# Spatial Error Analysis of Species Richness for a Gap Analysis Map

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#### Abstract

Variation in the distribution of species richness as a result of introduced errors of omission and commission in the Gap Analysis database for Oregon was evaluated using Monte Carlo simulations. Random errors, assumed to be independent of a species' distribution, and boundary errors, assumed to be dependent on the species' distribution, were simulated using ten rodent species. Error rates of omission and commission equal to 5 and 20 percent were used in the simulations. Indications are that predictions of species richness within a Gap Analysis database can be very sensitive to both types of errors with sensitivity to random error being much greater. Implications are that the inclusion of error modeling in applied GIS databases is critical to spatially explicit conservation recommendations.

#### Introduction

With increasing use of remote sensing and geographic information system (GIS) databases, the concern with accuracy and how to assess accuracy has grown (Goodchild and Gopal, 1989; Story and Congalton, 1986; Jansen and van der Wel, 1994). Sources of error include lack of spatial and thematic accuracy (Janssen and van der Wel, 1994), but lineage of the data and temporal accuracy can also be important (Thapa and Bossler, 1992; Lanter and Veregin, 1992). There is also a need to understand how error propagation can affect the results of a layer-based GIS (Veregin, 1989; Lanter and Veregin, 1992; Veregin, 1994).

The Gap Analysis Project (GAP), which utilizes a laverbased GIS, has emerged as a strategy for conserving biological diversity (Scott et al., 1987; Scott et al., 1993). GAP studies have been conducted on a state-by-state basis, and specific guidelines for conducting GAP studies are outlined in Ma and Redmond (1992), Scott et al. (1993), Jennings (1993), and USDI, National Biological Survey (1994). In general, the basic steps in a Gap Analysis are (1) the development of a vegetation map based on Landsat Thematic Mapper (TM) imagery and other information, (2) the development of a species distribution map based on existing range maps and other distributional data as well as the use of habitat-relationship models (see Morrison et al., 1992), and (3) combining these maps to identify habitats and species that are underrepresented in the current network of biodiversity management areas. One parameter of interest in a Gap Analysis is a map of species richness which is then combined with additional map layers containing land-management and ownership in-

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formation to identify "gaps" in the protection of species-rich areas, i.e., identify regions of high species richness (biodiversity) that are not currently within protected areas (see Scott *et al.*, 1993).

The most common procedures used in Gap Analyses to predict species occurrence are based on the intersection of coarse species range information as reflected in vegetation association and county-of-occurrence data (Scott *et al.*, 1993; Butterfield *et al.*, 1994). As such, the habitat selection problem is simplified in only being concerned with predicting species presence/absence. Although simpler, defining and characterizing the geographical range of a species is controversial and very imprecise (Rapoport, 1982).

Given these procedures, GAP studies require reasonably accurate habitat-type maps and sound habitat-relationship models. Unfortunately, there has been little work on quantifying the sensitivity of GAP results to errors associated with these basic components. It is widely recognized that sensitivity analyses and validation of habitat-based predictions of species occurrence are necessary to evaluate model performance (Lyon et al., 1987; Scott et al., 1993), yet few specieshabitat relationship databases have been evaluated (Berry, 1986). Stoms (1992) has examined the sensitivity of GAP studies to the effects of habitat-type map generalization by varying minimum mapping units, but additional study aimed at exploring how habitat-type errors impact GAP results remains to be done. Investigations of habitat-relationship models sometimes cast serious doubt on their reliability, which raises concerns regarding the performance of these models in GAP studies. For example, a sensitivity analysis of a habitatrelationship model for the California condor (Gymnogyps californianus) indicated that the model was relatively robust to uncertainties in input data (Stoms et al., 1992). But Block et al. (1994) tested habitat-relationship models for relatively well studied taxa such as amphibians, reptiles, birds, and small mammals in California and found that agreement between predictions and residency status ranged from 48 to 78 percent for two databases, with errors of omission (species were not predicted but in fact were observed) and commission (species were predicted but were not observed) ranging from 6 to 39 percent and 20 to 44 percent, respectively.

