# Habitat Mapping from Satellite Imagery and Wildlife Survey Data Using a Bayesian Modeling Procedure in a GIS

# Abstract

A method for using coarse resolution data from wildlife survey to classify a Landsat Thematic Mapper image and digital elevation model (DEM) is described. Classification is based on an analytical Bayesian probability method implemented within a GIS and is illustrated using a case study of Curlew in part of the Grampian Region, northeast Scotland, United Kingdom. Conditional probabilities for Curlew presence and absence are calculated for spectral values in the image bands and DEM. The conditional probabilities are then used to classify the image in conjunction with the DEM. The product of this analysis is a detailed map ("information surface") at the spatial resolution of the satellite image that describes the distribution of the specified species as probability of occurence. This can also be used as a map of habitat quality or suitability and analyzed further with a GIS.

### Introduction

Habitat maps have been derived from satellite imagery for many years (e.g., Laperriere et al., 1980; Dixon et al., 1982; Harris, 1983; Bowles, 1985; Ormsby and Lunetta, 1987; Tommervik and Lauknes, 1988; Belward et al., 1990) and have many applications. These include targeting field survey, support for management planning (Ormsby and Lunetta, 1987), habitat suitability mapping (Lyon, 1983; Epp, 1985; Palmeirim, 1988), conservation evaluation (Griffiths et al., in press), and input to models describing distribution and abundance of wildlife species (Avery and Haines-Young, 1990). Increasingly, these applications involve the use of Geographic Information Systems (GIS)(Davis et al., 1990; Stoms et al., in press).

Studies that use satellite imagery to map habitat for input to models of habitat suitability, distribution, or abundance of wildlife typically follow a common procedure. A spectral classification is produced with ecologically meaningful classes (e.g., Craighead *et al.*, 1988). This classification is usually independent of wildlife data although the process may use training areas defined by field survey of habitats to guide the image classification. The assumption inherent in this is that the habitat map produced has ecological relevance to the wildlife species of interest.

The habitat map produced can then be used in a number of ways to model habitat suitability, distribution, and abundance. The map can be restructured according to the spatial units used to record wildlife abundance (for example, 1-km squares, tetrads (2-km by 2-km squares), or patches). This

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0099-1112/93/5904-537\$03.00/0 ©1993 American Society for Photogrammetry and Remote Sensing puts the habitat and wildlife datasets into a common format, the standard statistical data model of cases and variables (Goodchild, 1991), and it allows numerical analysis with a range of statistical methods (e.g., stepwise multiple regression (Campbell, 1983; Griffiths et al., in press), logistic regression (Pereira and Itami, 1991), discriminant function analysis (Haworth and Thompson, 1990), and cannonical correspondence analysis (Hill, 1991)). GIS overlay functions can also be used to produce habitat suitability indices by applying weights and rules, the habitat map forming a key data input to this procedure (e.g., Stelfox, 1985; Palmeirim, 1985; 1988; Ormbsy and Lunetta, 1987; Stenback et al., 1987; Scepan et al., 1987; Agee et al., 1989; Brooks, 1990). Spatial analysis for wildlife-habitat assessment is also increasing as a wider variety of statistical and mathematical methods are integrated with GIS technology and spatial databases (e.g., Walker and Moore, 1988; Walker, 1990; Milne et al., 1989; Davis et al., 1990; Aspinall, 1991; Pereira and Itami, 1991).

An alternative approach to producing habitat information from satellite imagery is to use wildlife survey data to drive the image classification process. This is the approach used in this paper. The method is illustrated through an example. The species considered is Curlew (Numenius arquata), a relatively common wader species. The study site is an upland area in northeast Scotland, where there is a wide range of land-cover types and uses. Coarse resolution data from a wildlife survey are used to classify part of a Landsat Thematic Mapper image in conjunction with a digital elevation model (DEM). The wildlife survey used covers only 10 percent of the study area but allows a map to be produced for the whole study area. The product of classification is an "information surface" representing the probability of occurence for the wildlife species. These probability values can be considered to represent an index of habitat suitability or quality; the information surface provides the basis for describing the distribution of habitat patches and modeling abundance.

