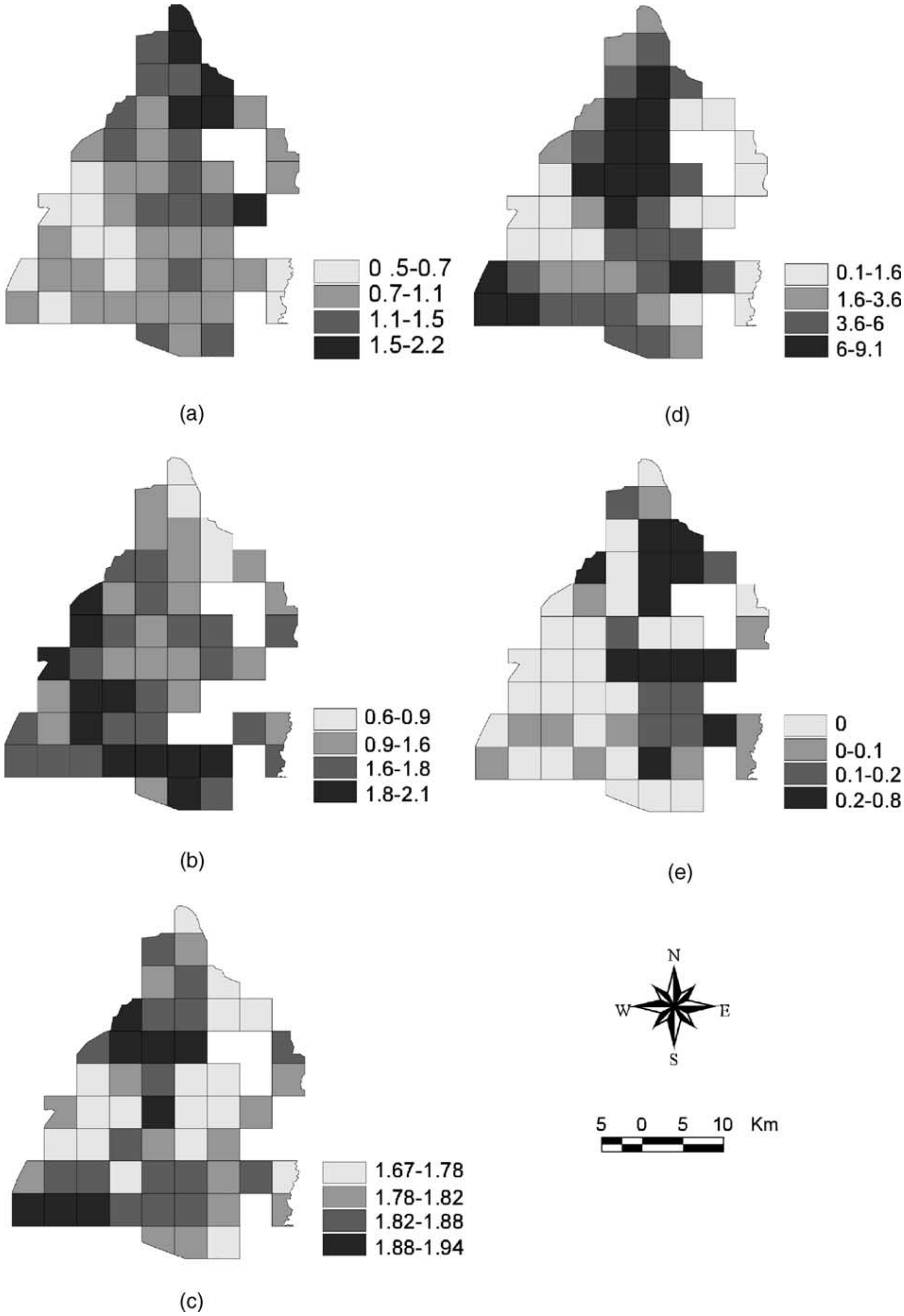

Fig. 6. Spatial maps of: (a) landscape diversity, (b) landscape dominance, (c) area-perimeter fractal dimension, (d) density of irrigation system, and (e) ratio of urban planning area.