It is inconceivable that either absolutely error-free habitat-type maps or perfect habitat-relationship models can be produced. Thus, GAP studies must incorporate some error from these sources. How these errors affect GAP results and interpretation of these results has not been thoroughly explored.

The objective of this study was to investigate how uncer-

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tainty in vertebrate species distributions would affect results of a contemporary GAP study. Specifically, we investigated how spatially independent errors and spatially dependent errors in species distribution would affect the distribution of species richness as measured by area. Note that no attempt was made to identify the cause of these errors. This study simply investigated results of errors likely to exist in many Gap Analysis projects, regardless of source.

### Methods

The Oregon GAP GIS database was used in this study (T. O'Neill, pers. comm., Oregon Department of Fish and Wildlife). The Oregon data consisted of a digital vegetation map that divided the state into over 12,000 vegetation polygons based on vegetation cover types (which were identified using satellite imagery), physiographic provinces (based on Puchy and Marshall (1993)), and political boundaries. The Oregon data also included habitat-relationship information for over 800 wildlife species that classified species occurrence based on vegetation type, physiographic region, and political subdivision data layers. By combining these digital layers, it was possible to construct a species distribution layer showing the presence or absence of each species in each vegetation polygon. Presence or absence data was then used to generate a map of vertebrate species richness.

The fundamental parameter manipulated in this study was the presence or absence of a particular species in a particular polygon based on vegetation/physiographic region/political subdivision. Four possible outcomes are possible from an accuracy assessment. If a species is actually present in a polygon and the GAP procedure predicts species presence, then no error occurs. Similarly, if a species is not present in a polygon and the procedure predicts species absence, then no error occurs. However, if a species is actually present in a polygon but the procedure indicates species absence, then an error of omission occurs. An error of commission occurs if, in fact, a species is not present in a polygon, but the procedure indicates species presence.

To evaluate the effect of errors of omission and commission on a GAP study, data received from the Oregon Department of Fish and Wildlife were considered "truth," i.e., errors were introduced into the Oregon database and estimated effects of these introduced errors were compared to the original Oregon GAP database. The independent variable was the level of uncertainty (errors of omission and commission) and the dependent variable was the distribution of species richness measured as total area in km<sup>2</sup>.

Monte Carlo computer simulation was used to simulate effects of error on vertebrate species distribution maps using ARC/Info and simulation routines written in C. Each iteration of the Monte Carlo simulation randomly introduced a predefined amount of error into the species distribution map, thereby producing a new error-filled species distribution map. Areas of vertebrate species richness in the error-filled map were then compared to areas of vertebrate species richness in the original map in order to quantify changes in the distribution of species richness as a function of the introduced errors. Two different techniques were used to introduce error into the species distribution map. The first technique introduced spatially independent errors (random errors) throughout the vegetation map without regard to the range of any particular wildlife species. Thus, any polygon in the habitat map where species X did occur was a candidate for an error of omission of species X and any polygon where species X did not occur was a candidate for an error of commission of species X. An example of these types of errors are inaccuracies of vegetation mapping - errors in such maps are unlikely to be dependent upon ranges of the wildlife species found in the mapped region.



Figure 1. Three physiographic regions of Oregon used in the simulations (Puchy and Marshall, 1993). Areas with a species richness  $\geq 5$  are illustrated in black.

The second technique introduced spatially dependent errors (*boundary errors*) along edges of each species "true" range, where the true range was assumed to be the species' range as determined by the original Oregon data. Thus, spatially dependent errors only occurred along boundaries of the species' range, with errors of omission occurring in polygons within the true range of the species and errors of commission occurring in polygons just outside the true range. Errors of this sort are likely to occur in GAP studies if inaccuracies in species predictions from habitat-relationship models occur at the boundary of a species range, or if there is difficulty associated with precisely defining boundaries of vegetation polygons.

