

# Sensitivity of Wildlife Habitat Models to Uncertainties in GIS Data

David M. Stoms, Frank W. Davis, and Christopher B. Cogan

Department of Geography, University of California, Santa Barbara, CA 93106

**ABSTRACT:** Decision makers need to know the reliability of output products from GIS analysis. For many GIS applications, it is not possible to compare these products to an independent measure of "truth." Sensitivity analysis offers an alternative means of estimating reliability. In this paper, we present a GIS-based statistical procedure for estimating the sensitivity of wildlife habitat models to uncertainties in input data and model assumptions. The approach is demonstrated in an analysis of habitat associations derived from a GIS database for the endangered California condor. Alternative data sets were generated to compare results over a reasonable range of assumptions about several sources of uncertainty. Sensitivity analysis indicated that condor habitat associations are relatively robust, and the results have increased our confidence in our initial findings. Uncertainties and methods described in the paper have general relevance for many GIS applications.

## INTRODUCTION

GEOGRAPHIC INFORMATION SYSTEMS (GIS) are playing an increasingly important role in conservation biology and wildlife management because they provide an efficient means for modeling potential distributions of species and habitats (Davis *et al.*, 1990). The usefulness of GIS technology is now limited more by data availability and quality and by the reliability of habitat preference models than by technological obstacles. Because expensive and politically sensitive decisions are being based on GIS analysis, it is important to have a means of characterizing the uncertainty of GIS output products. Analytical models of spatial error propagation are often not applicable in such cases. Sensitivity analysis has been recommended as an alternative means of estimating reliability (Lyon *et al.*, 1987; Openshaw, 1989; Lodwick *et al.*, 1990). Whereas error analysis compares output data with an independent measure of "truth," GIS sensitivity analysis compares the initial output product to alternative results derived from data that have been perturbed in some controlled, systematic way (Lodwick *et al.*, 1990). The goal is to determine whether the output seems valid over a set of reasonable assumptions about the nature of uncertainty (Openshaw, 1989).

The objective of this paper is to describe a sensitivity analysis of derived habitat associations to typical uncertainties in GIS observation and habitat data. We begin with a brief review of GIS habitat modeling and how sensitivity to typical uncertainties has been evaluated. Next we describe a habitat analysis of historical observations of the endangered California condor (*Gymnogyps californianus*). The two key GIS layers in the database and their potential errors are summarized. Then we describe the methods used to derive baseline habitat associations and the data manipulation that generated alternative data sets for the sensitivity analysis. Although the context is habitat modeling, the uncertainties encountered are typical of many GIS applications, and the sensitivity analysis methods can be employed both for management decision making and for scientific research.

## HABITAT MODELING AND SENSITIVITY ANALYSIS

GIS modeling of species' habitat associations is one form of land suitability analysis. Two approaches have generally been utilized, depending on objectives and data availability. The deductive approach extrapolates known habitat requirements to the spatial distributions of habitat factors. If more than one spatial data layer is involved, they are usually combined by either logical or arithmetic map overlay operations (e.g., Davis and Goetz, 1990). A habitat suitability index can also be calcu-

lated from the spatial configuration of a single data layer (Mead *et al.*, 1981). The GIS output product of the deductive approach is a map depicting levels of habitat suitability. This map can guide decisions regarding land acquisition or habitat preservation priorities, land management practices, or sites for reintroduction of endangered species. It should be noted that the model only identifies "potential" habitat, but does not imply that the species is actually present at a given location.

In many situations, the habitat requirements are not well-known, and a GIS is used to induce them from a sample of observations of the species georeferenced to one or more resource factor maps. Output in the inductive case is a tabular or textual summary describing the factors most significantly associated with the observed distribution of the species. Associations can be derived either from univariate or multivariate statistical analysis such as classification trees (Walker and Moore, 1988; Davis and Dozier, 1990). This inductive approach is more common in scientific research designed to increase our understanding of species distributions (Walker and Moore, 1988; Ferrier and Smith, 1990), but the results can be extrapolated to predict the spatial distribution of suitable habitat using the deductive method for habitat management purposes (Agee *et al.*, 1989).

In both approaches, there will always be uncertainty in the GIS output product due to errors and uncertainties in data inputs. Quality of the outputs is affected by the accuracy of the maps of habitat factors, which is influenced by the interaction of minimum mapping unit (MMU) size, resolution of source data, map generalization, analyst skill, and many other factors (Lodwick *et al.*, 1990). Tracking the propagation of errors as several map layers are combined into a habitat suitability map is often beyond our capabilities. The description of habitat preferences in the deductive approach can be inaccurate, usually to an unknown degree, and even the best model can only take into account a simplified set of factors that determine species' distributions. Stochastic processes, such as disturbance, weather fluctuations, or population dynamics, can prevent otherwise suitable habitat from being occupied. Similarly, field sampling to assess the accuracy of a habitat suitability map is hindered by the relatively small sample units of short duration in relation to the scale and assumptions of the map. Observation data used in the inductive approach are also subject to many sources of uncertainty, such as the accuracy of their locational coordinates. These data often cannot be tested because they record an event that occurred in the past. For the same reasons described above, it is difficult to assess the accuracy of the output description of



habitat preferences because of problems with field sampling (Raphael and Marcot, 1986).

There are two approaches to comprehensive error analysis of habitat modeling. In one approach, knowing the accuracy of input layers and having a model of how error propagates through GIS processing, errors in the output can be deduced. Conversely, the error propagation model and accuracy of the output can be used to deduce the magnitude of errors in the inputs. In habitat modeling, neither the input or output layer accuracies nor the theoretical error propagation model can be known, forcing analysts to either express caveats about their results or to turn to alternative methods of evaluating uncertainty.

Perhaps the most promising alternative is sensitivity analysis. Lodwick *et al.* (1990, p. 413) define geographical sensitivity analysis as "the study of the effects of imposed perturbations (variations) on the inputs of a geographical analysis on the outputs of that analysis." Input data are perturbed in systematic ways, such as degrading spatial resolution by a sequence of scale factors. Perturbations represent the range of reasonable assumptions about the nature of uncertainty in each data layer. A GIS output is considered sensitive to variation in a given input if the resulting sensitivity measure exceeds a predetermined significance level. Greater care should be taken in compiling inputs whose perturbations produce the greatest effect on the outputs. Because the exact nature of uncertainties can seldom be expressed by mathematical functions, geographical sensitivity analyses are usually conducted empirically.