A bayesian approach to decision making (Aspinall and Hill, 1983) is used here as an inductive learning process for pattern recognition (Grubb, 1988) to model distribution directly from satellite imagery and *DEM*. Bayes method has been used in a *GIS* as a basis for spatial analysis and has been applied to mineral exploration in geology (Agterberg, 1989; Bonham-Carter *et al.*, 1988, 1989; Bonham-Carter, 1991), integrating the output from trend surface and logistic

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multiple regression analyses to model habitat of the Mount Graham Red Squirrel (Pereira and Itami, 1991), and for modeling the distribution of Red deer *Cervus elaphus* (Aspinall, 1991) and White-tailed deer *Odocoileus virginianus* (Milne *et al.*, 1989).

Bayes Theorem provides a formal method for decision making under conditions of uncertainty, and is a framework for combining relative **values** of being right or wrong (subjective probabilities) with the **probabilities** of being right or wrong (conditional probabilities) (Aspinall and Hill, 1983); ("right" and "wrong" equate to decisions over presence and absence and are expressed as a probability). The Bayesian method is a normative and rational approach for decision making and emulates the way in which a wildlife expert might be expected to make decisions over habitat suitability for a species (Grubb, 1988).

# **Study Area**

The study area is located in the Grampian Region, northeast Scotland, and covers some 30 by 50 km of moorland, grassland, forestry, and agricultural land (Figure 1). The area is part of the northeast Grampian Highlands and has a relatively dry climate, largely a result of a rain shadow effect from the higher Cairngorm Mountains to the west. Within the study area the mountains are higher to the west and lower in the east, summits typically being between 600 and 900 metres above sea level. Valley bottoms are between 200

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and 300 metres. Slopes are generally smooth but complex, rising steeply from valley floors to broad summits of gentle slope.

#### Methods

The data used are from diverse sources, and it is important to consider their relative quality, integrity, and information content as well as the limitations imposed on analysis by different spatial units. The data are bird survey data on a 1km grid square basis, a digital elevation model with 100-m pixels derived from a 1:250,000-scale topographic map, and part of a Landsat Thematic Mapper image resampled to 25-m pixel resolution.

#### **Bird Data**

One hundred and fifty-two 1-km square areas (Figure 1) were visited by a bird survey team from the Nature Conservancy Council; this is a 10 percent sample of 1-km squares in the study area. These data were collected by transect survey between 8 April and 30 June 1988. A single visit was made to each 1-km square, four adjacent squares being visited on each survey day. Visits were made only when wind speeds were low (less than Force 5 on the Beaufort Scale) and visibility was good; no survey was carried out if it was raining or snowing. Visits began within the hour following dawn and lasted four hours; thus, each 1-km square was surveyed for one hour. This post-dawn period is when moorland breeding waders can most easily be detected (Reed *et al.*, 1983; 1985). A second survey was made in 1989 using the same survey methods; this provides data to test the output of the image analysis.

The survey was carried out by two observers walking transects across each site, the distance between observers being 250 m. Sites were crossed twice and no part of a site was less than 125 m from an observer. The location and activity of birds was recorded on a large-scale site map (1:10,000) using British Trust for Ornithology/NCC Common Bird Census format. These maps provide a means of eliminating double recordings from bird counts, and bird counts represent the number of individuals detected at each 1-km square. Although 125 m is a sufficiently short distance to "disturb" larger species such that they are seen, strict adherence to transects can lead to under-observing of some species, particularly at certain periods of the breeding season. Survey counts were reported as counts of birds in each 1-km grid square of the UK National Grid. Fledged young were not included in the counts.

There are three issues related to these bird survey data:

Sampling Frame for Survey Sites.

The sampling frame was originally chosen to provide a random sample for statistical analysis, although access restrictions resulted in the sample sites having a non-random distribution (Figure 1). Survey sites were, however, visited in random order (subject to limitations introduced by local weather conditions during the survey period) in tetrad groups (2-km by 2-km grid squares, equivalent to sets of four 1-km squares). Use of tetrads results in spatial autocorrelation between counts ( $r_s = 0.497$ , n = 238 for Curlew counts in the combinations of 1-km squares in tetrads).

· Count Accuracy.

Changes in behavior (detectability) or habitat use during the survey period of April to June impact count accuracy. Multiple site visits were not made and the accuracy of bird counts in any square and changes in detectability between habitats and through time cannot be quantified easily.