Total area for each level of species richness was evaluated for boundary and random error at simulated error rates of 5 percent and 20 percent. These rates were within the range found in other studies (cf. Flather *et al.*, 1997). For both random and boundary errors, we evaluated the hypothesis:

 $H_0$ : Errors of omission and commission of 5 percent and 20 percent introduce no change in the distribution and amount of total area of vertebrate species richness present in the results of the Oregon GAP.

We focused on "biological" significance rather than "statistical" significance (e.g., using Student's T-test), because statistical significance could have been attained by merely increasing the number of iterations for each simulation.

The Monte Carlo simulations were extremely time consuming and required large amounts of computer storage space; therefore, we subsetted the original data as follows. A smaller vegetation map was extracted from the original data and a subset of the 800 available species was chosen for analysis. The smaller map consisted of three of the 12 physiographic provinces (East Slope Cascades, Basin and Range, and Owyhee Uplands) from the original map and contained 3,238 vegetation polygons (Figure 1). We chose a taxonomically similar subset of the 800 available species. The selected species subset consisted of ten rodents: mountain beaver (Aplodontia rufa), deer mouse (Peromyscus maniculatus), yellow-pine chipmunk (Tamias amoenus), white-tailed antelope squirrel (Ammospermophilus leucurus), northern flying squirrel (Glaucomys sabrinus), California kangaroo rat (Dipodomys californicus), desert woodrat (Neotoma lepida), heather vole (Phenacomvs intermedius), water vole (Micotus richardsoni), and sagebrush vole (Lemmiscus curtatus). The reduced data sets were joined to create a digital map showing the distributions of each of the ten rodents throughout the study region, which then became the basis for the Monte Carlo simulations (Figure 1). The original base map for the three physiographic regions included approximately 89,195 km<sup>2</sup>. Approximately 82,904 km<sup>2</sup> (93 percent) of the base map had species richness of 0 to 4 and 6,291 km<sup>2</sup> (7 percent) had species richness of 5 or 6. No polygons had a species richness  $\geq$  7 for the original map. Subsets chosen were arbitrary, and implications of the choice of regions and species are addressed in the discussion section.

Each iteration of the Monte Carlo simulation introduced a predefined level of either random or boundary error into the original Oregon data map. Error amounts were measured as percentages. A 5 percent commission error for species X meant that each polygon where species X did not occur had a 5 percent chance of having species X introduced. A 5 percent omission error for species X meant that each polygon where species X occurred had a 5 percent chance of having species  $\hat{X}$  removed. Errors of commission and omission were simultaneously simulated at the chosen error level. For both random and boundary error, the simulation methods were identical except that, in the boundary-error simulations, errors could only occur in appropriate regions along edges of the various species ranges, whereas random errors could take place anywhere within the study area. Appropriate regions for boundary error of omission for species X were identified by finding the total area comprising the species' range and symmetrically contracting the boundary of the area until 90 percent of the original area remained. The region between the original boundary and the 90 percent contracted-area boundary were deemed to be suitable for errors of omission. Appropriate regions for boundary errors of commission were then identified by expanding the original species X range boundary by the same amount as it was decreased in the previous step and deeming the region between the original and expanded boundaries the appropriate region for commission errors.

The two error rates were used for both random and boundary error cases, resulting in a total of four Monte Carlo simulations. Each simulation consisted of 50 iterations, and each iteration produced a map with species richness for each polygon. The total area by species richness class (i.e., 0, 1, ..., 10 species) was recorded for each iteration. These results were then compared to the results for the original Oregon GAP database. Identification of areas of high species richness (hot spots) is one of the goals of GAP, but rather than arbitrarily defining some level of species richness as "hot" (e.g., polygons with more than five species), we present results based on changes in the amount of area for each species richness class. In the case of random error, where expected values for changes in area can be calculated, error matrices (Story and Congalton, 1986) are used to illustrate the results.

