RESEARCH PAPER

Geostatistical approaches and optimal additional sampling schemes for spatial patterns and future sampling of bird diversity

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ABSTRACT

Aim To evaluate geostatistical approaches, namely kriging, co-kriging and geostatistical simulation, and to develop an optimal sampling design for mapping the spatial patterns of bird diversity, estimating their spatial autocorrelations and selecting additional samples of bird diversity in a 2450 km^2 basin.

Location Taiwan.

Methods Kriging, co-kriging and simulated annealing are applied to estimate and simulate the spatial patterns of bird diversity. In addition, kriging and co-kriging with a genetic algorithm are used to optimally select further samples to improve the kriging and co-kriging estimations. The association between bird diversity and elevation, and bird diversity and land cover, is analysed with estimated and simulated maps.

Results The Simpson index correlates spatially with the normalized difference vegetation index (NDVI) within the micro-scale and the macro-scale in the study basin, but the Shannon diversity index only correlates spatially with NDVI within the micro-scale. Co-kriging and simulated annealing simulation accurately simulate the statistical and spatial patterns of bird diversity. The mean estimated diversity and the simulated diversity increase with elevation and decrease with increasing urbanization. The proposed optimal sampling approach selects 43 additional sampling sites with a high spatial estimation variance in bird diversity.

Main conclusions Small-scale variations dominate the total spatial variation of the observed diversity due to a lack of spatial information and insufficient sampling. However, simulations of bird diversity consistently capture the sampling statistics and spatial patterns of the observed bird diversity. The data thus accumulated can be used to understand the spatial patterns of bird diversity associated with different types of land cover and elevation, and to optimize sample selection. Co-kriging combined with a genetic algorithm yields additional optimal sampling sites, which can be used to augment existing sampling points in future studies of bird diversity.

Keywords

Bird diversity, co-kriging, genetic algorithm, kriging, optimal additional sampling, simulated annealing simulation, spatial pattern, variogram.

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INTRODUCTION

Ecologists recognize that nearly all macroecological and bio-diversity data show strong spatial patterns, driven by spatially structured biological processes. Consequently, such data are often spatially autocorrelated (Rangel *et al.*, 2006). Moreover, the spatial structures of ecological and biogeographical data are influenced by the spatial correlations of the observed variables, such as their abundance and richness, as well as by the spatial configuration of the sampling locations (Diniz-Filho *et al.*, 2003; Fortin & Dale, 2005; Rangel *et al.*, 2006). However, when estimating the mean density of individuals in a domain, the magnitude of the sampling selection bias varies according to the underlying spatial autocorrelation structure (Aubry & Debouzie,

2000). Although improvements in estimation models and software have increased the ability of mapping to represent the complex behaviour of ecologically observed variables, a measurable reduction in prediction errors cannot always be achieved by increasing the complexity of those variables (Peters *et al.*, 2004). Therefore, effective sampling and mapping approaches are required to estimate the spatial autocorrelation structure, and to produce reliable maps of spatial patterns with lower estimation variance.

Geostatistical techniques, such as kriging and co-kriging, can be used to improve a sampling strategy that considers spatial autocorrelation (Aubry & Debouzie, 2000, 2001; Lin & Rouhani, 2001). By using sample data and geostatistical methods, biologists can make optimal predictions about spatially dependent biological variables (e.g. the richness of a species) at unsampled sites (Carroll & Pearson, 2000). Kriging, is a linear interpolation procedure that provides the best linear unbiased estimator (BLUE) of quantities that vary spatially (Lin *et al.*, 2001). Co-kriging is an estimation method that minimizes the variance in the estimation error by exploiting the cross-correlations between several variables; the estimates are obtained from both secondary variables and primary variables (Isaaks & Srivastava, 1989). The usefulness of secondary variables is often enhanced if the primary variable of interest is under-sampled (Isaaks & Srivastava, 1989).

Moreover, geostatistical simulation techniques, such as simulated annealing simulation, can be used to generate multiple realizations, including an error component, which classical interpolation techniques do not consider (Lin *et al.*, 2001). These realizations match the sample statistics, while the conditioning data provide a visual and quantitative measure of spatial uncertainty (Goovaerts, 1996). Recent examples of the use of geostatistical methods to study bird distribution, species richness and biodiversity include the work of Fisher *et al.* (2001), Diniz-Filho *et al.* (2002), Maes *et al.* (2003), Rempel & Kushneriuk (2003), Foster *et al.* (2004), Royle & Rubenstein (2004), Bayliss *et al.* (2005), Couteron & Ollier (2005), Ferrer-Castán & Vetaas (2005), Fortin *et al.* (2005), Tchouto *et al.* (2005), Godet *et al.* (2006) and Jiguet & Julliard (2006). Numerous studies have also used geostatistical approaches to design or adjust sampling systems and quantify the information value of sampling data and its variations to improve the accuracy of spatial mapping of environmental or ecological data. Recent examples include the work of Aubry & Debouzie (2001), Lin & Rouhani (2001), Ferreyra *et al.* (2002), Passarella *et al.* (2003), Rempel & Kushneriuk (2003) and Yeh *et al.* (2006).

Birds are frequently used as indicator variables for ecological monitoring and assessment because they constitute a well-defined taxon that has been widely surveyed and it is relatively easy to carry out censuses of them. Furthermore, they are considered to be some of the best surrogates for biodiversity in conservation site planning (Saethersdal *et al.*, 1993; Reyers *et al.*, 2000). Several studies have focused on avian diversity, as well as its richness and abundance, and produced indices that reveal the relationship between diversity and vegetation variables (Welsh & Healy, 1993; Twedt *et al.*, 1999; Poulsen, 2002; Selmi & Boulinier, 2003; Crooks *et al.*, 2004; Sandström *et al.*, 2006). Diversity indices, such as those of Shannon and Simpson, are normally used to quantify the diversity of species in communities because they combine evenness and richness to produce a single metric (Payne *et al.*, 2005), and distil the information about the distribution of a species into a single statistic (Magurran, 2004). The normalized difference vegetation index (NDVI) is a measure of vegetation vigour (Oindo *et al.*, 2000) and represents vegetation productivity (Chong *et al.*, 1993; Bailey *et al.*, 2004). Moreover, remote sensing data may help identify a species-rich area with NDVI providing an estimate of primary productivity (Bailey *et al.*, 2004).

To delineate the spatial distribution of, and variations in, bird diversity in the Taipei Basin, we used variograms to quantify the spatial variability of Shannon and Simpson diversity indices of the observed bird data. We then applied kriging and co-kriging with NDVI to interpolate maps of bird diversity, and employed simulated annealing to simulate multiple realizations of that diversity. Furthermore, we designed a sampling system based on optimal geostatistical sampling approaches that use a genetic algorithm to reduce the estimation variance of kriging and co-kriging (with NDVI). Optimal sampling sites provide valuable information, and improve the identification and mapping of the spatial distribution and variation in bird diversity because they facilitate optimal selection of additional samples. Next, the estimated and simulated maps of bird diversity and the additional sampling points were superimposed on the geographical information system. We then used the system as a reference to analyse the spatial distribution, accuracy and variability of bird diversity associated with elevation and urbanization in the study area.

MATERIALS AND METHODS

Study area and data

The Taipei Basin is located in northern Taiwan (longitude 121° E and latitude 25° N) (Fig. 1). It has a total area of 2450.1 km² and includes Taipei City, Taipei County and Keelung City. Taipei City (272.4 km², the central part of the study area) is the capital of Taiwan. The Taipei metropolitan area, which has a low elevation, is bounded by Datu Mountain (maximum elevation 1092 m), Chishin Mountain (maximum elevation 1120 m) and Siamou Mountain (maximum elevation 643 m) to the north, the Linko mesa (elevation varies from 50 to 240 m) to the west, and the ridge of Syue Mountain to the south-east (maximum elevation 2100 m at the basin boundary). The highly urbanized area includes some parts of Taipei City and Taipei County in the central region of the Taipei Basin (Figs 1 & 2a). The basin is crossed by the Xindian River in the south, the Danshui River in the west and the Keelung River in the north (Fig. 1).