Objectives for sensitivity analysis in habitat modeling differ somewhat for the deductive versus the inductive methods. For deductive habitat modeling, the output is a map of potential distribution of habitat suitability. As this approach is common in a management decision or policy making context, the critical concern is whether the map is so sensitive to variation in inputs that a different decision would be reached with a different realization of the inputs. In the inductive approach, the issue is how confident we are in the derived habitat preferences.

While relatively common practice in fields such as planning (e.g., Alexander, 1989), sensitivity analysis is seldom employed

in GIS applications. Recent examples of GIS sensitivity analysis include testing the effects of classification errors (Ramapriyan *et al.*, 1981; Lyon *et al.*, 1987), grid cell size (Laymon and Reid, 1986; Lyon *et al.*, 1987; Turner *et al.*, 1989), map extent (Turner *et al.*, 1989), the number of thematic classes (Lyon *et al.*, 1987), and subjective weighting factors (Heinen and Lyon, 1989). For an excellent description of the types of sensitivities in spatial analysis, measures of sensitivity, and a mathematical treatment of geographical sensitivity analysis, the reader is referred to Lodwick *et al.* (1990).

#### CONDOR GIS DATABASE

The endangered California condor most recently inhabited the mountainous regions of southern and central California (Figure 1), feeding primarily in open woodland and grasslands. Since 1987, the species survives only in captivity. A breeding program is underway to restore the population to a viable level, with the eventual goal of reintroducing condors into the wild. We collaborated with the California Department of Fish and Game, the U.S. Fish and Wildlife Service, and the National Audubon Society to study historical patterns of habitat use by the species and to aid in identifying suitable sites for future release of captive reared birds (Scepan *et al.*, 1987). The GIS is being used to store and analyze the set of observations of wild condors over the past century and a map of land-use/land-cover (LU/LC) types, described briefly below. When completed, the database will cover the entire historic range. For this analysis, we only used the 1:250,000-scale Los Angeles quadrangle portion (see Figure 1), where 75 percent of the sightings occurred.

#### CONDOR SIGHTING DATA

Beginning in 1966, researchers with the National Audubon Society, the U. S. Forest Service, and the U. S. Fish and Wildlife Service compiled visual sighting records from a network of field biologists, fire lookout personnel, ranchers, and other interested members of the public (Wilbur *et al.*, 1972). These 7,341 sighting records were incorporated as a point coverage into the ARC/INFO GIS database, and include attributes such as the date

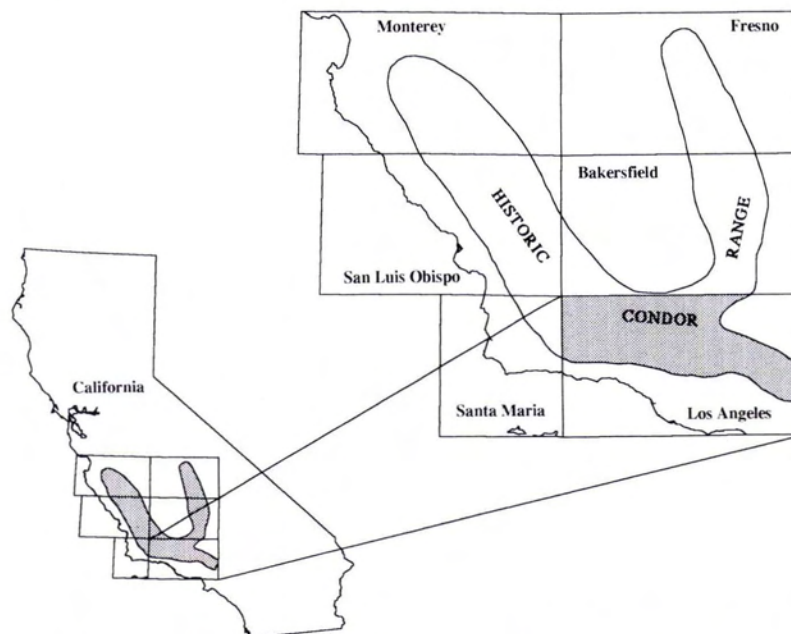


Fig. 1. Map of the historical range of the California condor. The index of 1:250,000-scale USGS quadrangle maps is also shown. The shaded region in the larger scale inset map shows the study area in the Los Angeles quadrangle.



of the observation and the bird's activity. The few scattered observations outside the historic range boundaries were not considered in the habitat association modeling. For this sensitivity analysis, the 508 feeding observations in the Los Angeles quadrangle were used.

Potential sources of uncertainty in the sighting data include errors in the recorded location and sampling bias. Locations were originally coded with 500-metre precision. Further, when the data were converted to GIS format, the transformation to UTM coordinates potentially introduced additional positional error. Observers may also have had difficulty in accurately mapping their location and that of the bird, especially given that condors can be identified at a distance of several kilometres (Johnson *et al.*, 1983). If the recorded location is displaced from the true location, it is conceivable that GIS analysis will associate the observation with a habitat type different from that which the condor actually used. The effect of positional error would be to lower the strength of the habitat model, indicating that habitat utilization was more random than was actually the case (White and Garrott, 1986).

Sightings of rare species tend to be located in places where they are expected to be seen (e.g., Snyder and Johnson, 1985) and that are most accessible to observers, such as near roads, trails, or other observation points. The condor sightings are certainly suspect in this regard, as much of the historic range is in remote, rugged terrain. The implication of biased sampling is that it may say more about the preferences of the observers than of the wildlife.