• Temporal and Spatial Comparability of Counts. Data from single visits also have an impact on analysis through confusion of spatial and temporal influences. Because the basis of distribution and abundance modeling typically is establishing relationships between bird numbers and areas of habitat types (see Introduction), an ability to remove any effects of temporal differences in counts is required. Single visits to a site, rather than multiple visits (typically two or four), is a limitation in this respect because detectability of species varies through the breeding season. This occurs both because of changes in bird behavior and because of inter- and intra-specific variation in timing of arrival in the breeding habitat.

Curlew show these effects less than other species. They begin to arrive in their moorland breeding areas in northeast Scotland from middle-late March (Buckland *et al.*, 1990) and are also more easily counted than other moorland breeding waders because they are relatively large and inquisitive.

#### Satellite Image Data

The satellite data are a subscene from a Landsat Thematic Mapper image from 17 April 1987. The subscene covers the moorland area of the bird survey and is about 30 km by 50 km (Figure 1). The image was geometrically corrected to the National Grid of Great Britain and georeferenced with the DEM and bird survey data in an ERDAS image processing system. Because the bird survey data refer only to the upland grassland and moorland area, agricultural areas were masked on the image using visual interpretation and were excluded from analysis; the upland plateau areas were partially snow covered. There are three important issues related to the satellite imagery:

#### Image Date.

The satellite image used was early in the growing season for moorland vegetation. Analysis based on multi-temporal imagery has greater discriminatory power than analysis of a single-date image (Belward *et al.*, 1990).

- Image Classification.
- The image classification is of fundamental importance because it is the basis for modeling bird distribution in areas outside the survey sites. The image classification must (1) be interpreted in a manner that gives regard to the spectral properties of the image and, (2) represent ecologically meaningful habitat information (in terms of impact on dispersion of the species considered).
- Relationship between the Classified Image and Habitat Types. Moorland and upland grassland vegetation is highly variable over short distances and displays gradual change in community type (Huntley, 1979). This variability makes distinguishing one type from another problematic, even for field survey, and is reflected in satellite imagery through high frequency variation in spectral values and a high proportion of mixed pixels (Wardley et al., 1987; Trodd, 1989; Wood and Foody, 1989). The variability of heather-dominated and grassland habitats has been used to argue for inclusion of ordination methods as preprocessing for satellite image classification in heathland areas (Wood and Foody, 1989; Trodd *et al.*, 1989). Mismatch between field records of vegetation and classes identified through image analysis need not be a limitation on use of the image classification for modeling, even though it is a limitation on interpretation of ecological description of image classes.

A map describing habitat distribution is also available which can be used to test the results of the image classification. This map has a scale of 1:50,000 and is the product of field mapping of semi-natural habitats at 1:25,000 scale and produced for Grampian Region, the administrative area within which the study area is located. There are 28 habitat classes mapped, of which 12 occur in the study area.

#### **Topography: Map Data**

A digital elevation model (DEM), derived from contours digitized from a 1:250,000-scale map, is used to provide altitude data. The DEM has 100-m pixels with an absolute vertical specification accuracy of  $\pm$  30 m (Smith *et al.*, 1989).

#### **Data Analysis**

The problem is to use the 1-km bird survey data in conjunction with the image data and DEM to produce a full (image) spatial resolution map of habitat quality for the chosen bird species. The data available can be used for this by adopting an iterative analytical approach based on Bayes Theorem. There are five assumptions: (1) subjective probabilities adequately represent the uncertainty over a particular event (here, a priori probabilities for presence and absence), (2) conditional probabilities are adequately expressed as relative frequencies of occurrence (here, presence/absence of a species compared with presence/absence of particular values of a habitat variable/image spectral value), (3) conditional probabilities are orderly expressions of relationships between datasets, (4) the Bayes Theorem provides an optimal (rational, normative) method for modifying subjective probabilities according to new information presented (conditional probabilities) (Edwards et al., 1963), and (5) predictor datasets are conditionally independent.

Analysis based on Bayes Theorem is used to classify the imagery and *DEM* by recoding based on conditional probabilities calculated from the different resolution datasets. The image and *DEM* are used in their most detailed form,



Figure 2. Curlew Habitat map produced through application of the method described above. The Bayesian modeling procedure was used with presence/absence data for Curlew (1-km squares), full resolution, categorized spectral scale, three-band satellite imagery (25-m resolution), and a 1:250,000-scale digital elevation model (100-m resolution) to produce this map of habitat patches and their suitability for Curlew. The areas shown in white are agricultural and forestry areas which were masked out of the image prior to analysis; these habitats were not part of this study. The map is referenced to the Ordnance Survey National Grid (shown as eastings and northings on the output). Units are probability on a scale of 0 to 1 but rescaled to 0 to 100.

namely, at full spatial resolution, and all image bands are used. These datasets can be considered to be independent, the image bands recording different spectral properties of surface cover according to wavelength, while the topographic information provides an element of locational context.