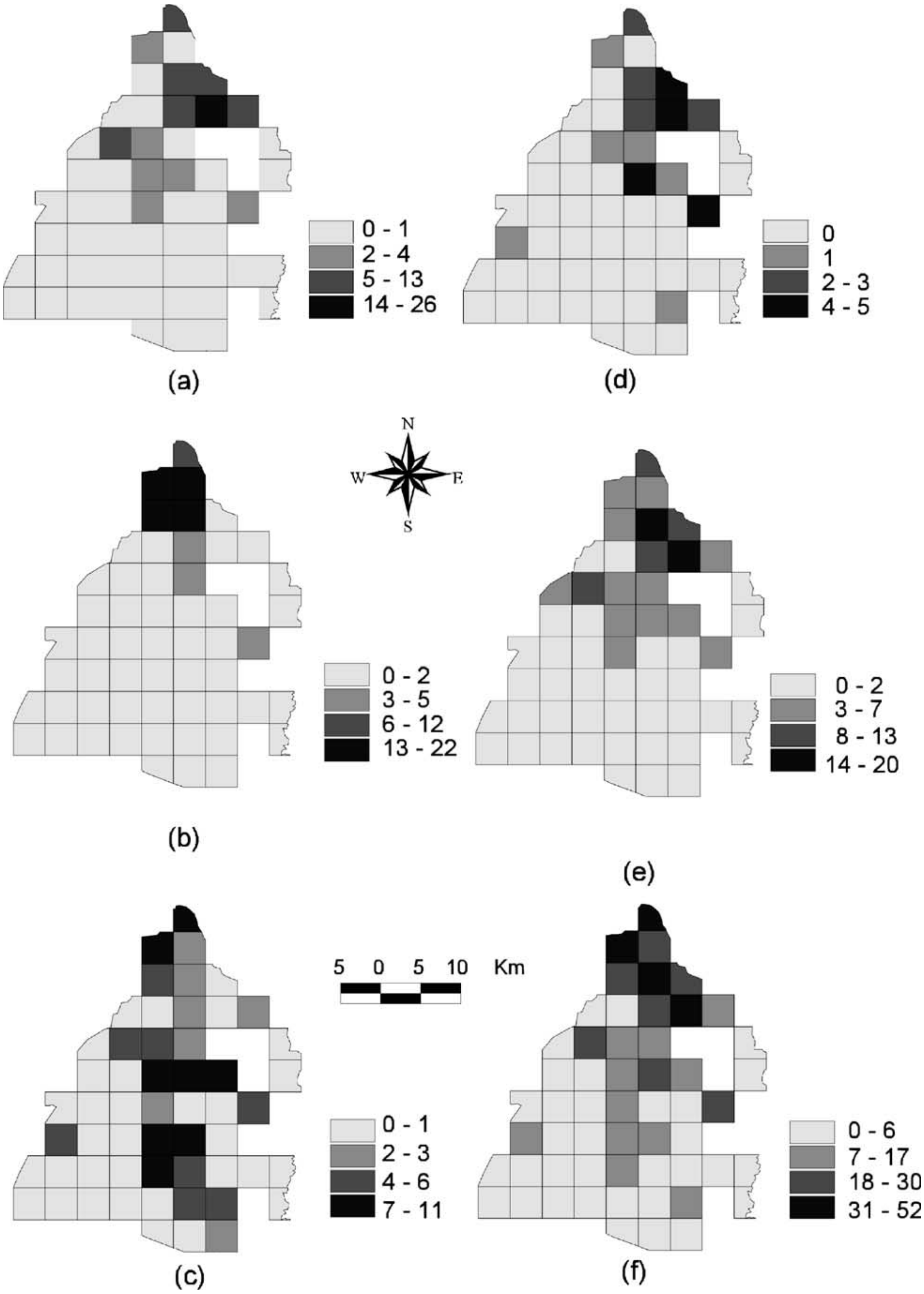

Fig. 7. Number of: (a) electroplating industrial, (b) textile industrial, (c) livestock industrial, (d) metal surface treatment industrial, (e) metal industrial, and (f) total number of industrial plants at each sampling site.