#### CONDOR HABITAT MAP

Land use and condor habitat were mapped over the 2.5 million ha range by photointerpretation of 1986 Landsat Thematic Mapper (TM) imagery (see Davis *et al.* (1988) for details). The classification system for mapping LU/LC was specifically designed to discriminate land surfaces that differ in quality as condor habitat. Based on field reconnaissance, we employed an MMU of 10 ha in an attempt to capture small grassland feeding habitats (potreritos) that condor biologists considered important to the species. Thematic accuracy of the land-use/land-cover map was estimated at 76 percent for the Los Angeles quadrangle (Davis *et al.*, 1989). The relatively low accuracy reflects the complexity of topography and vegetation in the study area and the difficulty in capturing that complexity at a relatively small map scale.

At least four aspects of the habitat map can be a source of uncertainty: (1) loss of detail from spatial generalization, (2) similar loss of detail due to the level of precision of the classification system, (3) errors in class label or boundary location, and (4) choosing a study area that is unrepresentative of the entire range. Here we concentrate on the first and fourth aspects.

### METHODS

#### BASIC HABITAT ASSOCIATIONS PROCEDURE

Using the inductive approach of habitat modeling, we overlaid point observation data and LU/LC maps for the Los Angeles quadrangle. A database program was written to generate contingency tables of land-cover types and condor activities. We then used a statistical package to compute the Chi-square statistic as a measure of the strength of association between cover types and observed condor activities. The null hypothesis proposes that condors utilize habitats in their range randomly. The expected frequency for each cover type was calculated by multiplying the total number of feeding observations by the proportion of the total area occupied by that cover type in the study area. The relative strength of association between condor activ-

ities and individual vegetation types was measured using the Bonferroni normal statistic approach described by Neu *et al.* (1974).

To simplify presentation of results, we have classified the measures of association into "positive," "negative," or "non-significant" levels based on the 90th percentile confidence intervals for an alpha significance level of 0.10. Positive association means condors appear to preferentially feed in that cover type. Negative association shows the birds selectively avoiding the cover type. A nonsignificant level of association occurs when the proportion of sightings in a cover type is similar to the proportion of area of that type. We emphasize that these levels are used only to facilitate the interpretation of a complex set of numerical comparisons, but should not be construed as formal significance testing based on independent random samples. The output product of this inductive procedure is a table listing the level of association of condor feeding with each LU/LC type.

#### ALTERNATIVE DATA SETS FOR SENSITIVITY ANALYSIS

To test the sensitivity of condor habitat associations to uncertainty about sighting locations, sampling bias, map generalization, and map extent, we generated six alternative data sets of sighting data, which are summarized in Table 1.

Errors in location of the sightings could place them into a different map polygon, with a higher probability of being in the wrong class for classes characterized by small polygons. A GIS

TABLE 1. CHARACTERISTICS OF ORIGINAL AND ALTERNATIVE DATA SETS USED IN THE SENSITIVITY ANALYSIS OF CONDOR HABITAT ASSOCIATIONS. EACH DATA SET CONTAINS THE MAPPED LAND-USE/LAND-COVER TYPE AT THE LOCATION OF EACH CONDOR SIGHTING.

| Data Set               | Characteristics   |
|------------------------|---|
| BASELINE               |   |
| A                      | Original Data. 508 feeding observations at their coded locations.   |
| LOCATIONAL UNCERTAINTY |   |
| B                      | Location Precision. As in A, but northing and easting coordinates are displaced by distances from a uniform random distribution with a maximum of 250 m. Based on the limits of precision of the coded coordinates. |
| C                      | Location Error. As in B, but displacement based on a normal random distribution with 95 percent of sightings within 1 km of their coded position. Assumes greater uncertainty in locations than B.                  |
| D                      | Location Error. As in C, but 95 percent of sightings within 2 km. 505 sightings used.   |
| SAMPLING BIAS          |   |
| E                      | Unique Locations. Subset of A with 137 observations such that, for each activity, locations where condors were sighted were only counted once.  |
| MAP GENERALIZATION     |   |
| F                      | Minimum Mapping Unit. Same as A, except the primary land-use/land-cover map polygons less than 20 ha on the original map were dissolved into larger neighboring polygons.   |
| MAP EXTENT             |   |
| G                      | Larger Sampling Domain. Same as A, except the primary land use/land cover and 77 feeding sightings for the Bakersfield 1:250,000-scale quadrangle were added to the analysis.                                       |



query reported the mean distance from sightings to the nearest polygon boundary in the study area to be about 500 m, ranging from 5 to 3100 m. In evergreen shrubland polygons, the average distance is over 800 m, so we would expect sightings in this class to be least affected by locational uncertainty. Grassland sightings were, on average, 400 m from boundaries, and all other classes averaged less than 250 m distance. Consequently, the deciduous shrubland and the forest sightings are most uncertain as to their true type.

Data Sets B, C, and D test the sensitivity of measured habitat association to locational uncertainty by displacing the coordinates. Displacements were randomly selected from two probability distributions (Figure 2) in the statistical software, and added to the original coordinates, from which new point coverages were generated. In Data Set B, sighting coordinates were randomly displaced by assuming errors are uniformly distributed up to 250 m in both UTM eastings and northings, reflecting the level of precision of the coded locations. In Data Sets C and D, coordinates have been displaced by assuming that locational errors are normally distributed around the recorded locations (White and Garrott, 1986). Set C assumes that 95 percent of the true locations occurred within 1 km of the encoded coordinates, whereas Set D assumes that 95 percent of the true locations were within 2 km. Only one realization of random error was tested for each model. In a more rigorous analysis, multiple realizations could be generated in a Monte Carlo simulation to determine the significance level at which effects were not different. For our purposes of exploratory analysis, we believe that the number of observations in each case (more than 500) was sufficiently large to provide a reasonable indication of the sensitivity of the habitat associations.

For Data Set E, we retained only one sighting at each location to reduce the effects of possible bias from frequent observations at fixed locations such as fire lookouts (see Figure 3). This reselection of points, retaining only one feeding observation within a buffer of 250 m radius centered on the coded locations, reduced the data set to 137 points. Observations made at sites where biologists placed animal carcasses for supplemental feeding of condors were excluded from all data sets.