We used data on bird communities in northern Taiwan (total number of species = 324) provided by the Taiwan Bird Record data base of the Wild Bird Federation of Taiwan (WBFT). The data base was compiled from reports made by the wild bird society of each county in Taiwan during 1998. Each society affiliated with the WBFT has its own volunteers who have been trained to observe birds and report the results of their investigations. The
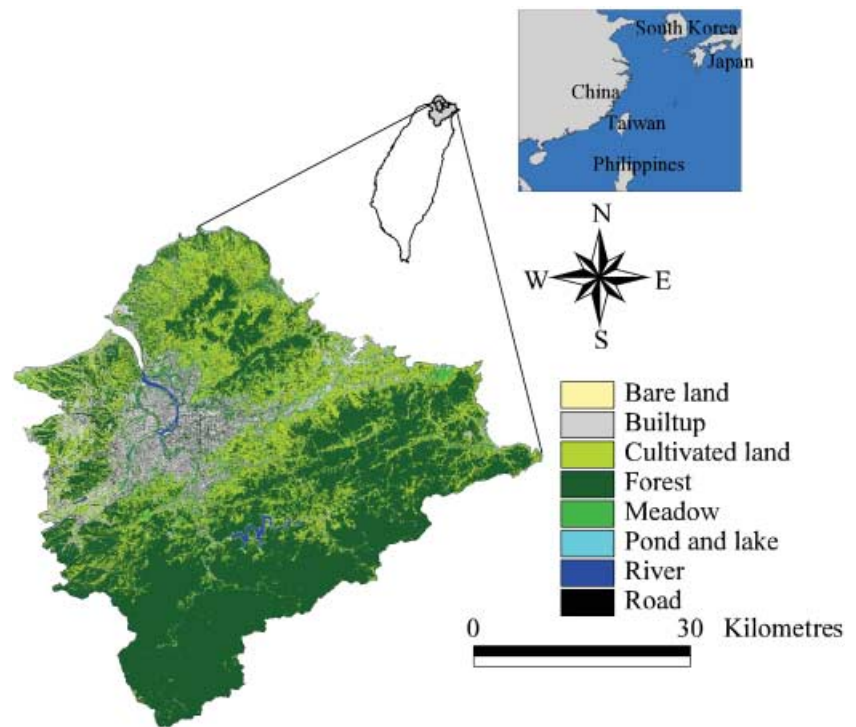
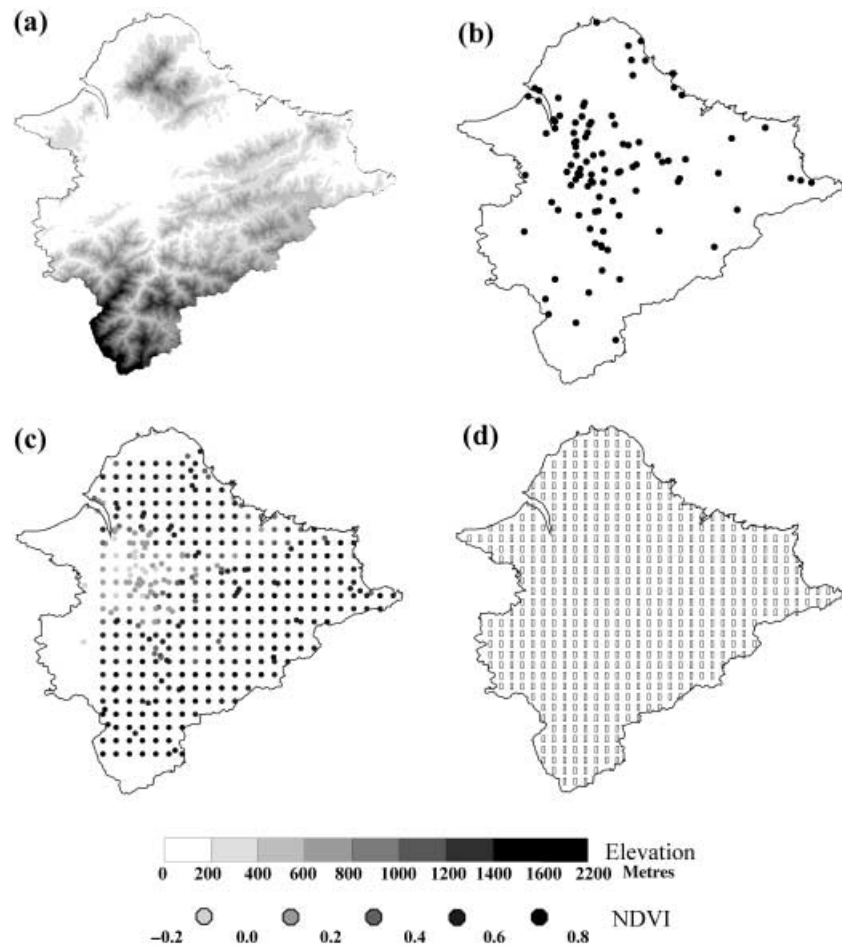**Figure 1** Location of the study area and land use.

Figure 2 (a) Elevation, (b) existing observation points, (c) NDVI samples and (d) candidate sites for further sampling.

Table 1 Variogram and cross-variogram models of bird diversity and NDVI.

Variables	Variogram model	C_0 (nugget)	$C_0 + C$ (sill)	A range (m)	R^2	RSS	MPE
Shannon diversity index	Spherical	0.229	0.660	15,500	0.634	0.0500	0.0080
Simpson diversity index	Spherical + Gaussian	7.220	1.780, 36.50	15,500, 37,572	0.947	595.763	−0.1200
NDVI	Spherical	0.003	0.047	22,300	0.848	0.0004	−0.0007
Shannon diversity–NDVI	Spherical	0.0001	0.077	15,400	0.661	0.0030	−0.0080
Simpson diversity–NDVI	Spherical + Gaussian	0.000	0.340, 0.420	15,500, 37,572	0.955	0.1516	0.0100

Spherical model: $C_0 + C[1.5(h/A) - 0.5(h/A)^3]$, $h \leq A$
$\qquad\qquad\quad C_0 + C$, $h > A$
Gaussian model: $C_0 + C(1 - e^{-h^2/A^2})$, $h \leq A$
$\qquad\qquad\quad C_0 + C$, $h > A$
RSS, model reduced sum of squares; MPE, mean prediction error $= \dfrac{1}{n}\sum_{i=1}^{n}(z_i - z_i^\star)$; n, number of existing samples.

observers recorded all birds seen or heard within a 200-m radius of each observation point, together with the locations where the data were collected. The observation points, shown in Fig. 2b, were randomly selected by the volunteers. The Shannon and Simpson reciprocal diversity indices were then used to calculate the bird diversity.

A cloud-free SPOT (Satellite Pour l'Observation de la Terre) image taken on 16 July 1998 was used to classify the land cover of the Taipei Basin. Atmospheric and topographic corrections of the SPOT image were made by the Center for Space and Remote Sensing Research in Taiwan. The image was first classified using supervised classification, together with maximum likelihood and fuzzy methods. Specifically, the supervised classification and fuzzy convolution procedures of the ERDAS IMAGINE software program, based on 1/25,000 black-and-white aerial photographs and ground-truth data, were used to obtain the land cover information (total accuracy = 89.1% and overall kappa value = 0.87), as illustrated in Fig. 1. The values of the NDVI were captured by the SPOT image (Fig. 2c). The NDVI value was calculated as the difference between the reflectance readings of the near-infrared (NIR) spectrum and those of the visible red (Red) light spectrum divided by the sum of both readings. The red and NIR light reflected by plants is a function of the photosynthetically active compounds they contain and is related to the total plant biomass (Tucker *et al.*, 1985; Bailey *et al.*, 2004). Raw NDVI values range from –1.0 to 1.0; higher positive values indicate high vegetation areas, while lower negative values indicate non-vegetation features or cloud-covered areas (Holben, 1986). In this study, we assume that the NDVI values are linearly related within a 500-m grid because such a grid is extremely small compared with the size of the study area. The statistics of the annual bird diversity at 97 sampling sites and the NDVI at 420 sampling sites (mean NDVI value within 500 m of each site) are shown in Table 1 and Fig. 2.

Kriging and co-kriging

To estimate the spatial distributions of the Shannon and Simpson indices of bird diversity, we used kriging and co-kriging to produce spatial maps of bird diversity in 500 m × 500 m grid systems for the entire study area. In geostatistics, variograms provide a means of quantifying the commonly observed relationship between the values of the samples and their proximity (Lin *et al.*, 2001). An experimental variogram for an interval lag distance class h, $\gamma_{zz}(h)$, is represented by

$$\gamma_{zz}(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [Z(x_i + h) - Z(x_i)]^2, \tag{1}$$

where h denotes the lag distance that separates pairs of points; $Z(x)$ denotes the bird diversity at location x; $Z(x + h)$ denotes the bird diversity at location $(x + h)$; and $n(h)$ represents the number of pairs separated by the lag distance h.