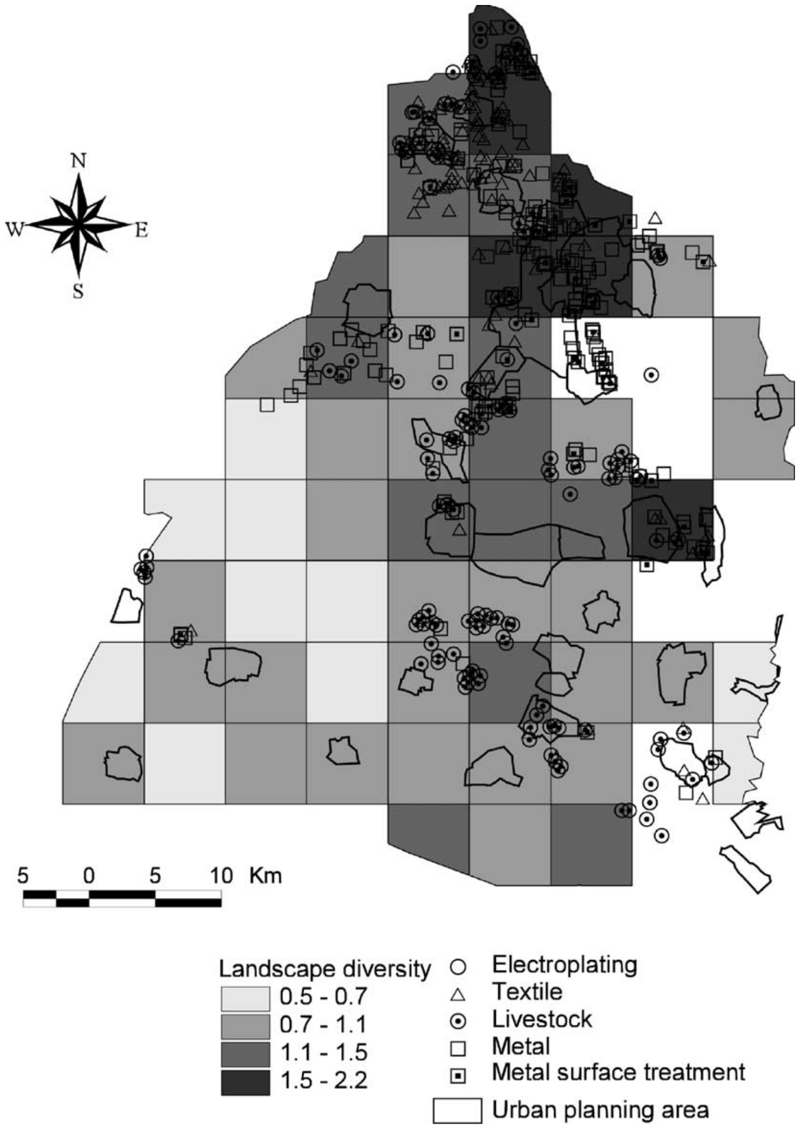

Fig. 8. Overlaying map of landscape diversity, urban planning area and industrial plants.

NL is not significantly correlated with the electroplating plants, metal surface treatment plants and metal plants. The correlations verified results from the overlaying map, which higher urbanization corresponds to higher industrialization (metal industry) across the study area. The landscape spatial pattern and correlation results reflect that industrialization was highly corresponded to urbanization, especially in north and east of Changhua county.

3.2. Correlation among soil heavy metals and landscape indices

Pearson correlation coefficients were calculated for 55 pairs of soil heavy metals and landscape indices, to identify relationships among the soil heavy metals and the landscape indices of these 55 sampling sites (Table 5). Cd was significantly correlated (0.28 and 0.34) with H and NE at the 0.05 probability level and