Data Set F was created by increasing the MMU size of the LU/LC map in order to assess the effects of the level of generalization. LU/LC polygons less than 20 ha, such as small potreros, were dissolved into larger neighboring classes, reducing the number of map polygons from 1,763 to 1,186. As with distance to boundaries, polygon size is also a function of LU/LC type. Average polygon size in the Los Angeles quadrangle is 520 ha. Average size of evergreen shrubland polygons is over twice the average of all types combined. Forest types tend to occur in smaller patches so sightings in the latter classes are more likely to change types as MMU increases.

The condor GIS database is being completed in stages, so a comprehensive habitat association analysis cannot yet be conducted. We recognized that the Los Angeles study area may not accurately represent the proportions of habitat availability for the condor range as a whole. Data Set G was produced by extending the analysis to include sighting and LU/LC data for both the Los Angeles and Bakersfield 1:250,000-scale quadrangles. The Bakersfield quadrangle contains a transition from the coastal Transverse Ranges of the Los Angeles quadrangle into the southern Sierra Nevada and San Joaquin Valley. Including this portion of the range greatly increases the proportion of grassland, agriculture, and woodland types while the prominence of shrub types diminishes. Only 77 sightings were added from the Bakersfield quadrangle, however, despite a 75 percent increase in total area.

Output data from the baseline habitat associations and the alternative data sets included tabulations of numbers of sight-

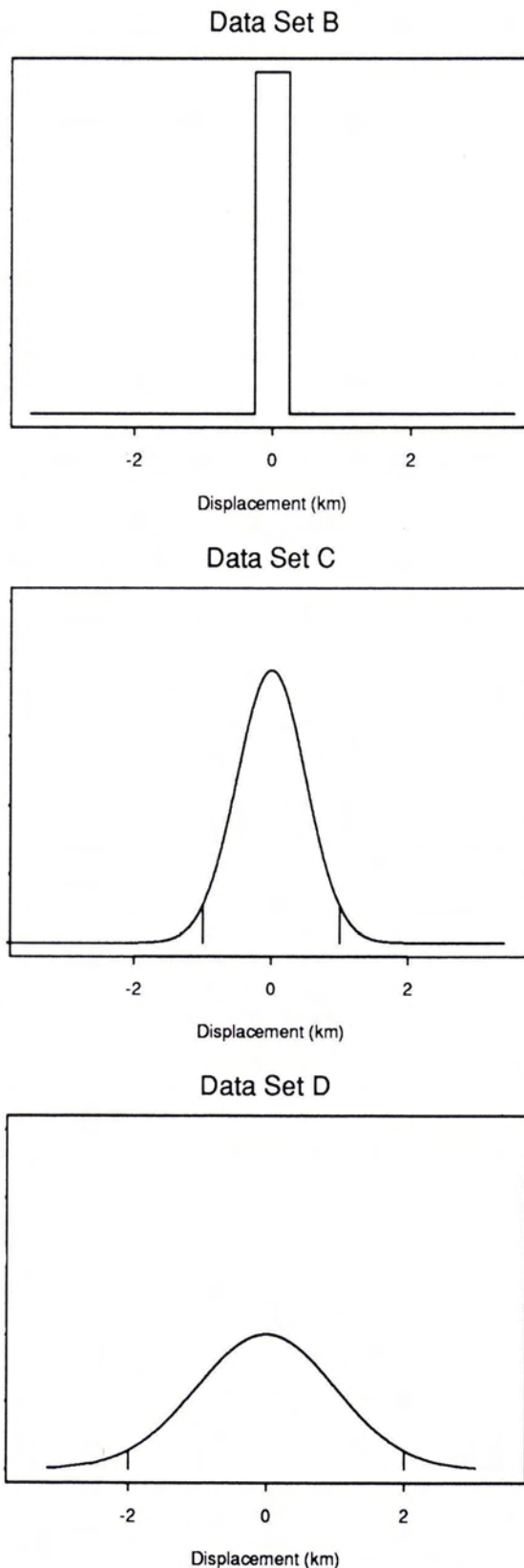


FIG. 2. Diagram of the random probability distributions used to displace locations of condor feeding sightings. For each sighting, a value was sampled from the probability distribution for both its easting and northing coordinate. These displacements were added to the coordinates to generate a new coverage.



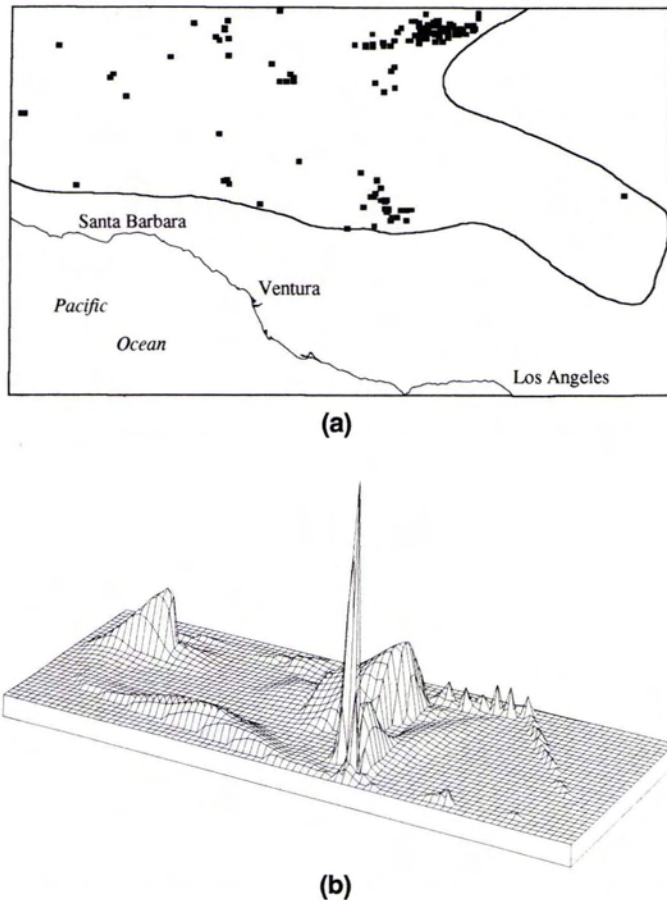


FIG 3. Map of condor feeding observations in the Los Angeles quadrangle: (a) distribution of sightings, and (b) number of sightings at each location represented by the height of peaks. The highest peak corresponds to 101 observations at a single site. This perspective is viewed from the southeast.

ings by LU/LC types, and the positive, non-significant, and negative levels of association. Each data set was summarized with the calculated Chi-square statistic (based on the expected number of observations by class), the number of LU/LC classes that changed in level of association between each alternative data set and Data Set A, the percent area of each level of association, and an area sensitivity measure (Lodwick *et al.*, 1990). This last measure is a sum of the proportion of map area that changed from one level to another.