The experimental cross-variogram $\gamma_{xy}(h)$ of the second-order stationary regionalized variables, $Z(x)$ and $Y(x)$ (NDVI), is expressed as follows:

$$\gamma_{xy}(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [Z(x_i + h) - Z(x_i)][Y(x_i + h) - Y(x_i)]. \tag{2}$$

Kriging is estimated using the weighted sums of the adjacent sampled concentrations. The weights depend on the correlation structure exhibited. The criterion used to determine the weights is whether they minimize the estimation variance. In this context, kriging estimates (BLUE) are considered the most accurate of all linear estimators. Accordingly, we used kriging to estimate the value of the random variable at an unsampled location x_0 based on the measured values in the linear form:

$$Z^\star(x_0) = \sum_{i=1}^{N} \lambda_{i0} Z(x_i), \tag{3}$$

where $Z^\star(x_0)$ is the estimated value at location x_0, λ_{i0} is the kriging estimation weight of $Z(x_i)$, x_i is the location of the sampling point for variable Z, and N is the number of the variables Z involved in the estimation.

Based on non-bias constraints and minimization of the estimation variance, the kriging estimation variance is represented by

$$\sigma^2_{\text{kriging}} = \sum_{i=1}^{N} \lambda_{i0} \gamma_{zz}(x_i - x_0) + \mu, \tag{4}$$

where μ is the Lagrange multiplier.

Co-kriging estimates the value of the random variable at an unsampled location x_0 based on the measured values in the linear form:

$$Z^\star(x_0) = \sum_{i=1}^{N} \lambda_{i0} Z(x_i) + \sum_{j=1}^{L} \omega_{j0} Y(x_j), \tag{5}$$

where ω_{j0} is the estimation weight of $Y(x_j)$, x_j is the location of variable Y, and L is the number of the variable Y.

Based on non-bias constraints and minimization of the estimation variance, the co-kriging estimation variance can be written as:

$$\sigma^2_{\text{co-kriging}} = \sum_{i=1}^{N} \lambda_{i0} \gamma_{zz}(x_i - x_0) + \sum_{j=1}^{L} \omega_{j0} \gamma_{xy}(x_j - x_0) - \mu. \tag{6}$$

Simulation by simulated annealing

To obtain conditional simulated realizations of the spatial bird diversity, we simulated 500 realizations (in 500 m × 500 m grid systems) of the spatial distributions of the Shannon and Simpson indices of bird diversity using the simulated annealing simulation method developed for this study. The annealing algorithm perturbs the image by simulating thermal perturbation (Deutsch & Cockerham, 1994). Simulated annealing is an optimization technique that generates an initial field by drawing random values from a given histogram (Lin *et al.*, 2001). Swapping the values in pairs of grid nodes that do not contain conditioning data can sequentially modify the initial field. Swaps are permitted when the value of the objective function is lower than the previous value of the objective function (Deutsch & Journel, 1992). The objective function (O) is defined as:

$$O = \sum_{h} \frac{[\gamma^\star(h) - \gamma(h)]^2}{\gamma(h)^2}, \tag{7}$$

where $\gamma(h)$ denotes the pre-specified variogram, and $\gamma^\star(h)$ represents the variogram of the simulated realization.

Optimal additional sampling

In this study, the kriging and co-kriging estimation variances were minimized to obtain an accurate spatial estimation of bird diversity via optimal selection of additional sampling sites using the genetic algorithm. As a result, 23, 43, 63, 83, 103 and 123 additional sampling sites (total sampling size from 120 to 220) were optimally selected from 596 pre-defined grid sampling candidate sites (Fig. 2d). To reduce the kriging estimation standard deviation of bird diversity, the objective function of the optimization problem is defined as follows:

$$\underset{I \subset \Omega}{\text{Min}} \ J(I) = \sum_{m \in M} \sigma_{\text{kriging}}(I). \tag{8}$$

subject to

$$N_I \leq n, \tag{9}$$

where σ_{kriging} is the kriging estimated standard deviation, and n denotes the number of additional sampling sites. In addition, Ω represents the index set that defines all the candidate sampling locations in the study region, I denotes a subset of Ω and a possible alternative sampling design, D is the set of all grids in the study region, N_I denotes the number of possible alternative sampling designs, I, and M represents the maximum number of additional sampling sites.

To reduce the co-kriging estimated standard deviation of bird diversity with NDVI, we define the objective function of the optimization problem as follows:

$$\underset{I \subset \Omega}{\text{Min}} \ J(I) = \sum_{m \in M} \sigma_{\text{co-kriging}}(I), \tag{10}$$

subject to

$$N_I \leq n, \tag{11}$$

where $\sigma_{\text{co-kriging}}$ denotes the co-kriging estimated standard deviation.

RESULTS

The spatial structure of bird diversity

We constructed an experimental variogram of bird diversity and a cross-variogram of bird diversity using NDVI at the same active lag (50 km) and lag interval (5000 m) with GS + (Gamma Design Software, 2004). To fit the variogram and cross-variogram models, a relatively consistent set of best-fit models was generated using the least-squares fitting technique with minimum reduced sum of squares (RSS), and maximum r^2 and minimum mean prediction error (MPE) values (Table 1). The small-scale variations (nugget effects) of the Shannon and Simpson bird diversity indices represented, respectively, 34.7% and 18.6% of the total variation of the diversity of the observed bird data. In the variogram model, the nugget effect values were 34.70% and 18.86% of the Sill values of the observed Shannon and Simpson reciprocal bird diversity indices, respectively. The Simpson reciprocal diversity variogram represented nested structures comprising the sum of a spherical model with a range of 15.5 km and a Gaussian model with a range of 37.57 km. The variogram nugget effect value was 5.80% of the Sill value of the observed NDVI. Furthermore, in the cross-variogram model of observed Shannon bird diversity–NDVI and Simpson diversity–NDVI, the nugget effects were 0.1% and 0.0% of the Sill values, respectively. The variography results show that the variogram models of bird diversity have a high nugget effect and display a high degree of small-scale variation. In contrast, the variogram of NDVI and the cross-variogram of bird diversity and NDVI have considerably lower levels of small-scale variation. The greater the range of the variogram model, the better the continuity of the observed bird diversity will be. The variogram range (22.3 km) of NDVI, which represents the spatial structure of vegetation within the geographical range, is approximately 1.44 and 0.59 times that of the bird diversity variogram model and the bird–NDVI cross-variogram model at short range (15.5 and 15.4 km) and long range (37.6 km), respectively.

Table 2 Descriptive statistics of the estimations and simulations of bird diversity.

		Mean	Median	Min.	Max.	SD	25th percentile	75th percentile
Shannon diversity index	Investigated	2.28	2.39	0.35	5.85	0.78	1.85	2.71
	Kriging	2.45	2.48	1.24	3.36	0.30	2.30	2.62
	Co-kriging	2.49	2.54	0.64	5.15	0.40	2.28	2.74
	Sim no. 1	2.29	2.40	0.35	5.85	0.77	1.85	2.70
	Sim no. 10	2.29	2.39	0.35	5.85	0.77	1.85	2.70
	Sim no. 50	2.27	2.39	0.35	5.85	0.77	1.84	2.70
	Sim no. 100	2.27	2.39	0.35	5.85	0.76	1.85	2.70
	Sim no. 500	2.29	2.39	0.35	5.85	0.77	1.85	2.71
Simpson diversity index	Investigated	7.28	6.67	1.25	22.20	4.33	3.96	9.96
	Kriging	9.27	8.98	2.74	17.06	2.35	7.77	10.60
	Co-kriging	8.74	8.11	1.96	18.70	3.04	6.67	10.34
	Sim no. 1	7.30	6.68	1.25	22.20	4.31	4.04	9.94
	Sim no. 10	7.29	6.69	1.25	22.20	4.28	4.26	9.89
	Sim no. 100	7.30	6.67	1.25	22.20	4.28	4.22	9.98
	Sim no. 200	7.27	6.63	1.25	22.20	4.32	4.01	9.90
	Sim no. 350	7.27	6.67	1.25	22.20	4.30	4.04	9.90

Sim no.: simulated realization no.