Table 4
Correlations matrix between landscape indices

	H	D	FD	DL	Raup	NE	NT	NL	NMs	NM	Np
H	1.00	−0.74**	0.02	0.12	0.63**	0.67**	0.42**	0.22	0.61**	0.72**	0.71**
D	−0.74**	1.00	0.19	0.02	−0.41**	−0.64**	−0.42**	−0.08	−0.52**	−0.68**	−0.065**
FD	0.02	0.19	1.00	0.46**	0.13	−0.06	0.07	−0.02	−0.17	0.04	−0.00
DL	0.12	0.02	0.46**	1.00	0.08	0.03	0.05	0.09	0.04	0.10	0.08
Raup	0.63**	−0.41**	0.13	0.08	1.00	0.64**	0.14	−0.00	0.50**	0.57**	0.49**
NE	0.67**	−0.64**	−0.06	0.03	0.64**	1.00	0.23	0.08	0.74**	0.86**	0.77**
NT	0.42**	−0.42**	0.07	0.05	0.14	0.23	1.00	0.31*	0.22	0.52**	0.72**
NL	0.22	−0.077	−0.02	9.09	−0.00	0.08	0.31*	1.00	0.24	0.26	0.49**
NMs	0.61**	−0.52**	−0.17	0.04	0.50**	0.74**	0.22	0.24	1.00	0.72**	0.69**
NM	0.72**	−0.68**	0.04	0.10	0.57**	0.86**	0.52**	0.26	0.72**	1.00	0.92**
Np	0.71**	−0.65**	−0.01	0.08	0.49**	0.77**	0.72**	0.49**	0.69**	0.92**	1.00

* $P < 0.05$ level (two-tailed).
** $P < 0.01$ level (two-tailed).

(0.45) with NMs at the 0.01 probability level, according to the two-tailed test. The correlation coefficients of Cr with landscape indices, H, NE and NMs, are 0.374, 0.377 and 0.448, respectively, revealing a significant relationship at the 0.01 probability level. Cu was significantly related to NE and NMs at the 0.05 probability level. Landscape indices (H, NE and NMs) were significantly related to Ni, at the 0.01 probability level. Zn was significantly correlated with NE and NMs (0.28 and 0.29, respectively) at the 0.05 probability level.

According to our results, the soil heavy metals Cr, Cd and Ni were significantly related to the location and number of the electroplating and metal surface treatment industrial plants. The concentrations of these three heavy metals were also significantly correlated with the landscape diversity index. Therefore, higher Cr, Cd and Ni concentrations were associated with greater urbanization and industrialization. Moreover, Cu was also correlated with the locations of electroplating, metal surface treatment and metal industrial plants. This correlation analysis also reveals that local urbanization and industrialization may have dominated the local characteristics of soil heavy metal pollution in Taiwan's Changhua county, especially in north and east of this study county.

3.3. Factor analysis of heavy metals and landscape indices

Factor analysis results revealed that the four-group model explained 94.1% of the total variation of the

Table 5
Correlations of soil heavy metals with landscape indices

	As	Cd	Cr	Cu	Hg	Ni	Pb	Zn
H	0.07	0.28*	0.37**	0.22	−0.01	0.36**	0.10	0.25
D	−0.01	−0.31*	−0.32*	−0.12	0.20	−0.31*	0.03	−0.10
DL	0.04	0.14	0.11	0.17	−0.15	0.13	0.06	0.15
Raup	0.02	0.14	0.18	0.16	0.15	0.17	0.06	0.15
NE	0.18	0.34*	0.38**	0.30*	0.06	0.39**	0.10	0.28*
NT	−0.04	−0.08	0.12	0.22	−0.05	0.02	0.03	0.11
NL	0.15	−0.15	−0.14	−0.10	−0.04	−0.13	−0.21	−0.13
NMs	0.24	0.45**	0.45**	0.31*	0.00	0.47**	0.07	0.29*
NM	0.15	0.15	0.25	0.30*	−0.08	0.21	0.02	0.26
Np	0.15	0.13	0.25	0.28*	−0.04	0.21	0.00	0.21

* $P < 0.05$ (two-tailed).
** $P < 0.01$ (two-tailed).

Table 6
Eigenvalues and amount of variance of four factors

Factor	Eigenvalue	Variance (%)	Cumulative (%)
1	2.77	34.6	34.4
2	2.73	34.1	68.8
3	1.01	12.7	81.4
4	1.01	12.6	94.1