## RESULTS

### BASELINE ASSOCIATION OF CONDOR SIGHTINGS WITH MAPPED HABITATS

The distribution of sightings among cover types differ greatly from that expected in a random distribution (Table 2). Extrapolation of these levels of association of habitats are portrayed graphically in Figure 4. Some of the associations are what one would predict based on known life history attributes. For example, feeding observations occur with strong positive association in grassland and with strong negative association in agricultural areas. On the other hand, some feeding habitat preferences are unexpected, such as positive association with mixed forest and broadleaf forest. Even though 193 observations are associated with evergreen shrubland, this is actually slightly fewer than expected at random. Far fewer observations occur in deciduous shrubland than expected at random.

TABLE 2. FEEDING OBSERVATIONS OF CALIFORNIA CONDOR IN THE LOS ANGELES QUADRANGLE AND ASSOCIATIONS WITH PRIMARY LAND USE. CRITICAL VALUE OF CHI-SQUARE STATISTIC = 27.7, FOR  $\alpha = 0.01$ , AND 13 DEGREES OF FREEDOM. EXPECTED OBSERVATIONS COMPUTED BY MULTIPLYING THE PROPORTION OF TOTAL AREA IN LAND-COVER TYPE BY TOTAL NUMBER OF OBSERVATIONS. LEVEL: '+' MEANS LAND-COVER TYPE IS SIGNIFICANTLY SELECTED BY THE CONDOR MORE THAN THE HABITAT'S AVAILABILITY IN THE LANDSCAPE; '-' MEANS LAND-COVER TYPE IS SIGNIFICANTLY AVOIDED; AND '0' MEANS USE IS NOT SIGNIFICANTLY DIFFERENT FROM RANDOM. SIGNIFICANCE LEVEL  $\alpha = 0.1$ , 90 PERCENT FAMILY OF CONFIDENCE INTERVALS FOR  $k = 14$  CLASSES (NEU *et al.*, 1974).

| Primary Land Cover    | Proportion of Total Area | Feeding Data |          |       |
|-----------------------|--------------------------|--------------|----------|-------|
|                       |                          | Observed     | Expected | Level |
| Agriculture           | 0.041                    | 0            | 20.8     | -     |
| Water                 | 0.005                    | 0            | 2.5      | -     |
| Bare Land             | 0.013                    | 0            | 6.6      | -     |
| Grassland             | 0.228                    | 215          | 115.6    | +     |
| Evergreen Shrubland   | 0.412                    | 193          | 208.9    | 0     |
| Deciduous Shrubland   | 0.199                    | 15           | 100.9    | -     |
| Conifer Woodland      | 0.050                    | 3            | 25.4     | -     |
| Mixed Woodland        | 0.015                    | 21           | 7.6      | 0     |
| Broadleaf Woodland    | 0.008                    | 7            | 4.1      | 0     |
| Conifer Forest        | 0.001                    | 0            | 0.5      | -     |
| Mixed Forest          | 0.009                    | 30           | 4.6      | +     |
| Broadleaf Forest      | 0.008                    | 24           | 4.1      | +     |
| Savanna               | 0.002                    | 0            | 1.0      | -     |
| Urban                 | 0.011                    | 0            | 5.6      | -     |
| Total                 | 1.000                    | 508          | 508.0    |       |
| Calculated Chi-square |                          | 482.1        |          |       |

### SENSITIVITY OF HABITAT ASSOCIATIONS

Results of the Chi-square analysis of the baseline and six alternative data sets are compared in Table 3. For condor feeding, the significance of use of each primary land-cover type is displayed. The "frequency" columns tabulate the number of data sets in which the levels of association for each cover type are positive, negative, or not significant.

Locational errors seem to be relatively unimportant. All three data sets with locational displacements produce results significantly different from random, and all are similar to the utilization pattern in Data Set A (Table 3). All changes are between adjoining levels, such as from significant to neutral, or vice-versa. The most noteworthy changes occur in association of condor feeding with grassland. Association is strongly positive in Data Sets A and B, but less in C. Recall that sightings in grassland habitat were closer to polygon boundaries than the average distance. In Data Set D, the association is negligible, such that the total area positively associated with condor feeding drops to less than three percent of the study site. These results suggest that the habitat associations are robust, if the assumption is true that the locational accuracy is better than one kilometre.

The 508 feeding observations in Data Set A occur at only 137 unique locations. Patterns of association between feeding activity and habitat based on unique locations are not much different than those based on all feeding observations (Table 3). The primary difference between E and A is that the extensive evergreen shrubland class becomes negatively associated in E. The area sensitivity measure is highest for this data set, indicating that while only two classes changed level, one (evergreen shrubland) was the largest class in the Los Angeles quadrangle.