### Results

#### Random Error

When random error was simulated, areas of species richness changed substantially when compared to the original map (Figure 2). With a 5 percent random error, total area decreased for species richness of 0, 1, and 4 by an average of 21 to 30 percent and increased for species richness of 2, 3, 5, and 6 by an average of 35 to 158 percent. With a 20 percent random error, the same species richness categories decreased and increased in area, but the effects were magnified with decreases ranging from 50 to 72 percent and increases ranging from 57 to 506 percent. For both error rates, there was an increase in total average area for species richness of 7 from 0 km<sup>2</sup> in the original data to 292 km<sup>2</sup> and 2878 km<sup>2</sup> for 5 percent and 20 percent error, respectively.

Based on the original species richness categories and a



simulated 5 percent error of omission and commission for each category, an error matrix, using the expected values for the binomial distribution, can be calculated (Table 1). Simulated and expected results based on area of species richness were very similar, as can be seen by comparing the Expected Row Total and Simulated Results. Overall theoretical map accuracy was 63 percent and errors of omission range from 35 to 40 percent while errors of commission range from 12 to 76 percent. The high variability in errors of commission are largely dependent on the area size of the nearest species rich category. For example, commission error for species richness of 3 was 63 percent. This result is largely due to the fact that species richness equal to 4 in the original map covered 45,667 km<sup>2</sup>; consequently, a larger portion, 5,901 km<sup>2</sup>, was converted to a species richness of 3 after the simulations. The expected error matrix when a 20 percent error of omission and commission is simulated had an overall map accuracy of only 28 percent with errors of omission ranging from 40 to 83 percent and errors of commission ranging from 23 to 95 percent (Table 2).

Figure 3 illustrates how the total area with a species richness of 4 and 5 varies for the 50 repetitions of the random error simulations (a species richness of 4 and 5 were chosen arbitrarily for purposes of illustration, and variability in distributions were similar for other species richness categories). Coefficient of variation of the total average area for species richness of 4 was 5.7 percent and 10.1 percent for random error of 5 and 20 percent, respectively. Coefficient of variation of the total average area for species richness of 5 was 13.8 percent and 12.3 percent for random error of 5 and 20 percent, respectively.

#### **Boundary Error**

For boundary error simulations, average areas of species richness changed little when compared to the change due to random error (Figure 2 versus Figure 4). Total area decreased on average for a species richness of 0, 1, 4, 5, and 6 by 1 to 21 percent and increased on average for species richness of 2 and 3 by 5 and 8 percent when a 5 percent spatial error was simulated. With a 20 percent boundary error, the same spe-

TABLE 1.	ERROR MATRIX (STORY	AND CONGALTON, 1	1986), BAS	ED ON TH	E EXPECTED VAL	UES FOR THE BI	NOMIAL DISTRIBUTION	, FOR SPECIES RICHN	ESS BY AREA WHEN
5 PERCEN	T ERRORS OF OMISSION	AND COMMISSION	ARE SIMULA	TED WITH	THE ORIGINAL O	REGON GAP ANA	LYSIS DATABASE COM	NSIDERED TRUTH (I.E.,	"COLUMN TOTAL"
IS THE	ACTUAL AREA BY SPECI	ES RICHNESS IN TH	E "TRUE"	MAP AND,	"Row Totals"	ARE THE AVER	AGE SPECIES RICHNE	SS EXPECTED AND ACT	iual After 50
					SIMULATIONS)	, and a second			