Table 7
Factor loadings of soil heavy metals

Factor	1	2	3	4
As	0.09	0.05	−0.04	0.99
Cd	0.97	0.15	−0.02	0.10
Cr	0.81	0.55	−0.05	−0.02
Cu	0.39	0.87	0.00	0.04
Hg	−0.04	0.11	0.99	−0.04
Ni	0.90	0.38	0.01	0.08
Pb	0.12	0.89	0.16	0.04
Zn	0.44	0.84	0.04	0.03

soil heavy metal (As, Cd, Cr, Cu, Hg, Pb and Zn) data over this study area (Table 6). Table 7 displays the varimax rotated factor scores. Fig. 9 shows the factor loading maps of the 55 sampling sites. The first and second factors explained 68.7% of the total variation. The first factor, explaining 34.6% of the total variation, exhibited a high positive factor loading on Cd, Cr and Ni. The second factor exhibited a high positive factor loading on Cu, Pb and Zn. The first and second factors were directly related to electroplating and metal treatment industrial plants. The first three factors explained 81.4% of the total variation of the soil heavy metal data. The third and fourth factors showed a high positive factor loading on Hg and As, respectively. According to the soil classes defined by EPA (Table 1), As soil concentrations between 4 and 9 mg/kg are background values in Taiwan. Hg soil

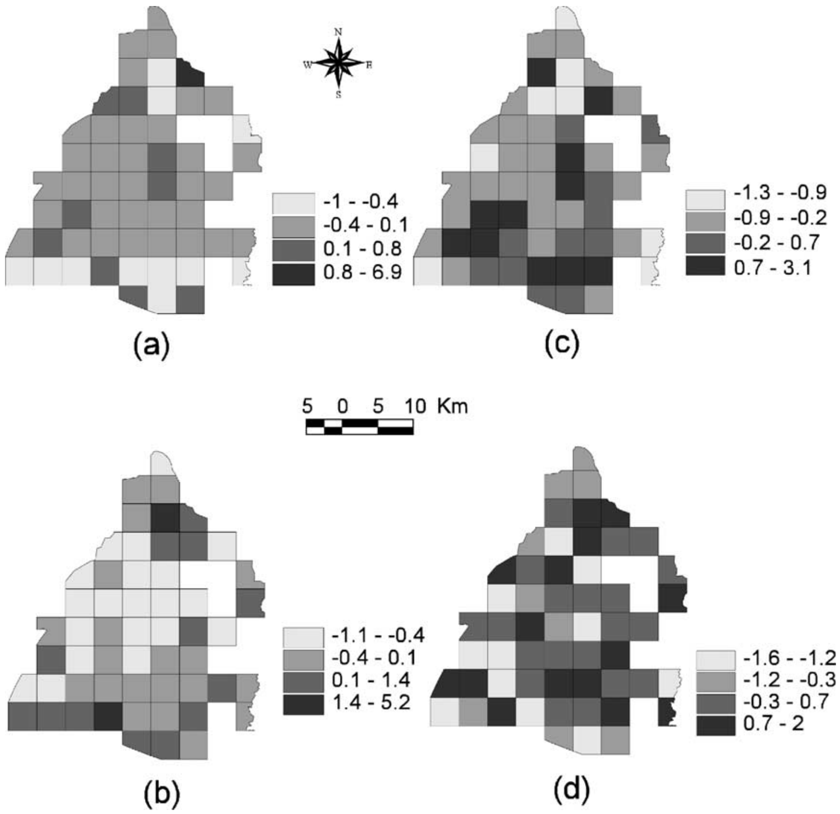

Fig. 9. Spatial maps of factors loading of: (a) factor 1, (b) factor 2, (c) factor3, and (d) factor 4.

concentrations between 0.1 and 0.39 mg/kg are also background values. Accordingly, the mineralogy of the parent material dominates the total As and Hg content of the soil (Chang et al., 1999).

A six-factor model accounted for 82.0% of the total variation of the soil heavy metals and landscape indices data (Tables 8 and 9). The first factor explained 34.5% of the total variation of the soil heavy metals