The effect of larger MMU size, represented by Data Set F, was very minor. A net of 39 observations changed LU/LC class from grassland to evergreen shrubland as small potrero polygons were dissolved into the background chaparral mosaic. This shift



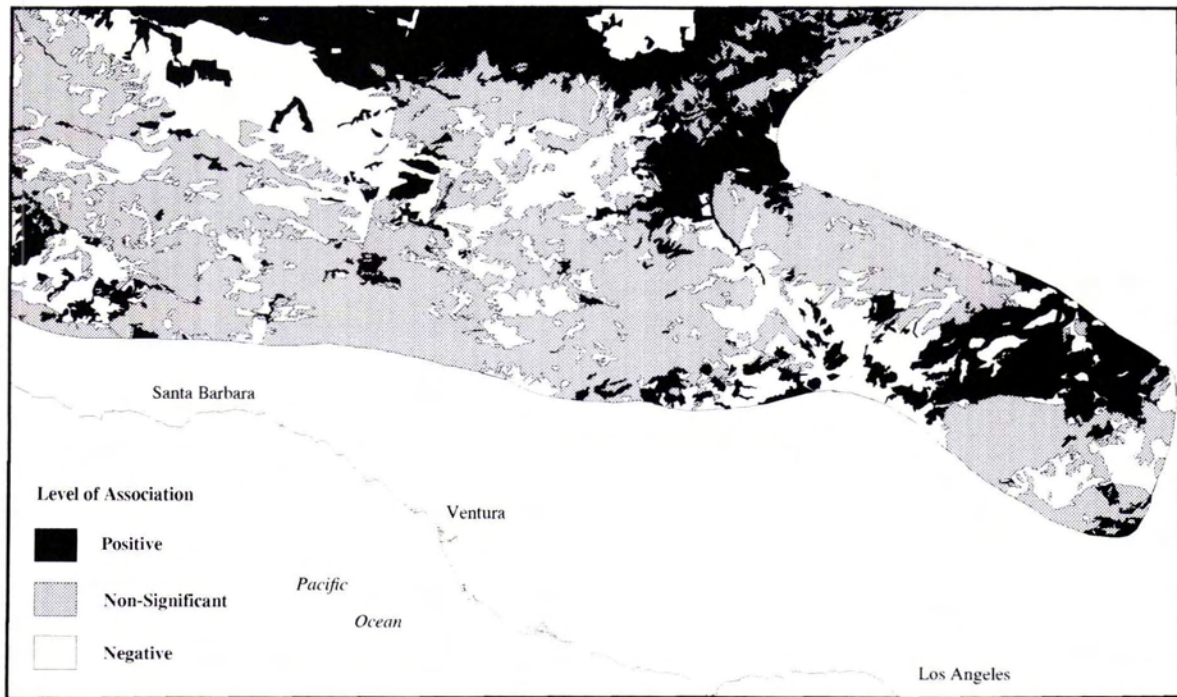


FIG. 4. Map of level of association of primary land cover types for feeding by condors in the Los Angeles quadrangle, based on Data Set A.

TABLE 3. COMPARISON OF SIGNIFICANCE OF UTILIZATION OF LAND-USE/LAND-COVER TYPES FOR FEEDING IN BASELINE AND ALTERNATIVE DATA SETS. CRITICAL VALUE OF CHI-SQUARE STATISTIC = 27.7, FOR  $\alpha = 0.01$ , AND 13 DEGREES OF FREEDOM. LEVEL: SAME DEFINITIONS AS FOR TABLE 2.

| Primary Land Cover    | Data Set A Base | Data Set B 250m | Data Set C 1 km | Data Set D 2 km | Data Set E Unique | Data Set F MMU | Data Set G Extent | Frequency |   |   |
|-----------------------|-----------------|-----------------|-----------------|-----------------|-------------------|----------------|-------------------|-----------|---|---|
|                       |                 |                 |                 |                 |                   |                |                   | +         | 0 | - |
| Agriculture           | -               | -               | -               | -               | -                 | -              | -                 | 0         | 0 | 7 |
| Water                 | -               | -               | -               | -               | -                 | -              | -                 | 0         | 0 | 7 |
| Bare Land             | -               | -               | -               | 0               | -                 | -              | -                 | 0         | 1 | 6 |
| Grassland             | +               | +               | +               | 0               | +                 | +              | +                 | 6         | 1 | 0 |
| Evergreen Shrubland   | 0               | 0               | 0               | 0               | -                 | 0              | 0                 | 0         | 6 | 1 |
| Deciduous Shrubland   | -               | -               | -               | -               | -                 | -              | -                 | 0         | 0 | 7 |
| Conifer Woodland      | -               | -               | -               | -               | 0                 | -              | -                 | 0         | 1 | 6 |
| Mixed Woodland        | 0               | +               | +               | 0               | 0                 | 0              | +                 | 3         | 4 | 0 |
| Broadleaf Woodland    | 0               | 0               | 0               | +               | 0                 | 0              | 0                 | 1         | 6 | 0 |
| Conifer Forest        | -               | -               | -               | -               | -                 | -              | -                 | 0         | 0 | 7 |
| Mixed Forest          | +               | +               | +               | +               | +                 | +              | +                 | 7         | 0 | 0 |
| Broadleaf Forest      | +               | +               | +               | +               | +                 | +              | +                 | 7         | 0 | 0 |
| Savanna               | -               | -               | -               | -               | -                 | -              | -                 | 0         | 0 | 7 |
| Urban                 | -               | -               | -               | -               | -                 | -              | -                 | 0         | 0 | 7 |
| Changes from Set A    |                 | 1               | 1               | 3               | 2                 | 0              | 1                 |           |   |   |
| Calculated Chi-square | 482.1           | 454.2           | 527.6           | 481.4           | 359.0             | 426.3          | 397.5             |           |   |   |
| % Area + association  | 24.5            | 26.0            | 26.0            | 2.5             | 24.5              | 24.4           | 39.0              |           |   |   |
| % Area 0 association  | 43.5            | 42.0            | 42.0            | 66.8            | 7.3               | 43.6           | 30.3              |           |   |   |
| % Area - association  | 32.2            | 32.2            | 32.2            | 30.9            | 68.4              | 31.9           | 30.7              |           |   |   |
| Area sensitivity      | 0.000           | 0.015           | 0.015           | 0.249           | 0.462             | 0.000          | 0.015             |           |   |   |

was not enough, however, to change the level of association for any land-cover class.

Including additional historic range in the analysis of Data Set G likewise made little difference in the level of association. Only the mixed woodland type became positively associated because of a large number of sightings in this map class in the Bakersfield quadrangle. The two largest types did, however, shift to the brink of changing levels. Grassland, with its large gain in area, nearly became nonsignificant, while evergreen shrubland

almost became positively associated as its proportional area declined.