			Original 1							
Expected Species Richness	0	1	2	3	4	5	6	Expected Row Total	Actual Row Total	Commission Error
0	1746	516	10	1	0	0	0	2273	2307	0.23
1	919	10053	387	59	16	0	0	11434	11462	0.12
2	218	4698	3799	1143	459	4	0	10321	10187	0.63
3	31	984	1561	7520	5901	81	3	16081	16045	0.53
4	3	121	285	2683	29180	783	37	33092	33420	0.12
5	0	10	30	419	8875	3098	283	12715	12499	0.76
6	0	1	2	37	1153	783	929	2905	2968	0.68
7	0	0	0	2	80	81	188	351	292	0.46
8	0	0	0	0	3	4	15	22	14	0.32
9	0	0	0	0	0	0	1	1	1	
10	0	0	0	0	0	0	0	0	0	
Column Total	2917	16383	6074	11864	45667	4834	1456	89195	89195	
Omission Error	0.40	0.39	0.37	0.37	0.36	0.36	0.36		Map Accuracy	0.63

cies richness categories decreased and increased in area, but effects were larger with decreases ranging from 4 to 25 percent and increases ranging from 16 to 29 percent.

When 50 repetitions were simulated with boundary errors, distributions in total area for species richness of 4 and 5 were much less variable than for random error (Figure 3 versus Figure 5). Coefficient of variation of the total average area for species richness of 4 was 0.34 percent and 1.20 percent for spatial error of 5 and 20 percent, respectively. Coefficient of variation of the total average area for species richness of 5 was 0.18 percent and 0.65 percent for boundary error of 5 and 20 percent, respectively.

#### Discussion

The two types of errors simulated in this study can be viewed as extremes of a continuum. *A priori*, it is reasonable to expect that our method of simulating random error throughout the vegetation map without regard to a species range should have the greatest effect on determining areas of high species richness because errors of omission and commission are allowed to enter in areas where animals might obviously not exist. Alternatively, the method for simulating boundary error should result in fewer changes in areas associated with high species richness because our method assumes that animals have some definable range, and errors in omission and commission can only occur within a restricted area of the range boundary. Our implementation of boundary error is conservative, though, because restricting errors to a region of  $\pm 10$  percent of a species' range is of a finer scale than Gap Analyses which predict species occurrence at the resolution of polygons defined by vegetation type, physiographic region, and county.

Wildlife data used in Gap Analyses are compiled from a variety of sources such as range maps, state Natural Heritage program databases, museum specimens, and other available information and literature (Scott *et al.*, 1993). The types and

TABLE 2. ERROR MATRIX (STORY AND CONGALTON, 1986), BASED ON THE EXPECTED VALUES FOR THE BINOMIAL DISTRIBUTION, FOR SPECIES RICHNESS BY AREA WHEN 20 PERCENT ERRORS OF OMISSION AND COMMISSION ARE SIMULATED WITH THE ORIGINAL OREGON GAP ANALYSIS DATABASE CONSIDERED TRUTH (I.E., "COLUMN TOTAL" IS THE ACTUAL AREA BY SPECIES RICHNESS IN THE "TRUE" MAP AND "ROW TOTALS" ARE THE AVERAGE SPECIES RICHNESS EXPECTED AND ACTUAL AFTER 50 SIMULATIONS).

			Original							
Expected Species Richness	0	1	2	3	4	5	6	Expected Row Total	Actual Row Total	Commission Error
0	313	440	41	20	19	1	0	834	862	0.62
1	783	2748	408	274	335	11	1	4560	4543	0.39
2	881	4947	1376	1400	2316	94	10	11024	11154	0.88
3	587	4535	1911	3270	7955	432	58	18748	18658	0.83
4	257	2525	1438	3617	14080	1107	199	23223	22785	0.39
5	77	37	662	2228	12545	1546	400	18378	18911	0.92
6	16	4	196	832	6239	1107	448	9063	8811	0.95
7	2	0	38	194	1831	432	253	2787	2878	0.91
8	0	0	5	28	316	94	74	521	548	0.86
9	0	0	0	2	30	11	11	54	45	0.80
10	0	0	0	0	1	1	1	3	1	0.67
Column Total	2916	16381	6075	11865	45667	4836	1455	89195	89196	
Omission Error	0.89	0.83	0.77	0.72	0.69	0.68	0.69		Map Accuracy	0.27