All wildlife survey squares may be expected to contain both suitable and unsuitable habitat for a species; this will result in "noise." The difference in resolution of the wildlife survey and the satellite imagery can be used to advantage however, to reduce the influence of "noise." The 1-km square bird survey data are used as a sampling frame to calculate relationships between presence and absence of birds and spectral properties of the image data and altitude. These are established as conditional probabilities by iterating through a large number of subsamples of the image data within the 1-km squares, bird "presence" being assumed for all pixels in 1-km squares where presence was recorded dur-ing the bird survey and "absence" being assumed for all pixels in 1-km squares where no birds were seen. Spectral (and altitude) values that consistently are associated with either presence or absence will have a relatively low variability in conditional probabilities between subsamples. The spectral information in the image bands and the altitude data of the DEM are then recoded with Bayes Theorem using the calculated mean conditional probabilities for presence and absence. This provides a map at the full spatial resolution of

the imagery. Variability estimates are used to generate a map of uncertainty associated with the output.

This type of full image resolution assessment of birdhabitat relationships provides a link between the coarse resolution of the bird survey data and the fine spatial resolution of the satellite image. It allows the bird data to drive the image classification with regard to the spectral properties of the image and altitude classes expressed in the DEM.

# Results

#### A Habitat Map for Curlew

An example of the use of this approach is presented for Curlew, output being shown in Figure 2. Curlew were recorded for 76 of the 152 sample 1-km squares visited during the bird survey in 1988. Number varied between 1 and 13 in these squares. During 1989 a second survey was carried out for a randomly selected set of 68 1-km squares; in these, Curlew were present in 14 and absent in 54 squares. As in 1988, the maximum number of Curlew reported in any survey squares was 13. The data for 1989 allow some testing of the map produced.

Each image band initially is reclassified into fewer spectral categories by sub-dividing the 256 class scale into 52 classes of 5 dn interval. This is necessary to prevent large numbers of zero probabilities occuring for each value, there being only 152 sample squares in the bird survey dataset. Each 1-km<sup>2</sup> is represented by 1600 pixels of 25 m<sup>2</sup> in the satellite image. An image pixel is selected at random from within each of the 152 1-km squares of the bird survey; these pixels are coded according to whether Curlew were recorded as present or absent in that 1-km square and used to calculate conditional probabilities for presence and absence. Repeat calculation using different (random) selections of pixels allows means (and standard deviations) to be calculated for conditional probabilities for presence and absence. This is carried out for each of the categories of spectral values in each of the image bands and for the heights recorded in the DEM.

The mean values for conditional probabilities are then used to combine the image bands and *DEM* using Bayes Theorem. Because the number of records of presence and absence were equal in the bird data, prior probabilities for presence and absence are both set to 0.5 (which effectively removes the subjective element of this approach in this example). The product is a map whose information content represents the probability of Curlew being present (Figure 2); the standard deviations can be used to provide an objective assessment of the spatial pattern of error associated with this map (Figure 3). It should be noted that Figure 3 only represents the spatial pattern of error and not the absolute error (as probability values). This is because the data in Figure 2 are rescaled ( $0 \le p \le 1$ ) with Bayes Theorem while the data in Figure 3 are not rescaled.

#### **Testing the Output**

The information map output can be tested in two ways. First, the map can be compared with a map of semi-natural habitats produced by a field survey. Second, the probability values can be compared with the results of the survey of Curlew carried out in 1989.

Table 1 compares the map probability scores with the map of semi-natural habitats. The values are the percentage of habitat types from the habitat map which coincide with different probability scores in the output from the image classification. A high percentage of the area of grassland,



Figure 3. The spatial pattern and magnitude of the error associated with the Curlew Habitat map (Figure 2). Units are multiplied by 100 but note that these units are not directly comparable with the probability units in Figure 2 because they are not rescaled as  $0 \le p \le 1$ . As in Figure 2, the areas shown in white are agricultural and forestry areas which were masked out of the image prior to analysis; these habitats were not part of this study. The map is referenced to the Ordnance Survey National Grid (shown as eastings and northings on the output).

dry-heath, and grass-heath scrub vegetation types are associated with high probabilities (0.61 to 1.00) of Curlew presence. Conversely, high percentages of the area of woodland scrub and sub-alpine vegetation types are associated with low probabilities of Curlew presence. There results are in agreement with observed habitat preferences of Curlew.