## DISCUSSION

Some end users of GIS analysis accept output products uncritically. Others assume a more pessimistic view that uncertainties are so overwhelming that GIS outputs simply can not be trusted. Acknowledging the uncertainties in the condor database, we sought a middle ground by conducting a sensitivity



analysis of habitat associations. The results have increased our confidence that GIS-based analysis provides a reasonable model of condor feeding habitat. Generally speaking, the habitat associations are relatively robust across the set of sensitivity analyses shown in Table 3. For the three most extensive or most heavily used cover types—i.e., grassland and evergreen and deciduous shrubland—the associations are particularly consistent. Of all the data sets, Set D, with the greatest locational displacements, has the highest number of changes in association level. Set E, using only unique locations, is most sensitive in terms of area affected, as indicated by the largest area sensitivity measure (Table 3).

Of course, there is no guarantee that sensitivity analysis will support the initial GIS results, as seen in several published studies. White and Garrott (1986) simulated the effects of locational errors in radio-tracking data and found that such errors could seriously decrease the predicted importance of preferred habitat. When computer simulation indicates significant sensitivity to locational accuracy, the wildlife biologist can reduce the effects either by improving the accuracy of the telemetry system or by increasing sample size of observations (White and Garrott, 1986). Where sample size is sufficiently large, observations close to boundaries between habitat polygons can be dropped from the habitat modeling to minimize uncertainty (White and Garrott, 1990). Condor habitat associations were probably not very sensitive to locational uncertainty, in part, because of the large number of feeding observations in our GIS database.

Other authors have found significant effects on habitat suitability indices as spatial resolution is degraded and small or rare habitats drop out (Laymon and Reid, 1986; Lyon *et al.*, 1987; Turner *et al.*, 1989). We tested the effects of coarser spatial resolution by eliminating polygons that are less than 20 ha, approximately one-third of the total number. Although nearly 8 percent of the feeding observations change from grassland to evergreen shrubland through this procedure, we observed no significant effects on the levels of association from changing MMU size over the small range of sizes we tested. This finding might suggest that the land-cover map is more detailed than necessary for modeling condor habitat. We believe, however, that the finer resolution of the original land-cover map will still be valuable for other GIS analysis, such as identifying potential release sites. Further generalization could determine at what MMU the habitat associations break down, but this has not been done.

Lyon *et al.* (1987) found that even a 5 percent change in classification accuracy of a land-cover map made a significant difference in levels of a habitat suitability index. Their results have strong implications for GIS habitat modeling with land cover maps, which always contain some degree of misclassification. We have not yet tested the sensitivity of condor habitat associations to assumptions about classification error. Such a test would be useful in determining the critical threshold of classification accuracy above which habitat associations would be reliable.

Any choice of study area boundaries is relatively arbitrary, yet it can affect analytical results (Wiens, 1986). Turner *et al.* (1989) observed that, as map extent expanded, more cover types were incorporated and their landscape indices increased in value. In our study, the baseline map extent was restricted to the historic condor range of the Los Angeles quadrangle map. Our results were only slightly different when we analyzed habitat associations over a larger portion of the range. When the database is completed, it will be possible to test the sensitivity of the derived associations for the entire range. It should be noted that the estimated associations may have been significantly stronger if habitat outside the historic range such as the Mojave Desert were also included in the analysis. This would have the

effect of increasing the number of cover types, decreasing the expected number of observations in cover types preferred by condors, and thereby inflating the calculated Chi-square statistic. While producing greater statistical significance, little if anything would be added to our knowledge of condor behavior, and we could even conclude erroneously that some cover types are more critical to condor survival than may actually be the case. The risk of such a mistake when considering the reintroduction of an endangered species could be catastrophic.

All previous examples of GIS sensitivity analysis we have seen were done with raster format data. Using grid cells has many advantages for sensitivity analysis, such as the relative ease of changing resolution or systematically adding error to a thematic map (Goodchild, 1990). Our study used vector format, including point data for the observations. This allowed us to test the effects of locational precision and accuracy that would not have been possible in a raster format unless grid cell size had been prohibitively small.

Sensitivity analysis should be considered in any GIS analysis where absolute truth cannot be determined and where the management decision could be controversial. If conducted at the pilot study stage, sensitivity analysis can be used to determine critical levels of resolution and accuracy needed to achieve the objectives of the database. It need not be technically difficult; the application demonstrated here used only standard GIS and statistical routines. Someday, a sensitivity analysis capability may even be a generic GIS function (Openshaw, 1989). Sensitivity analysis has the advantage that sources of error and their propagation do not need to be known exactly. The analyst need only make reasonable assumptions about data uncertainties. The risk in sensitivity analysis is in potentially adopting a "black box" view of the model, ignoring important questions about error propagation in GIS analyses. The benefit of sensitivity analysis would be in providing a measure of reliability of GIS output products to decision makers.

#### ACKNOWLEDGMENTS

The GIS database development was funded by California Department of Fish and Game (CDF&G) Contract C-2077. The senior author was supported by NASA Grant NAGW-1743 during the writing of the paper. We would like to thank Ron Jurek and Sherry Teresa of CDF&G, Linda Blum of the National Audubon Society, and the staff of the U. S. Fish and Wildlife Service office in Ventura, California, for their collaboration in this project. Much of the data input (drafting, digitizing, labeling, and editing the land-use/land-cover maps) was performed by a large number of undergraduate interns at UCSB. Joe Scepan, Marco Painho, and Brean Duncan played key roles in the design and development of the condor GIS database. Their collective efforts are warmly appreciated. Our thanks also to Mike Goodchild for thoughtful comments on the manuscript.