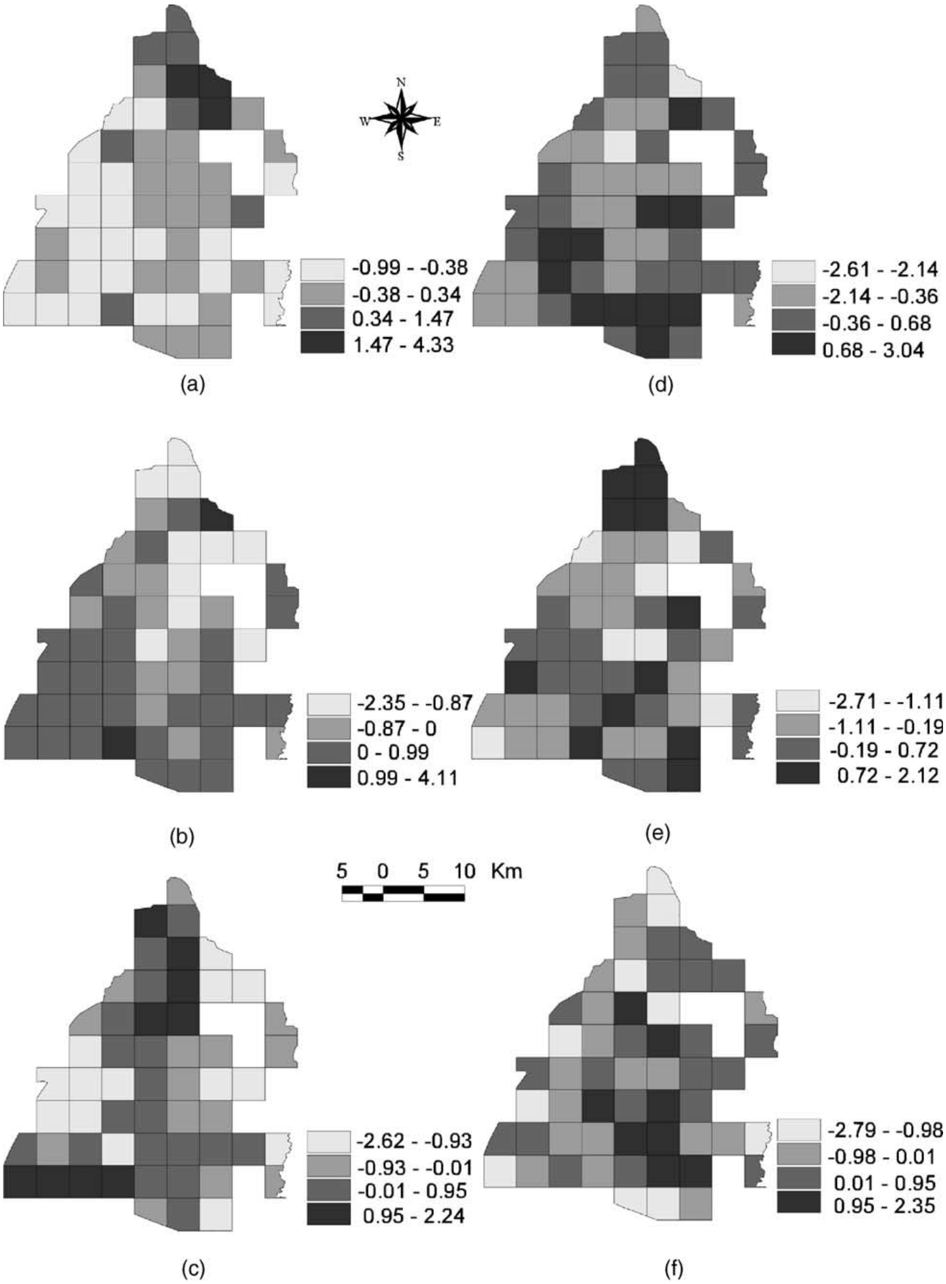

Fig. 10. Spatial maps of factors loading of (a) factor 1, (b) factor 2, (c) factor3, (d) factor 4, (e) factor 5, and (f) factor 6.

Table 8
Eignevalues and amount of variance of six factors

Factor	Eigenvalue	Variance (%)	Cumulative (%)
1	6.55	34.5	34.5
2	3.56	18.7	53.2
3	1.68	8.9	62.1
4	1.39	7.3	69.4
5	1.27	6.7	76.0
6	1.12	5.9	82.0

and landscape indices, and had positive factor loadings on Cd, Cr, Cu Ni, Zn, H, RAup, NE, NMs, NM and Np (Table 9). These variables included not only urbanization (H and RAup) and industrialization indices (NE, NMs, NM and NP), but also soil heavy metals (Cd, Cr, Cu, Ni and Zn). The first factor was related to the impact of urbanization and industrialization (metal industry) on soil heavy metals. The second factor explained 18.7% of the total variation of the variables, and exhibited positive factor loadings on Pb, but moderate factor loadings on Cd, Cr, Cu, Ni and Zn (Table 9), perhaps because soil Pb might not only be dominated by industrial activity, but also controlled by other human activities such as traffic use. The third factor explained 8.9% of the total variation of variables, and represented patch shapes of landscapes. The fourth and sixth factors explained 7.3 and 5.9% of the total variation of variables, respectively, and had high positive factor loading on Hg and As, perhaps dominated by the mineralogy of the parent material. The fifth factor, representing the textile and livestock industries, explained 6.7% of the total variation of variables.