Figure 3. Distribution of total area for 50 simulations summed over all polygons when species richness equals 4, (A) 5 percent and (C) 20 percent random error, and when species richness equals 5, (B) 5 percent and (D) 20 percent random error.

magnitudes of errors associated with each of these sources could be quite variable, but it is conceivable that lineage, spatial, thematic, and temporal errors exist (Thapa and Bossler, 1992; Lanter and Veregin, 1992; Williams, 1996). Random errors that can arise during vegetation mapping (Thapa and Bossler, 1992) may propagate through habitat-based models of species occurrence in a manner similar to our implementation of random errors. Boundary errors might arise because the functional relationships used in the wildlife habitat relationship models are biased. Consequently, errors that exist in a GAP data set are probably a combination of random and boundary errors.

In our simulations, random error resulted in large changes in species rich areas. Failure to recognize this type of error could result in extremely unreliable information. Changes in species richness areas due to boundary error were much smaller relative to the size of the base map area. Still, these small changes could be important ecologically, politically, and economically when making spatially explicit conservation recommendations.

In a GAP study, one might define an area of high species richness. For example, the highlighted area in Figure 1 represents areas with a species richness of 5 or greater (approximately 6,291 km<sup>2</sup>). The area subject to change under the boundary error simulations would be  $\pm$  10 percent, or approximately 1,300 km<sup>2</sup>. The simulations resulted in a 9 and 33 percent decline in area (118-km<sup>2</sup> and 428-km<sup>2</sup> decline for a 5 and 20 percent error rate, respectively) when focusing exclusively on the 1,300-km<sup>2</sup> affected area. As suggested by Scott *et al.* (1993), if the GAP study is used to make a preliminary determination of species rich areas, the implications of not considering random and boundary errors could result in focusing the preliminary study on a large number of incorrect areas.

Error rates for omission and commission found in Block et al. (1994) and Edwards et al. (1996) suggest that the 5 and 20 percent error rates used in this study are not unreasonable (and compared to some studies, our rates may be conservative). Both types of errors might directly be attributable to the vegetation layer, wildlife habitat relationship models, or from inaccuracies in the species database due to poor data or insufficient sampling. In addition, simple habitat relationship models do not account for community and ecosystem processes that may be important in determining species occurrences (Conroy and Noon, 1996).

An alternative to using species richness, termed "setcoverage" or "representativeness," has been proposed for GAP (Wright et al., 1994; Kiester et al., 1996; Scott et al., 1996). A prioritization analysis defines the minimum number of polygons needed to ensure that all species are represented at least once in the entire area (Margules et al., 1988). This approach may lead to a more comprehensive representation of species within a state, but it probably will do nothing to mitigate the effects of errors in omission and commission. Recently, Freitag et al. (1996) compared the selection of conservation reserve areas based on species richness using an iterative reserve selection algorithm (set-coverage). They compared the results when reserve selection was based on a species distributional database taken from published range maps versus an actual species records database. Freitag et al. (1996, p. 695) stated that "... the real problem revolves around data input. Should we accept and tolerate a higher degree of false-positives [commission errors] (as represented by the overestimates of distribution maps) or false-negatives [omission errors] (found in the less well surveyed grid squares of the point data base)?" They did not evaluate effects of these errors on set coverage, but we hypothesize that set-coverage methods may be more sensitive to such errors, partially because the approach may more closely emulate random error.





#### km<sup>2</sup> (x 100)

Figure 5. Distribution of total area for 50 simulations summed over all polygons when species richness equals 4, (A) 5 percent and (C) 20 percent boundary error, and when species richness equals 5, (B) 5 percent and (D) 20 percent boundary error.