Comparative statistical estimation and simulation

The ordinary kriging estimates, co-kriging estimates and simulations were based on the above variogram models and 97 bird diversity observations. Table 2 lists the descriptive statistics for ordinary kriging and co-kriging, as well as the simulated annealing results for the Shannon and Simpson bird diversity indices in the study area. The descriptive statistics of the kriging and co-kriging results did not capture the statistics of the investigated bird diversity data well (Table 2). However, the descriptive statistics of the bird diversity simulations using simulated annealing were almost identical to those of the Shannon and Simpson reciprocal indices of the investigated bird diversity data (Table 2).

Spatial structures, patterns of estimation and simulations

The experimental variograms of the measured, estimated and simulated values were constructed using the same lag interval to compare the spatial structures of the measured, estimated and simulated bird diversity (Fig. 3). These experimental variograms show that the estimations of ordinary kriging yielded a well-structured (low nugget effect and long range) variogram with low spatial variability, but they did not capture the spatial structure and small-scale variation of the investigated values accurately, as shown in Fig. 3. From the figure, we observe that the experimental variograms of all the simulations fit the experimental variogram of the observed bird diversity data.

Figure 4a,b shows, respectively, the kriged and co-kriged maps of low bird diversity areas in the Taipei metropolitan area, where the elevation is low. Significantly the co-kriged map shows that the areas with low bird diversity closely match the patterns of urbanization in Taipei City. The values of the Shannon and Simpson diversity indices increased as urbanization decreased.

The estimated maps also show an area of higher bird diversity surrounding the metropolitan area. Ordinary kriging estimate maps of bird diversity confirmed that kriging tended to smooth extreme values of the empirical bird diversity data set. The co-kriging estimation variances were considerably lower than the kriging estimated variances over the entire study area. However, the kriging and co-kriging standard deviation maps also show high estimation errors in areas that were not sampled or that provided few samples. Figure 4c,f shows the simulation maps of bird diversity in the study area. Like the kriging map, the simulation maps indicate low bird diversity in the Taipei metropolitan area. The simulation maps also demonstrate the spatial discontinuity and variability of bird diversity in the metropolitan area, and reveal areas of high discontinuity and variability of bird diversity in the areas that were not sampled or that had few sampling sites.

Optimal additional sampling

The multiple optimal additional sampling sites were also chosen using the proposed optimal sampling approach to reduce both the kriging and the co-kriging estimation of the variance of the Shannon and Simpson (co-kriging only) bird diversity indices. Adding 23, 43, 63, 83, 103 and 123 extra sampling sites reduced the kriging estimation of the variance of the Simpson bird diversity index in the study area by 12.7%, 17.7%, 21.5%, 24.2%, 26.2% and 27.5%, respectively. Meanwhile, adding 23, 43, 63, 83, 103 and 123 optimal sampling sites reduced the co-kriging estimation variance of the Shannon bird diversity in the investigated area by 9.3%, 13.2%, 15.2%, 16.7%, 18.1% and 18.9%, respectively. Note that the additional sampling locations for a particular set were not included in other sets. By increasing the number of sampling sites in increments of 20 from 23 to 123 additional sites (total sample size between 120 and 220), the
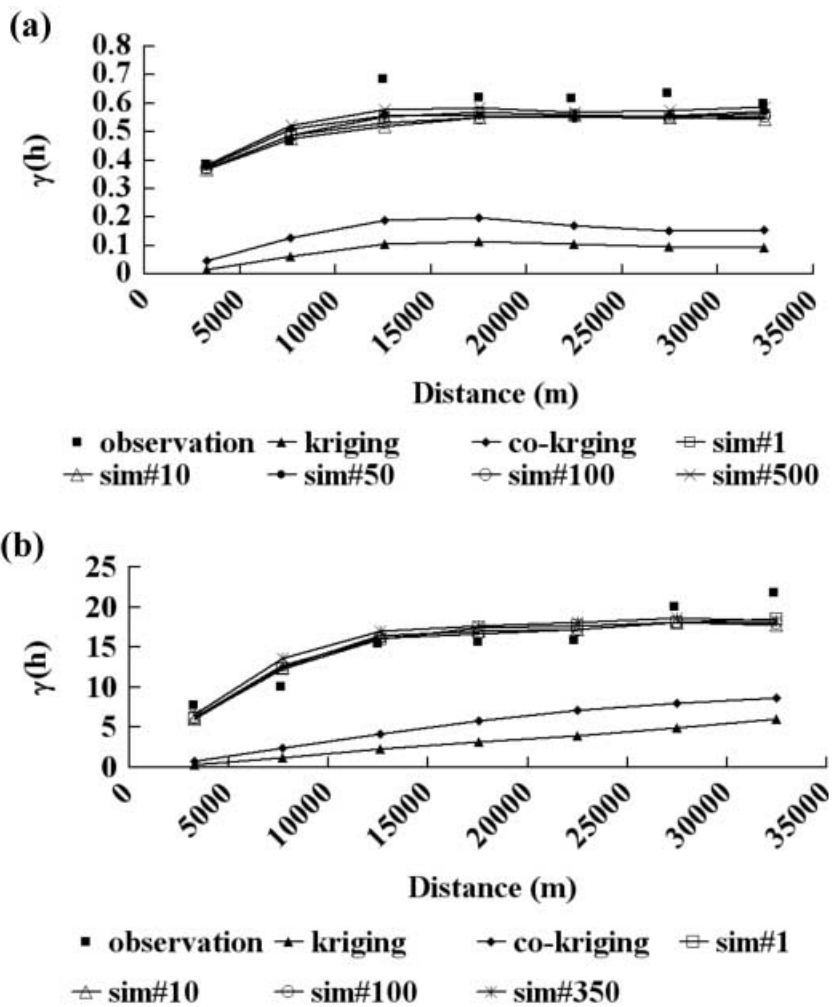
Figure 3 Experimental variograms of (a) the observed, estimated and simulated Shannon bird diversity index and (b) the observed, estimated and simulated Simpson bird diversity index (sim no.: simulated realization no.)

difference in the percentage of kriging variance reduction tended asymptotically towards a nearly constant percentage variance reduction in the kriging standard deviation (less than 3.0%) when the number of additional sampling sites exceeded 63. Furthermore, by increasing the number of sampling sites in increments of 20 from 23 to 123 additional sites (total sample size between 120 and 220), the difference in the percentage of co-kriging variance reduction tended asymptotically towards a constant (less than 3.0%) when the number of additional sites exceeded 43. The locations of the additional sampling sites are shown in Fig. 5. The additional samples derived by reducing the optimal co-kriging variance and the optimal kriging variance were different. Moreover, nearly all the additional samples were obtained from a few sampling areas with high discontinuity in the simulated maps. Adding 23, 43, 63, 83, 103 and 123 sampling sites reduced the kriging estimation variance of the Simpson reciprocal bird diversity index by 16.9%, 20.2%, 22.3%, 23.0%, 25.0% and 25.6%, respectively. By increasing the number of sampling sites in increments of 20 from 23 to 123 additional sites (total sample size between 120 and 220), the difference in the percentage of co-kriging variance reduction for the Simpson reciprocal index tended asymptotically towards a constant (less than 3.0%) when the number of additional sampling sites exceeded 43.