Table 9
Factor loadings of soil heavy metals and landscape indices

Factor	1	2	3	4	5	6
As	0.20	0.03	0.00	−0.38	0.07	0.74
Cd	0.62	0.52	−0.30	−0.33	−0.13	−0.00
Cr	0.75	0.59	−0.11	−0.01	0.072	−0.14
Cu	0.65	0.58	0.26	0.13	0.22	−0.01
Hg	0.00	0.13	0.03	0.75	−0.04	0.37
Ni	0.71	0.57	−0.22	−0.20	0.00	−0.02
Pb	0.38	0.64	0.28	0.33	0.13	0.04
Zn	0.64	0.62	0.20	0.13	0.15	0.09
H1	0.77	−0.36	0.01	0.05	−0.14	−0.11
D1	−0.67	0.40	0.25	0.08	0.05	0.34
FD	−0.03	0.03	0.80	−0.10	−0.36	0.01
DL	0.15	0.08	0.63	−0.44	−0.31	−0.06
Raup	0.57	−0.31	0.05	0.30	−0.52	0.08
NE	0.81	−0.31	−0.13	0.11	−0.25	0.13
NT	0.42	−0.40	0.33	0.09	0.51	−0.31
NL	0.13	−0.47	0.21	−0.22	0.50	0.33
NMs	0.78	−0.22	−0.21	−0.07	−0.06	0.25
NM	0.79	−0.50	0.10	0.05	−0.02	0.02
Np	0.78	−0.55	0.15	0.03	0.23	0.03

Fig. 10 displays all factor loadings maps of the 55 sampling sites. These maps indicated that most sample sites with high first factor loadings were highly correlated to the urban planning areas and distribution of metal industrial plants (Figs. 3(a), (c) and 10(a)). Moreover, the highest factor loading was located in the north of this study area. These patterns of factor loading may show that the soil quality was influenced by industrialization and urbanization, especially in and around urban planning areas. Most high second factor scores were at sampling sites with high Pb values, in the south of the study area (Fig. 10(b)). Moreover, the patterns of the third factor loadings were highly correlated with the distribution and forms of irrigation systems (Figs. 3(b) and 10(c)). This result reveals that irrigation systems may be governed by land use geometry in the study area. Higher irrigation network density corresponds to more fragmented land use. The fifth factor exhibited high factor loadings around sampling sites with low irrigation density and fragmentation. The high factor loadings of the fourth and sixth factors were randomly distributed across the county (Figs. 10(d) and (f)), which results may be verified by the previous factor analyses of heavy metal data and EPA classifications. Natural factors mainly determine As concentration.

4. Conclusions

This study determined landscape patterns and soil heavy metal pollution patterns using landscape indices, multivariate analyses, correlation analysis, and a geographic information system, to establish references for landscape management and to understand the effects of urbanization and industrialization on soil pollution. Landscape indices, landscape diversity, dominance, area-perimeter fractal dimension, density of irrigation ditches, number of electroplating plants, number of textile plants, number of livestock plants, number of metal surface treatment plants and number of metal plants, total number of industrial plants, and the ratio of urban planning area to total area, effectively elucidated the spatial patterns of land use, urbanization and industrialization across the study area.

The correlation analysis of soil heavy metals and landscape indices indicated that heavy metal pollution of soil was dominated by local human activity and urban and industrial land uses in Changhua county in Taiwan. Factorial analysis can classify soil heavy metals and landscape indices into a six-factor model to identify soil pollution in relation to landscape patterns and human activities in Changhua county. Finally, a Geographic information system can comprehensively display the spatial patterns and relationships among of landscape indices and soil heavy metals in the study area.

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