As was the case with this study, using simulation modeling to evaluate GIS applications can be very computer intensive (Veregin, 1994). As such, we only used a portion of the entire state of Oregon GAP database and within this region we arbitrarily chose a subset of ten species for these simulations. Nevertheless, we argue that the general pattern of our results would not change substantially if a different region or a different subset of species were used. The trends should be the same, with some species resulting in less variation and some resulting in more variation. Alternatively, had the entire database been used, we predict the impact would be greater, with larger variations in species richness over the entire Oregon map as a result of error propagating through over 800 species. For example, Veregin (1989, pp. 12-13) illustrates how composite map error increases as the number of data layers increases, and this would be the case as each additional species layer is included in the analysis.

Many authors have argued for incorporation of error modeling into GIS (Chrisman, 1989; Veregin, 1989; Lanter and Veregin, 1992; Veregin, 1994). As Lanter and Veregin have stated, "In such applications input data quality is often not ascertained ... . Such omissions do not imply that errors are of such low magnitude that they can simply be ignored." Without some indication of the sensitivity of GAP to the types of errors evident in GIS databases, choosing areas based on attributes derived from mapped information will prove difficult. Incorporation of error modeling or sensitivity analysis capabilities into a GAP seems essential; otherwise, users of GAP will be unaware of the uncertainty associated with their analyses.

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### References

- Berry, K.H., 1986. Introduction: Development, testing, and application of wildlife-habitat models, Wildlife 2000: Modeling Habitat Relationships of Terrestrial Vertebrates (J. Verner, M.L. Morrison, and C.J. Ralph, editors), University of Wisconsin Press, Madison, pp. 3–4.
- Block, W.M., M.L. Morrison, J. Verner, and P.N. Manley, 1994. Assessing wildlife-habitat-relationships models: A case study with California oak woodlands, *Wildlife Society Bulletin* 22:549–561.
- Butterfield, B.R., B. Csuti, and J.M. Scott, 1994. Modeling vertebrate distributions for Gap Analysis, *Mapping the Diversity of Nature* (R.I. Miller, editor), Chapman and Hall, New York, N.Y.
- Chrisman, N.R., 1989. Modeling error in overlaid categorical maps, *The Accuracy of Spatial Databases* (M. Goodchild and S. Gopal, editors), Taylor and Francis, New York, N.Y., pp. 21–34.
- Conroy, M.J., and B.R. Noon, 1996. Mapping of species richness for conservation of biological diversity: Conceptual and methodological issues, *Ecological Applications*, 6:763–773.
- Edwards, T.C., Jr., E.T. Deshler, D. Foster, and G.G. Moisen, 1996. Adequacy of wildlife habitat relation models for estimating spatial distributions of terrestrial vertebrates, *Conservation Biology*, 10:263–270.
- Flather, C.H., K.R. Wilson, D.J. Dean, and W.C. McComb. 1997. Mapping diversity to identify gaps in conservation networks: of indicators and uncertainty in geographic-based analyses, *Ecological Applications*, 7:531–542.
- Freitag, S., A.O. Nichols, and A.S. van Jaarsveld, 1996. Nature reserve selection in the Transvaal, South Africa: What data should we be using? *Biodiversity and Conservation*, 5:685–698.
- Goodchild, M., and S. Gopal (editors), 1989. The Accuracy of Spatial Databases, Taylor and Francis, New York, N.Y.
- Jennings, M.D., 1993. Natural Terrestrial Cover Classification: Assumptions and Definitions, Gap Analysis Tech. Bull. 2, U.S. Fish and Wildlife Service, Idaho Cooperative Fish and Wildlife Research Unit, Moscow, 28 p.
- Jensen, L.L.F., and F.J.M. van der Wel, 1994. Accuracy assessment of satellite derived land-cover data: a review, *Photogrammetric En*gineering & Remote Sensing, 60:419–426.
- Kiester, A.R., J.M. Scott, B. Csuti, R.F. Noss, B. Butterfield, K. Sahr, and D. White, 1996. Conservation prioritization using GAP data, *Conservation Biology*, 10:1332–1342.
- Lanter, D.P., and H. Veregin, 1992. A research paradigm for propagating error in layer-based GIS, *Photogrammetric Engineering & Remote Sensing*, 58:825–833.
- Lyon, J.G., J.T. Heinen, R.A. Mead, and N.E.G. Roller, 1987. Spatial data for modeling wildlife habitat, *Journal of Surveying Engineering*, 113:88–100.
- Ma, Z., and R.L. Redmond, 1992. Building Attribute Tables for Raster GIS Files with ARC/INFO, Gap Analysis Tech. Bull., National GAP Analysis Research Project, U.S. Fish and Wildl. Serv., Idaho Coop. Fish and Wildl. Res. Unit, Univ. Idaho, Moscow, 2 p.
- Margules, C.R., A.O. Nicholls, and R.L. Pressey, 1988. Selecting network reserves to maximise biological diversity, *Biological Con*servation, 43:63–76.
- Morrison, M.L., B.G. Marcot, and R.W. Mannan, 1992. Wildlife-Habi-