#### REFERENCES

- Agee, J.K., S.C.F. Stitt, M. Nyquist, and R. Root, 1989. A geographic analysis of historical grizzly bear sightings in the North Cascades. *Photogrammetric Engineering & Remote Sensing*, 55:1637-1642.
- Alexander, E. R., 1989. Sensitivity analysis in complex decision models. *Journal of the American Planning Association*, 55:323-333.
- Davis, F. W., J. E. Estes, J. Scepan, M. Painho, and D. Stoms, 1988. *California Condor Database Project*. Final Report-Year 1, California Department of Fish and Game Contract C-2077, Sacramento.
- Davis, F. W., J. Scepan, M. Painho, D. Stoms, B. Duncan, and C. Cogan, 1989. *California Condor Database Project*. Final Report-Year 2, California Department of Fish and Game Contract C-2077, Sacramento.
- Davis, F. W., and J. Dozier, 1990. Information analysis of a spatial



- database for ecological land classification. *Photogrammetric Engineering & Remote Sensing*, 56:605-613.
- Davis, F. W., and S. Goetz, 1990. Modeling vegetation pattern using digital terrain data. *Landscape Ecology*, 4:69-80.
- Davis, F. W., D. M. Stoms, J. E. Estes, J. Scepán, and J. M. Scott, 1990. An information systems approach to the preservation of biological diversity. *International Journal of Geographical Information Systems*, 4:55-78.
- Ferrier, S., and A. P. Smith, 1990. Using geographical information systems for biological survey design, analysis, and extrapolation. *Australian Biologist*, 3:105-116.
- Goodchild, M. F., 1990. Modeling error in spatial databases, *Proceedings of GIS/LIS'90*, Anaheim, California, 7-10 November 1990, American Society for Photogrammetry and Remote Sensing and American Congress on Surveying and Mapping, Bethesda, Maryland, pp. 154-162.
- Heinen, J. T., and J. G. Lyon, 1989. The effects of changing weighting factors on wildlife habitat index values: A sensitivity analysis. *Photogrammetric Engineering & Remote Sensing*, 55:1445-1447.
- Johnson, E. V., D. L. Aulman, D. A. Clendenen, G. Guliasi, L. M. Morton, P. I. Principe, and G. M. Wegener, 1983. California condor: Activity patterns and age composition in a foraging area. *American Birds*, 37: 941-945.
- Laymon, S. A., and J. A. Reid, 1986. Effects of grid-cell size on tests of a Spotted Owl HSI model, *Wildlife 2000: Modeling Habitat Relationships of Terrestrial Vertebrates* (Jared Verner, Michael L. Morrison, and C. John Ralph, editors), The University of Wisconsin Press, Madison, Wisconsin, pp. 93-96.
- Lodwick, W. A., W. Monson, and L. Svoboda, 1990. Attribute error and sensitivity analysis of map operations in geographical information systems. *International Journal of Geographical Information Systems*, 4:413-428.
- 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.
- Mead, R. A., T. L. Sharik, S. P. Prisely, and J. T. Heinen, 1981. A computerized spatial analysis system for assessing wildlife habitat from vegetation maps. *Canadian Journal of Remote Sensing*, 7:395-400.
- Neu, C. W., C. R. Byers, and J. M. Peek, 1974. A technique for analysis of utilization-availability data. *Journal of Wildlife Management*, 38:541-545.
- Openshaw, S., 1989. Learning to live with errors in spatial databases, *The Accuracy of Spatial Data Bases* (Michael Goodchild and Sucharita Gopal, editors), Taylor & Francis, London, pp. 263-276.
- Ramapriyan, H. K., R. K. Boyd, F. J. Gunther, and Y. C. Lu, 1981. Sensitivity of geographic information system outputs to errors in remotely sensed data, *Proceedings of Machine Processing of Remotely Sensed Data Symposium*, pp. 555-566.
- Raphael, M. G., and B. G. Marcot, 1986. Validation of a wildlife-habitat relationships model: Vertebrates in a douglas-fir sere, *Wildlife 2000: Modeling Habitat Relationships of Terrestrial Vertebrates* (Jared Verner, Michael L. Morrison, and C. John Ralph, editors), The University of Wisconsin Press, Madison, Wisconsin, pp. 129-138.
- Scepán, J., F. Davis, and L. L. Blum, 1987. A geographic information system for managing California condor habitat, *Proceedings of GIS'87*, 26-30 October 1987, San Francisco, California, American Society for Photogrammetry and Remote Sensing and American Congress on Surveying and Mapping, Falls Church, Virginia, pp. 476-486.
- Snyder, N. F. R., and E. V. Johnson, 1985. Photographic censusing of the 1982-1983 California condor population. *The Condor*, 87: 1-13.
- Turner, M. G., R. V. O'Neill, R. H. Gardner, and B. T. Milne, 1989. Effects of changing spatial scale on the analysis of landscape pattern. *Landscape Ecology*, 3: 153-162.
- Walker, P. A., and D. M. Moore, 1988. SIMPLE: An inductive modelling and mapping tool for spatially-oriented data. *International Journal of Geographical Information Systems*, 2:347-363.
- White, G. C., and R. A. Garrott, 1986. Effects of biotelemetry triangulation error on detecting habitat selection. *Journal of Wildlife Management*, 50: 509-513.
- , 1990. *Analysis of Wildlife Radio-Tracking Data*. Academic Press, Inc., San Diego.
- Wilbur, S. R., W. D. Carrier, J. C. Borneman, and R. W. Mallette, 1972. Distribution and numbers of the California condor, 1966-1971. *American Birds*, 26: 819-823.
- Wiens, J. A., 1986. Spatial scale and temporal variation in studies of shrubsteppe birds, *Community Ecology* (Jared Diamond and Ted J. Case, editors), Harper & Row, New York, pp. 154-172.

## 1st Australian Conference on Mapping & Charting "Mapping for A Green Future"

Adelaide, South Australia  
14-17 September 1992

The Australian Institute of Cartographers is hosting a conference focusing on the role of cartography in monitoring and managing the nation's resources. Conference themes include:

Remote Sensing & Geographic Data for Environmental Management • Mapping Management & Professional Practice • Future Directions in Education & Training • Development of Mapping & Charting • International Mapping Opportunities • Thematic Cartography • GIS/LIS Development

For further information, contact:

Conference Secretariat  
1st Australian Conference on Mapping and Charting  
GPP Box 1922, Adelaide  
SOUTH AUSTRALIA