DISCUSSION

Consideration of the spatial variation in species richness and community composition is important for understanding the ecological patterns and underlying processes that produce them (Rosenzweig, 1995; Nichols *et al.*, 1998). The spatial pattern of the richness of a bird species frequently involves a combination of large-scale biogeographical variation and fine-scale ecological variation (Wiens, 1989; Noss, 1992; Luoto *et al.*, 2004). The field of geostatistics has provided ecology with some novel tools for interpreting the spatial patterns of organisms, the numerous environmental components they interact with and the joint spatial dependence between the organisms and their environment (Rossi *et al.*, 1992). In this study, the variogram of Shannon's bird diversity index with a high nugget effect ratio represents a high level of small-scale variation or observation errors in bird diversity. The small-scale variations might be due to a lack of sampling and variations in environmental factors in the Taipei metropolitan area. The higher the degree of spatial autocorrelation among sites, the smoother the changes between places within the geographical range (Maurer, 1994; Maurer & Taper, 2002). However, the correlation within the range separating sampling sites can be explained by the characteristic distribution of the
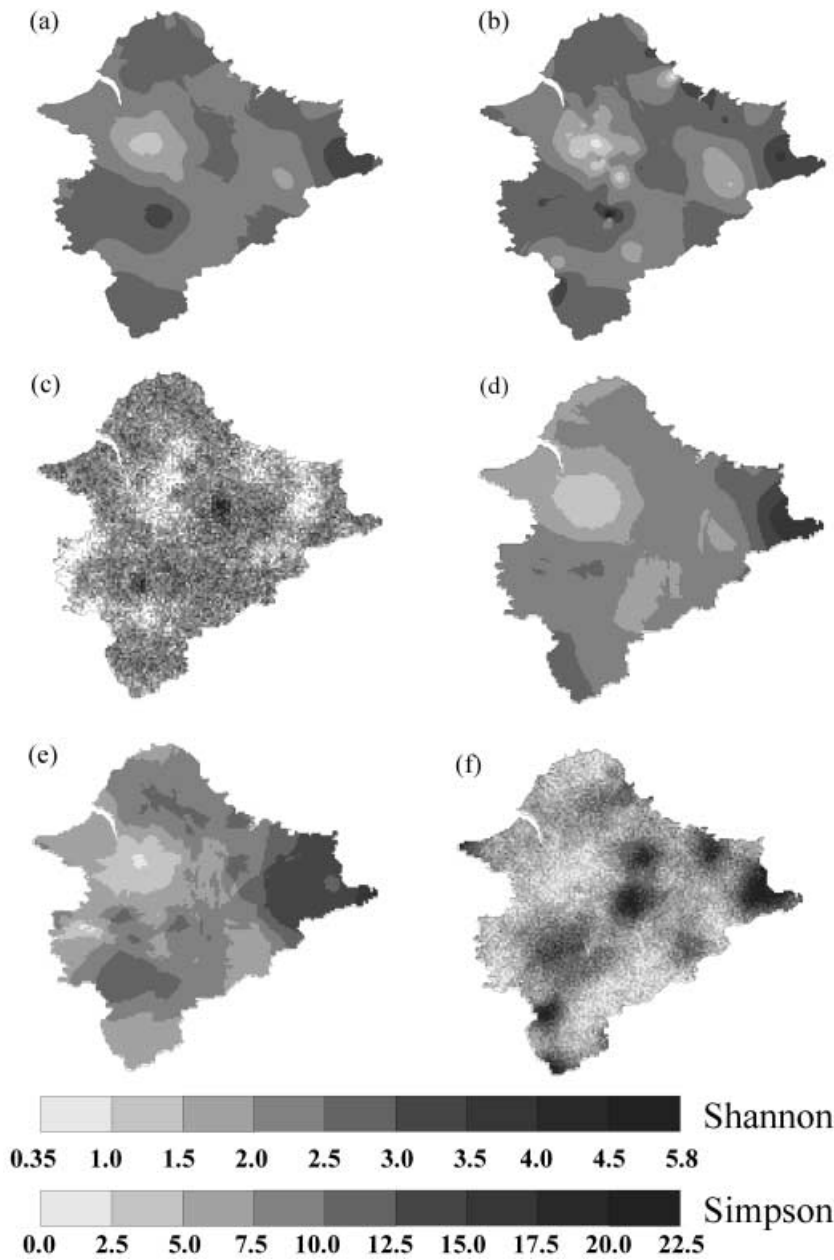
Figure 4 Spatial patterns of (a) kriging, (b) co-kriging, (c) sim no. 100 for the Shannon bird diversity index, (d) kriging, (e) co-kriging, (f) sim no. 350 for the Simpson bird diversity index (sim no.: simulated realization no.).

abundance of a species within a geographical range (Villard & Maurer, 1996). The variography results imply that the bird diversity values at the sampling sites were spatially correlated within a micro-scale (15.5 km) and a macro-scale (37.57 km). These correlations can be explained by the characteristic distribution of bird diversity within a geographical range.

The magnitude of the NDVI is related to the level of photosynthetic activity in the observed vegetation (Oindo *et al.*, 2000). Significantly, a positive correlation has been reported between bird richness and the maximum values of NDVI (Oindo *et al.*, 2000; Bailey *et al.*, 2004; Seto *et al.*, 2004). In this study, the cross-variograms of bird diversity and NDVI had spatial structures (low nugget effect and large range) that indicated two spatial correlations between bird diversity and NDVI within 15.4 km and 37.75 km, respectively, in the Taipei Basin. The variography

results also demonstrate a spatial correlation between bird diversity and primary productivity. The nested spatial structures of the Simpson reciprocal diversity index confirm that it can capture the variance of a species' distribution, and demonstrate that it is one of the most meaningful and robust diversity indices available (Magurran, 2004). Although the Simpson reciprocal index is the most widely used form of the Simpson index, Rosenzweig (1995) noted that it can exhibit a severe variance problem (Magurran, 2004). Therefore, other forms of the Simpson index should be considered in future studies. Moreover, the cross-variogram results show that, within certain ranges, NDVI values and bird diversity are highly correlated spatially. When the distances between samples are greater than the ranges of the cross-variogram models, NDVI values and bird diversity are not correlated. The variogram results of this study extend those
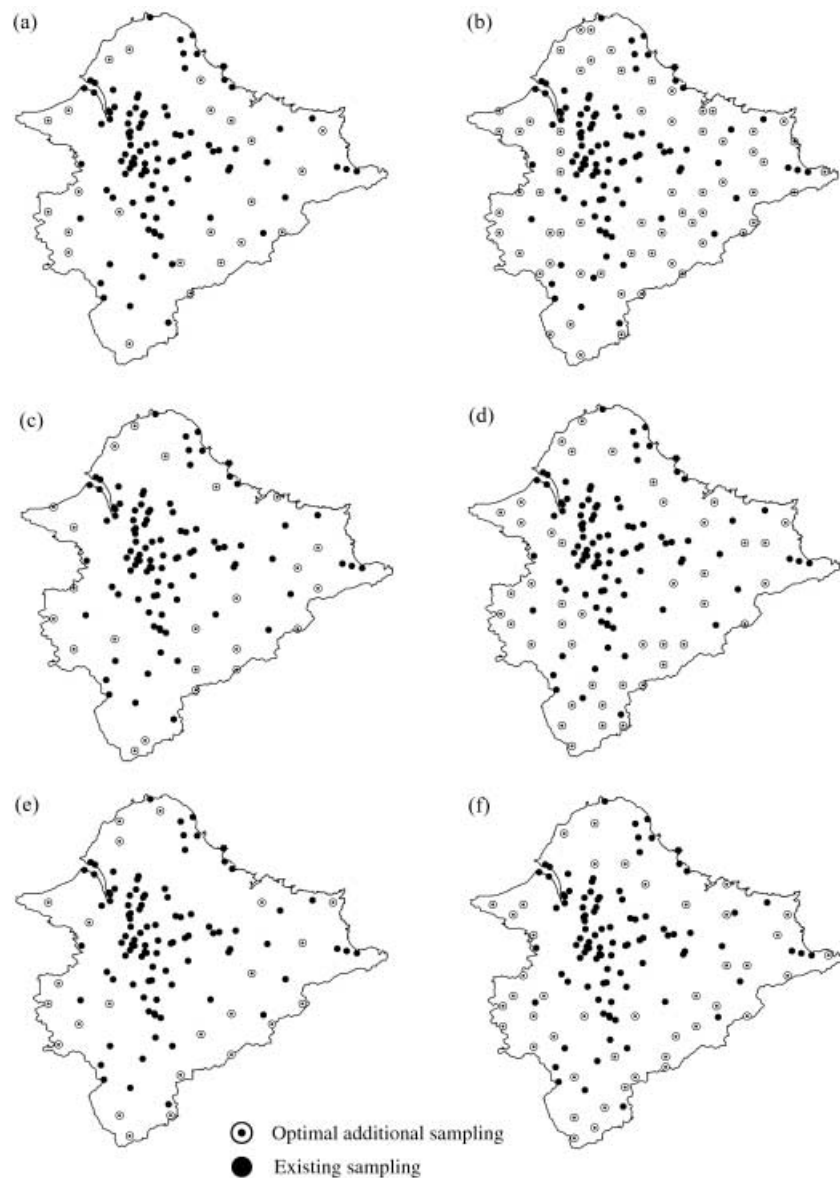
Figure 5 Additional sampling sites (a) 23 and (b) 63 for the Shannon diversity index (kriging), (c) 23 and (d) 43 for the Shannon diversity index (co-kriging), (e) 23 and (f) 43 for the Simpson diversity index (co-kriging).

⊙ Optimal additional sampling
● Existing sampling

reported by other studies. Therefore, NDVI is an important factor that should be considered in bird diversity studies within particular ranges.