The mean probability scores in 1-km squares of the 1989 survey of Curlew can be calculated. For squares where Curlew were present, the mean probability is 0.73 and for squares where Curlew were absent the mean is 0.49. However, this test can only be indicative because it is based on a 1-km square framework which has limitations because both suitable and unsuitable habitat are present in 1-km squares. Not surprisingly, therefore, the variance of probability scores is very high for both presence (sd = 0.56, n = 14) and absence (sd = 0.32, n = 54).

#### Discussion

Successful classification of an image using this approach offers a number of benefits that complement the more general advantages of satellite imagery for wide area habitat mapping.

The method is based on use of presence and absence data from wildlife survey rather than abundance counts (although these can be used). These data are increasingly available from atlases and digital databases. Where absence data are not recorded, presence can be compared with a large random sample (Aspinall, 1991). The method also requires only a sample survey of wildlife (here 10 percent of the study area); this makes it appropriate for use as part of a rapid survey and increases its benefit for targeting field survey.

By mapping directly from a wildlife survey, the method reduces the dependence on establishing a close relationship between image classes (spectral habitat types) and "ecological" habitat types with which the species is known to be associated and on which suitability indices depend. The strength of this relationship is fundamental to the overall accuracy of all analyses of habitat maps within a GIS in which rules and weights are used to combine datalayers to produce maps of habitat suitability based on composite indices. With the method described here, relationships between wildlife distibution and habitat are inherent in the map output.

Improvements to the output here would derive from a better estimation of altitude, through use of a larger scale topographic source map or a smaller pixel size where this is supported by the cartographic and survey properties of the source map. Additionally, in the context of modeling bird distribution, a Triangulated Irregular Network (TIN) can represent important topographical features not capable of representation with a raster DEM that has a relatively large and fixed cell size; because topographic features are often important for delimiting bird territories (Ratcliffe, 1976), this may have an impact on habitat definition for Curlew.

The digitally derived habitat map is also fully integrated into a Geographic Information System for further spatial analysis, and, because the classification process is quantified, subsequent error analysis can use uncertainty information associated with this habitat map input. Additionally, because the map is at the full spatial resolution of the satellite imagery, further analysis of habitat relationships need not depend on restructuring the habitat map to the spatial units of the wildlife survey but can investigate habitat structure with the full mapping resolution of the satellite imagery used. In this respect, the map output produced offers great potential for analysis of species distribution, notably through applying the principles of landscape ecology (Forman and Godron, 1986: Turner and Gardner, 1991). A GIS provides a highly suitable analytical environment for the identification and quantitative description of spatial pattern of habitat structures in the data presented in the map. Functional elements can also be identified through analysis of topological relationships between habitat structure. Focusing on habitat structure and function within an analytical GIS retains spatial properties of habitat information; this is likely to lead to models of distribution that are ecologically more acceptible than models based on statistical analysis of data which have

TABLE 1. CLASSES OF A PROBABILITY MODEL FOR CURLEW DISTRIBUTION (DERIVED FROM BAYESIAN CLASSIFICATION OF THREE BANDS OF A LANDSAT THEMATIC MAPPER IMAGE AND A DIGITAL ELEVATION MODEL) COMPARED WITH CATEGORIES OF SEMI-NATURAL VEGETATION FROM A MAP OF NATURAL HABITAT AT 1:50,000 SCALE. VALUES ARE THE PERCENTAGE OF EACH HABITAT CLASS ASSOCIATED WITH THE PROBABILITY RANGES IN THE OUTPUT MAP (FIGURE 1).