tat Relationships: Concepts and Applications, University of Wisconsin Press, Madison, 343 p.

- Puchy, C.A., and D.B. Marshall, 1993. Oregon Wildlife Diversity Plan, Second Edition, Oregon Fish and Wildlife Commission and Oregon Department of Fish and Wildlife.
- Rapoport, E.H., 1982. Areography: Geographical Strategies of Species, Pergamon Press, New York, N.Y., 269 p.
- Scott, J.M., B. Csuti, J.D. Jacobi, and J.E. Estes, 1987. Species richness: a geographic approach to protecting future biological diversity, *BioScience*, 37:782–788.
- Scott, J.M., F. Davis, B. Csuti, R. Noss, B. Butterfield, C. Groves, H. Anderson, S. Caicco, F. D'Erchia, T.C. Edwards, Jr., J. Ulliman, and G. Wright, 1993. Gap Analysis: A Geographic Approach to Protection of Biological Diversity, Wildlife Monograph 123, 41 p.
- Scott, J.M., M. Jennings, and R.G. Wright, 1996. Landscape approaches to mapping biodiversity (in Letters to the Editor), Bio-Science, 46:77-78.
- Stoms, D.M., 1992. Effects of habitat map generalization in biodiversity assessment, *Photogrammetric Engineering & Remote* Sensing, 58:1587–1591.
- Stoms, D.M., F.W. Davis, and C.B. Cogan, 1992. Sensitivity of wildlife habitat models to uncertainties in GIS data, *Photogrammetric Engineering & Remote Sensing*, 58:843–850.

- Story, M., and R.G. Congalton, 1986. Accuracy assessment: a user's perspective. *Photogrammetric Engineering & Remote Sensing*, 52:397–399.
- Thapa, K., and J. Bossler, 1992. Accuracy of spatial data used in geographic information systems, *Photogrammetric Engineering & Remote Sensing*, 58:835–841.
- U.S. Department of the Interior, National Biological Survey, 1994. A Handbook for Gap Analysis: A Geographical Approach to Planning for Biological Diversity, U.S. Department of the Interior, National Biological Survey, Washington, D.C.
- Veregin, H., 1989. Error modeling for the map overlay operation, *The Accuracy of Spatial Databases* (M. Goodchild and S. Gopal, editors), Taylor and Francis, New York, N.Y., pp. 3–18.
- —, 1994. Integration of simulation modeling and error propagation for the buffer operation in GIS, *Photogrammetric Engineering & Remote Sensing*, 60:427–435.
- Williams, B.K., 1996. Assessment of accuracy in the mapping of vertebrate biodiversity, *Journal of Environmental Management*, 47: 269–282.
- Wright, R.G., J.G. MacCracken, and J. Hall, 1994. An ecological evaluation of proposed new conservation areas in Idaho: Evaluating proposed Idaho National Parks, *Conservation Biology*, 7:207– 216.
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