Statistical analysis of the estimates and simulations showed that simulated annealing reproduced observed bird diversity statistics and provided results that matched the global statistics of bird diversity measurements more closely than those derived by co-kriging and kriging. Additionally, the statistics of estimates obtained by co-kriging with NDVI matched bird diversity better than those obtained by kriging alone. Minimizing the variance of the kriging prediction error involves smoothing the actual variability. Furthermore, kriging produces smoothed data that cannot capture the distribution or spatial changes of the observed bird diversity data, however, it may capture the local distribution of bird diversity because it yields the best unbiased linear estimation.

Scaling up is another important issue that should be considered when dealing with spatial data in fine-resolution data sets. The

effect of scaling on NDVI values may depend on the characteristics of the land cover and the size of the study area. Some studies have found that the effect of scaling from individual bands to NDVI is small and can be ignored; that is, lumped and distributed NDVI can be considered as being the same (Aman et al., 1992; Hall et al., 1992), but other studies have found that scaling is significant (Hu & Islam, 1997). Van der Meer et al. (2001) found that vegetation indices, including NDVI, were consistent with the spatial scale of observations in their five study sites. When the sum of the red and NIR reflectance of vegetation nearly equals that of soil, the spatial scaling effect of NDVI can be ignored (Zhang et al., 2006). For moderately heterogeneous surfaces, such as agricultural land, the scaling differences in NDVI can be overlooked because of the small changes in the types of land use (Tian et al., 2005). A situation where the surface is heterogeneous implies that NDVI should show more spatial scaling effects (Zhang et al., 2006). In this study, we assume that NDVI values are linearly
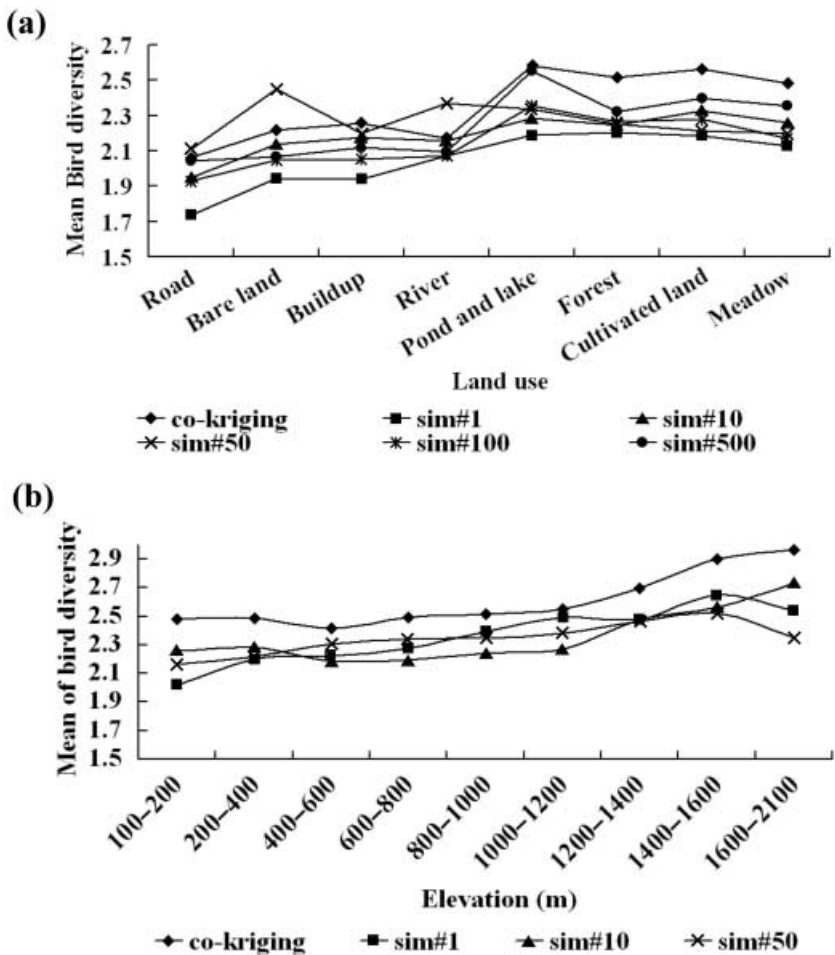
Figure 6 Estimated and simulated Shannon bird diversity indices associated with (a) land cover, (b) elevation. (sim no.: simulated realization no.).

related within a 500-m grid. Future research should investigate the relationships between NDVI values in various scales in related spatial bird diversity studies.

Species richness or diversity is generally lower in urban areas, where the avian community is dominated by a few species, often introduced ones (Beissinger & Osborne, 1982; Cam *et al.*, 2000; Marzluff *et al.*, 2001; Chace & Walsh, 2006). Regional landscape effects may be especially strong in urban areas and control the diversity and community structure at the local scale (Gehrt & Chelsvig, 2004). The richness of avian species is strongly influenced by habitat diversity and land-use patterns, although these effects appear to predominate at relatively small (local) scales (Flather, 1996; Böhning-Gaese, 1997; Diniz-Filho *et al.*, 2002). In this study, we used kriging as well as co-kriging with related variable NDVI to interpolate the spatial distribution of bird diversity. Kriged, co-kriged and simulated maps of bird diversity demonstrated low diversity in the Taipei metropolitan area, which is highly urbanized and of low elevation. The means of the estimated and simulated bird diversity in the urban vegetation land cover were greater than those for roads and built-up areas, but lower than for natural vegetation (Fig. 6). Lee *et al.* (2004) reported that, for the range of NDVI > 0.5, bird species richness showed a significant positive increase with increases in NVDI in Taiwan. They also found that urbanization decreased with elevation, NDVI

decreased with urbanization, and bird species richness decreased with urbanization and increased with increases in NVDI.

The mapping results of this study also confirm that bird species richness decreases with increasing urbanization in Taiwan. Moreover, the boundary of low values of bird diversity estimates matches the shape of the Taipei metropolitan area. The bird population in urban environments is influenced by complex combinations of environmental factors (Germaine *et al.*, 1998), such as parks, open spaces and fragmented habitats. According to the kriging, co-kriging and simulation maps, metropolitan areas have low values and exhibit certain levels of spatial variability in bird diversity. Confirming the variography results, the spatial phenomena of bird diversity maps represent the small-scale variations in bird diversity and the effects of urbanization on bird diversity at the local scale in the study area. The mean bird diversity of the co-kriging estimations and simulations (simulation no. 1, simulation no. 10, simulation no. 50) increased with elevation (Fig. 6b). These results confirm that bird species richness increases with elevation, peaks at around 1600–2000 m and then decreases with further increases in elevation reaching its minimum at the highest elevation in Taiwan (Lee *et al.*, 2004). Our estimation results also demonstrate that distribution constraints imposed by continental boundaries, together with the tendency of ranges to be continuous at larger scales of analysis,

can influence the geography of species richness, with higher levels of species richness expected in the middle of bounded domains (Jetz & Rahbek, 2002).

The quality of ecological and biological data is influenced by how the data are collected, i.e. the configuration of spatial sampling sites (Diniz-Filho *et al.*, 2003; Fortin & Dale, 2005; Rangel *et al.*, 2006). Moreover, the magnitude of the sampling selection bias varies according to the underlying spatial autocorrelation structure (Aubry & Debouzie, 2000). The sampling and mapping approaches used to estimate spatial autocorrelation and produce reliable maps can reproduce spatial patterns with lower estimation variance. We adopted an optimal sampling approach that considered spatial autocorrelation in order to obtain optimal additional sampling sites that substantially improved the kriging and co-kriging estimation of the spatial distribution of bird diversity. The marginal percentage reduction in the kriging estimation variance was approximately 27.5% when 123 extra sampling sites were added. Moreover, the co-kriging estimation variance was reduced and became extremely small when the number of additional sampling sites was increased to a sufficient level (43 additional sites). It is noteworthy that the additional sites located in areas of insufficient bird sampling with NDVI samples and high variability not only improved the co-kriging estimate but also reduced some of the spatial variance in estimating the observed bird diversity due to inadequate sampling. The optimal co-kriging variance reduction approach, which considers bird diversity sampling and NDVI values that represent vegetation biomass, is more cost-effective than the kriging variance reduction approach.