Probability Cover Type	0-0.20	0.21-0.40	0.41-0.60	0.61– <mark>0.8</mark> 0	0.81-1.00
Her-Rich Grassland	6.8	1.2	4.7	20.1	67.3
Rough Grassland	8.2	1.5	5.1	24.1	61.2
Dry Heath	14.1	5.0	14.4	32.9	33.7
Wet Heath	25.5	8.8	20.9	26.2	18.7
Grass-Heath Scrub	15.3	0.7	2.0	12.4	69.7
Bracken	28.5	0.1	2.2	14.9	54.1
Mires	20.1	9.3	26.6	25.1	19.0
Sub-Alpine Heath	67.6	14.7	11.7	5.2	0.9
Woodland Scrub	41.2	3.7	5.2	28.4	21.5

been rearranged to conform to the basic spatial unit used for the wildlife survey.

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# 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.
- Agterberg, F. P., 1989. Systematic approach to dealing with uncertainty of geoscience information in mineral exploration. *Proceedings 21st APCOM Symposium*, Las Vegas, March. Chapter 18, pp. 165-178.
- Aspinall, R. J., 1991. Use of an inductive modeling procedure based on Bayes Theorem for analysis of pattern in spatial data. Computer Modeling in the Environmental Sciences (D. G. Farmer and M. J. Rycroft, editors), Institute of Mathematics and its Applications Conference Series No. 28, Oxford University Press, Oxford, pp. 325-339.
- Aspinall, P. J., and A. R. Hill, 1983. Clinical inferences and decisions – I. Diagnosis and Bayes' Theorem. Ophthalmic Physiology Optician, 3:295-304.
- Avery, M. I., and R. H. Haines-Young, 1990. Population estimates for the dunlin Calidris alpina derived from remotely sensed satellite imagery of the Flow Country of northern Scotland. *Nature*, 344:860-862.
- Barnes, R. F. W., 1987. Long-term declines of Red Grouse in Scotland. Journal of Applied Ecology, 24:741-745.
- Belward, A. S., J. C. Taylor, M. J. Stuttard, E. Bignal, J. Matthews, and D. Curtis, 1990. An unsupervised approach to the classification of semi-natural vegetation from Landsat Thematic Mapper data. A pilot study on Islay. *International Journal of Remote* Sensing, 11:429-445.
- Bonham-Carter, G. F., 1991. Integration of geoscientific data using GIS. Geographical Information Systems. Vol. 2, Applications (D. J. Maguire, M. F. Goodchild, and D. W. Rhind, editors), Longman, London, pp. 171-184.
- Bonham-Carter, G. F., F. P. Agterberg, and D. F. Wright, 1988. Integration of geological datasets for gold exploration in Nova Scotia. Photogrammetric Engineering & Remote Sensing, 54(11):1585-1592.

—, 1989. Weights of evidence modeling: A new approach to mapping mineral potential. Statistical Applications in the Earth Sciences (F. P. Agterberg and G. F. Bonham-Carter, editors), Geological Survey of Canada, Paper 89-9, pp. 171-183.

Bowles, L. M., 1985. Integrated automated LANDSAT mapping into a large scale moose census program in northern Manitoba. Land/ Wildlife Integration No. 3 (H. A. Stelfox and G. R. Ironside, editors). Ecological Land Classification Series No. 22. Land Conservation Branch, Environment Canada, pp. 99-104.