The effects of grid size are important in spatial sampling design. Based on the spatial structure (variogram), the grid's systematic sampling candidates were utilized to select additional sampling sites. Therefore, an irregular original data set may not significantly affect the selection of additional sampling sites when the grid size is small or the number of additional sites is large (i.e. the percentage of variance reduction is sufficiently small). We estimated the spatial distributions of the Shannon and Simpson bird diversity indices by using kriging, co-kriging and simulations to produce spatial maps of bird diversity in 500 m × 500 m grid systems for the entire study area. However, a very small grid size and/or an irregular sampling selection typically consume significant amounts of computational time and only marginally improve the efficiency of additional sampling. To examine the effects of the grid size on the selection of optimal samples, we selected 43 additional sampling sites for co-kriging the Shannon diversity–NDVI and another 43 for co-kriging the Simpson diversity–NDVI in cases of increasing and decreasing grid size (151 grid sampling sites and 2384 sampling sites). The optimal sampling results showed that the selected sampling sites and the percentages of variance reduction were identical for the 43 additional sites for co-kriging Shannon and co-kriging Simpson diversity cases at 151, 596 and 2384 sampling sites. The results also indicate that 43 additional sampling sites were sufficient for both the Shannon and Simpson diversity indices, even when the sampling grid size was increased or decreased by 0.25–4 times.

CONCLUSION

In studies of species richness, it is essential to use an optimal sampling scheme to estimate spatial autocorrelations and the best interpolation technique to reliably map patterns of distribution and abundance. This study demonstrated significant multiscale variations in measured bird diversity data and mapped the spatial distribution of bird diversity within the area of interest using geostatistical approaches, such as kriging, co-kriging with NDVI and conditional simulations. Although kriging, co-kriging with NDVI and simulated annealing simulation identified the patterns of bird diversity, the statistics and spatial structure of bird diversity reproduced by kriging were not as accurate as those derived by simulation techniques and co-kriging. In addition to reproducing the spatial variation of the measured bird diversity, simulated annealing simulation reflected the spatial patterns of bird diversity. Compared with global statistics and the spatial patterns of bird diversity measurements, the simulated annealing method yielded more accurate results than kriging or co-kriging. The simulated realizations were consistent in presenting the spatial patterns of observed bird diversity. Moreover, the proposed optimal sampling approach efficiently obtained additional sampling sites for measuring the amount of bird diversity, thereby improving the kriging and co-kriging estimations. The additional sampling sites derived by reducing the co-kriging variance were particularly effective. The conditional simulated realization of bird diversity can be used to assess discontinuity in an area and obtain optimal sampling selections using the proposed optimal sampling approach. Hence, the additional sampling sites should be used to augment existing sampling points in future studies of bird diversity in the Taipei Basin. Future studies should also analyse the temporal variation and sampling frequency of bird diversity to improve spatio-temporal mapping and sampling of investigated bird data. Finally, multiscale variations in the spatial distribution of the bird community as well as the anisotropic and spatial trends of investigated bird data should also be considered.

REFERENCES

Aman, A., Randriamanatena, H.P., Podaire, A. & Froutin, R. (1992) Upscale integration of normalized difference vegetation index: the problem of spatial heterogeneity. *IEEE Transactions on Geoscience and Remote Sensing*, **30**, 326–338.

Aubry, P. & Debouzie, D. (2000) Geostatistical estimate variance for the spatial mean in two-dimensional systematic sampling. *Ecology*, **81**, 543–553.

Aubry, P. & Debouzie, D. (2001) Estimate of the mean from a

two-dimensional sample: the geostatistical model-based approach. *Ecology*, **82**, 1484–1494.

Bailey, S.-A., Horner-Devine, M.C., Luck, G., Moore, L.A, Carney, K.M, Anderson, S., Betrus, C. & Fleishman, E. (2004) Primary productivity and species richness: relationships among functional guilds, residency groups and vagility class at multiple spatial scales. *Ecography*, **27**, 207–217.

Bayliss, J.L., Simonite, V. & Thompson, T. (2005) The use of probabilistic habitat suitability models for biodiversity action planning. *Agriculture, Ecosystems and Environment*, **108**, 228–250.

Beissinger, R.S. & Osborne, D.R. (1982) Effects of urbanization on avian community organization. *Condor*, **84**, 75–83.

Böhning-Gaese, K. (1997) Determinations of avian species richness at different spatial scales. *Journal of Biogeography*, **24**, 49–60.

Cam, E., Nichols, J.D., Sauer, J.R., Hines, J.E. & Flather, C.H. (2000) Relative species richness and community completeness: birds and urbanization in the mid-Atlantic states. *Ecological Applications*, **10**, 1196–1210.

Carroll, S.S. & Pearson, D.L. (2000) Detecting and modeling spatial and temporal dependence in conservation biology. *Conservation Biology*, **14**, 1893–1897.

Chace, J.F. & Walsh, J.J. (2006) Urban effects on native avifauna: a review. *Landscape and Urban Planning*, **74**, 46–69.

Chong, D.L.S., Mougin, E. & Gastellu-Etchegorry, J.P. (1993) Relating the global vegetation index to net primary productivity and actual evapotranspiration over Africa. *International Journal of Remote Sensing*, **14**, 1517–1546.

Couteron, P. & Ollier, S. (2005) A generalized, variogram-based framework for multi-scale ordination. *Ecology*, **86**, 828–834.

Crooks, K.R., Suarez, A.V. & Bolger, D.T. (2004) Avian assemblages along a gradient of urbanization in a highly fragmented landscape. *Biological Conservation*, **115**, 451–462.

Deutsch, C.V. & Cockerham, P. (1994) Practical considerations in the application of simulated annealing to stochastic simulation. *Mathematical Geology*, **26**, 67–82.

Deutsch, C.V. & Journel, A.G. (1992) *Geostatistical software library and user's guide*. Oxford University Press, New York.

Diniz-Filho, J.A.F., Bini, L.M. & Hawkins, B.A. (2003) Spatial autocorrelation and red herrings in geographical ecology. *Global Ecology and Biogeography*, **12**, 53–64.

Diniz-Filho, J.A.F., de Sant'Ana, C.E.R., de Souza, M.C. & Rangel, T.F.L.V.B. (2002) Null models and spatial patterns of species richness in South American birds of prey. *Ecological Letters*, **5**, 47–55.

Ferrer-Castán, D. & Vetaas, O.R. (2005) Pteridophyte richness, climate and topography in the Iberian Peninsula: comparing spatial and nonspatial models of richness patterns. *Global Ecology and Biogeography*, **14**, 155–165.

Ferreyra, R.A., Apezteguia, H.P., Rereno, R. & Jones, J.W. (2002) Reduction of soil water spatial sampling density using scaled semivariograms and simulated annealing. *Geoderma*, **110**, 265–289.

Fisher, R.N., Suarez, A.V. & Case, T.J. (2001) Spatial patterns in abundance of the coastal horned lizard. *Conservation Biology*, **16**, 205–215.

Flather, C.H. (1996) Fitting species-accumulation functions and

assessing regional land use impacts on avian diversity. *Journal of Biogeography*, **23**, 155–168.

Fortin, M.-J. & Dale, M.R.T. (2005) *Spatial analysis: a guide for ecologists*. Cambridge University Press, Cambridge.

Fortin, M.-J., Keitt, T.H., Maurer, B.A., Taper, M.L., Kaufman, D.M. & Blackburn, T.M. (2005) Species' geographic ranges and distributional limits: pattern analysis and statistical issues. *Oikos*, **108**, 7–17.

Foster, J., Tweed, E., Camp, R. & Woodworth, B.L. (2004) Long-term population changes of native and introduced birds in the Alaka'I Swamp Kaua'I. *Conservation Biology*, **18**, 716–725.

Gamma Design Software (2004) *GS+: geostatistics for the environmental sciences*, Version 5.0. Gamma Design Software, Plainwell, MI.

Gehrt, S.D. & Chelsvig, J.E. (2004) Species-specific patterns of bat activity in an urban landscape. *Ecological Applications*, **14**, 625–635.

Germaine, S.S., Rosenstock, S.S., Schweinsburg, R.E. & Richardson, W.S. (1998) Relationships among breeding birds, habitat, and residential development in greater Tucson, Arizona. *Ecological Applications*, **8**, 680–691.

Godet, L., Devictor, V. & Jiguet, F. (2006) Estimating relative population size included within protected areas. *Biodiversity and Conservation* (published online, DOI: 10.1007/s10531-006-9020-2).

Goovaerts, P. (1996) Stochastic simulation of categorical variables using a classification algorithm and simulated annealing. *Mathematical Geology*, **28**, 909–921.

Hall, F.C., Huemmrich, K.F., Goetz, S.J., Sellers, P.J. & Nickeson, J.E. (1992) Satellite remote sensing of surface energy balance: success, failures, and unresolved issues in FIFE. *Journal of Geophysical Research*, **97**, 19061–19089.

Holben, B.N. (1986) Characteristics of maximum-value composite images from temporal AVHRR data. *International Journal of Remote Sensing*, **7**, 1417–1434.

Hu, Z. & Islam, S. (1997) A framework for analyzing and designing scale invariate remote sensing algorithms. *IEEE Transactions on Geoscience and Remote Sensing*, **35**, 747–755.

Isaaks, E.H. & Srivastava, R.M. (1989) *An introduction to applied geostatistics*. Oxford University Press, New York.

Jetz, W. & Rahbek, C. (2002) Geographic range size and determinants of avian species richness. *Science*, **297**, 1548–1551.

Jiguet, F. & Julliard, R. (2006) Inferences from common species communities for selecting conservation areas. *Biodiversity and Conservation*, **15**, 799–815.

Lee, P.F., Ding, T.S., Hsu, F.H. & Geng, S. (2004) Breeding bird species richness in Taiwan: distribution on gradients of elevation, primary productivity and urbanization. *Journal of Biogeography*, **31**, 307–314.

Lin, Y.P. & Rouhani, S. (2001) Multiple-point variance analysis for optimal adjustment of a monitoring network. *Environmental Monitoring and Assessment*, **69**, 239–266.

Lin, Y.P., Chang, T.K. & Teng, T.P. (2001) Characterization of soil lead by comparing of sequential Gaussian simulation, simulated annealing simulation and kriging methods. *Environmental Geology*, **41**, 189–199.

Luoto, M., Virkkala, R., Heikkinen, R.K. & Rainio, K. (2004) Predicting bird richness using remote sensing in boreal agricultural-forest mosaics. *Ecological Applications*, **14**, 1946–1962.

Maes, D., Gilbert, M., Titeux, N., Goffart, P. & Dennis, R.L. (2003) Prediction of butterfly diversity hotspots in Belgium: a comparison of statistically focused and land use-focused models. *Journal of Biogeography*, **30**, 1907–1920.

Magurran, A.E. (2004) *Measuring biological diversity*, Blackwell, Oxford.

Marzluff, J.M., Bowman, R. & Donnelly, R. (2001) *Avian ecology and conservation in an urbanizing world*. Kluwer Academic Publishers, Boston, MA.

Maurer, B.A. & Taper, M.L. (2002) Connecting geographical distributions with population processes. *Ecology Letters*, **5**, 223–231.

Maurer, B.A. (1994) *Geographical population analysis: tools for the analysis of biodiversity*. Blackwell Scientific, Oxford.

Nichols, J.D., Boulinier, T., Hines, J.E., Pollock, K.H. & Sauer, J.R. (1998) Inference methods for spatial variation in species richness and community composition when not all species are detected. *Conservation Biology*, **12**, 1390–1398.

Noss, R.F. (1992) Issues of scale in conservation biology. *Conservation biology* (ed. by P.L. Fieldler and S.K. Jain), pp. 239–250. Chapman & Hall, New York.

Oindo, B.O., de By, R.A. & Skidmore, A.K. (2000) Interannual variability of NDVI and bird species diversity in Kenya. *International Journal of Applied Earth Observation and Geoinformation*, **2**, 172–180.

Passarella, G., Vurro, M., D'Agostino, V. & Barcelona, M.J. (2003) Cokriging optimization of monitoring network configuration based on fuzzy and non-fuzzy variogram evaluation. *Environmental Monitoring and Assessment*, **82**, 1–21.

Payne, L.X., Schindler, D.E., Parrish, J.K. & Temple, S.A. (2005) Quantifying spatial pattern with evenness indices. *Ecological Applications*, **15**, 507–520.

Peters, D.P.C., Herrick, J.E., Urban, D.L., Gardner, R.H. & Breshears, D.D. (2004) Strategies of ecological extrapolation. *Oikos*, **106**, 627–636.

Poulsen, B.O. (2002) Avian richness and abundance in temperate Danish forests: tree variables important to birds and their conservation. *Biodiversity and Conservation*, **11**, 1551–1566.

Rangel, T.F., Diniz-Filho, J.A. & Bini, L.M. (2006) Towards an integrated computational tool for spatial analysis in macroecology and biogeography. *Global Ecology and Biogeography*, **15**, 321–327.

Rempel, R.S. & Kushneriuk, R.S. (2003) The influence of sampling scheme and interpolation method on the power to detect spatial effects of forest birds in Ontario (Canada). *Landscape Ecology*, **18**, 741–757.

Reyers, B., van Jaarsveld, A.S. & Kruger, M. (2000) Complementarity as a biodiversity indicator strategy. *Proceedings of the Royal Society B: Biological Sciences*, **267**, 505–513.

Rosenzweig, M.L. (1995) *Species diversity in space and time.* Cambridge University Press, New York.

Rossi, R.E., Mulla, D.J., Journel, A.G. & Franz, E.H. (1992) Geostatistical tools for modeling and interpreting ecological spatial dependence. *Ecological Monographs*, **62**, 277–314.

Royle, J.A. & Rubenstein, D.R. (2004) The role of species abundance in determining breeding origins of migratory birds with stable isotopes. *Ecological Applications*, **14**, 1780–1788.

Saethersdal, M., Line, J.M. & Birks, H.J.B. (1993) How to maximize biological diversity in nature reserve selection: vascular plants and breeding birds in deciduous woodlands, western Norway. *Biological Conservation*, **66**, 131–138.

Sandström, U.G., Angelstam, P. & Mikusi'nski, G. (2006) Ecological diversity of birds in relation to the structure of urban green space. *Landscape and Urban Planning*, **77**, 39–53.

Selmi, S. & Boulinier, T. (2003) Breeding bird communities in southern Tunisian oases: the importance of traditional agricultural practices for bird diversity in a semi-natural system. *Biological Conservation*, **110**, 285–294.

Seto, K.C., Fleishman, E., Fay, J.P. & Betrus, C.J. (2004) Linking spatial patterns of bird and butterfly species richness with Landsat TM derived NDVI. *International Journal of Remote Sensing*, **25**, 4309–4324.

Tchouto, M.G.P., Yemefack, M., De Boer, W.F., De Wilde, J.J.F.E., Van Der Maesen, L.J.G. & Cleef, A.M. (2005) Biodiversity hotspots and conservation priorities in the Campo-Ma'an rain forests, Cameroon. *Biodiversity and Conservation*, **15**, 1219–1252.

Tian, J., Sun, X.-M., Zhang, R.-H., Zhu, Z.-L., Zhou, Y.-L., Xu, J.-P. & Li, Z.-L. (2005) Further validation for the scaling rule of the spatial independent variables on the basis of the image assimilation and simultaneous experiment, *IEEE Geoscience and Remote Sensing Symposium*, **1**, 673–676.

Tucker, C.J., Vanpraet, C.L., Sharman, M.J. & Van Ittersum, G. (1985) Satellite remote sensing of total herbaceous biomass production in the Senegalese Sahel: 1980–1984. *Remote Sensing of Environment*, **17**, 233–249.

Twedt, D.J., Wilson, R.R., Henne-Kerr J.L. & Hamilton, R.B. (1999) Impact of forest type and management strategy on avian densities in the Mississippi alluvial valley, USA. *Forest Ecology and Management*, **71**, 129–136.

Van der Meer F., Bakker, W., K., Scholte, A., Skidmore, S. de Jong, Clevers, J., Addink, E. & Epema, G. (2001) Spatial scale variations in vegetation indices and above-ground biomass estimates: implications for MERIS. *International Journal of Remote Sensing*, **22**, 3381–2296.

Villard, M.A. & Maurer, B.A. (1996) Geostatistics as a tool for examining hypothesized declines in migratory songbirds. *Ecology*, **77**, 59–68.

Welsh, C.J.E. & Healy, W.M. (1993) Effects of even-aged timber management on bird species diversity and composition in northern hardwoods of New Hampshire. *Wildlife Society Bulletin*, **21**, 143–154.

Wiens, J.A. (1989) Scale problems in avian censusing. *Studies in Avian Biology*, **6**, 513–521.

Yeh, M.S., Lin, Y.P. & Chang, L.C. (2006) Designing an optimal multivariate geostatistical groundwater quality monitoring network using factorial kriging and genetic algorithms. *Environmental Geology*, **50**, 101–121.

Zhang, X., G. yang, Li, Q., Li, Z.-L., Wan, H. & Guo, Z. (2006) Evaluating the fraction of vegetation cover based on NDVI spatial scale correction model. *International Journal of Remote Sensing*, **27**, 5359–5373.

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