- Brooks, R. T., 1990. Wildlife habitat evaluation tools: The U. S. Forest Service's Forest Inventory and Analysis. Proceedings of the International Union of Forestry Research Organisations XIXth World Congress, Montreal, 1(2):163-172.
- Buckland, S. T., M. V. Bell, and N. Picozzi, 1990. The Birds of North-East Scotland, 480 p.
- Campbell, L. H., 1983. Habitat features as a means of identifying areas of importance for moorland breeding birds. Bird Census and Atlas Studies (K. Taylor, R. J. Fuller, and P. Lack, editors). Proceedings of the VIIIth International Conference on Bird Census and Atlas Work, British Trust for Ornithology, pp. 269-272.
- Craighead, J. J., F. L. Craighead, D. J. Craighead, and R. L. Redmond, 1988. Mapping Artic Vegetation in Northwest Alaska Using Landsat MSS Imagery. National Geographic Research, 4:496-527
- Davis, F. W. D., D. M. Stoms, J. E. Estes, J. Scepan, and J. M. Scott, 1990. An information systems approach to the preservation of biological diversity. *International Journal of Geographical Information Systems*, 4:55-78.
- Dixon, R., B. Knudsen, and L. M. Bowles, 1982. A pilot study of the application of LANDSAT data in the mapping of White-tailed Deer habitat in Manitoba. *Land/Wildlife Integration No. 2* (H. A. Stelfox, and G. R. Ironside, editors). Lands Directorate, Environment Canada, pp. 91-95.
- Edwards, W., H. Lindman, and L. J. Savage, 1963. Bayesian statistical inference for psychological research. *Psychological Review*, 70:193-242.
- Epp, H., 1985. Application of satellite data and image analysis to wildlife habitat inventory. Land/Wildlife Integration No. 3 (H. A. Stelfox and G. R. Ironside, editors). Ecological Land Classification Series No. 22, Land Conservation Branch, Environment Canada, pp. 69-81.
- Forman, R. T., and M. Godron, 1986. Landscape Ecology. John Wiley and Sons, New York, 620 p.
- Goodchild, M. J., 1991. Integrating GIS and environmental modeling at global scales. GIS-LIS '91 Proceedings, 1:117-127.
- Griffiths, G. H., J. M. Smith, N. Veitch, and R. J. Aspinall, in press. The ecological interpretation of satellite imagery with special reference to bird habitats. *Landscape Ecology and Geographical Information Systems* (R. H. Haines-Young and S. R. Cousins, editors), Taylor and Francis.
- Grubb, T. G., 1988. Pattern Recognition A Simple Model for Evaluating Wildlife Habitat. USDA Forest Service Research Note RM-487, 5 p.
- Harris, R., 1983. Remote sensing support for the Omani White Oryx Project. Remote Sensing for Rangeland Monitoring and Management. Proceedings of the Ninth Annual Conference of the Remote Sensing Society, Silsoe College, Bedford, pp. 17-24.
- Haworth, P. F., and D. B. A. Thompson, 1990. Factors associated with the breeding distribution of upland birds in the south Pennines, England, *Journal of Applied Ecology*, 27:562-577.
- Hill, M. O., 1991. Patterns of species distribution in Britain elucidated by canonical correspondence analysis, *Journal of Biogeog*raphy, 18:247-255.
- Hudson, P. J., 1988. Spatial variations, patterns and management options in upland bird communities. *Ecological Change in the Uplands*, (M. B. Usher and D. B. A. Thomspson, editors), Blackwells, Oxford, pp. 381-397.
- Huntley, B., 1979. The past and present vegetation of the Caenlochan National Nature Reserve, Scotland. New Phytologist, 83:215-283.
- Isaacson, D. L., D. A. Leckenby, and C. J. Alexander, 1982. The Use of Large-Scale Aerial Photography for Interpreting Landsat Digital Data in an Elk Habitat-Analysis Project, Journal of Applied Photogrammetric Engineering, 8(1):51-57.
- Laperriere, A. J., P. C. Lent, W. C. Gassaway, and F. A. Nodler, 1980. Use of LANDSAT data for moose habitat analyses in Alaska, *Journal Wildlife Management*, 44:881-887.

- Lyon, J. G., 1983. Landsat-derived land-cover classifications for locating potential Kestrel nesting habitat, *Photogrammetric Engi*neering & Remote Sensing, 49:245-250.
- Milne, B. T., K. M. Johnston, and R. T. T. Forman, 1989. Scale-dependent proximity of wildlife habitat in a spatially-neutral Bayesian model, *Landscape Ecology*, 2(2):101-110.
- Ormsby, J. P., and R. S. Lunetta, 1987. Whitetail deer food availability maps from Thematic Mapper data, *Photogrammetric Engineering & Remote Sensing*, 53(8):1081-1085.
- Palmeirim, J. M., 1985. Using LANDSAT TM imagery and spatial modelling in automatic habitat evaluation and release site selection for the Ruffed Grouse (Galliformes : Tetraonidae). Proceedings 19th International Symposium of Remote Sensing and Environment, pp. 729-738.
  - ——, 1988. Automatic mapping of avian species habitat using satellite imagery, Oikos, 52:59-68.
- Pereira, J. M. C., and R. M. Itami, 1987. GIS-based habitat modeling using logistic multiple regression: a study of the Mount Graham Red Squirrel, *Photogrammetric Engineering & Remote Sensing*, 57(11):1475-1486.
- Ratcliffe, D. A., 1976. Observations on the breeding of the Golden Plover in Britain, *Bird Study*, 23:63-116.
- Reed, T. M., J. C. Barrett, C. Barrett, and D. R. Langslow, 1983. Diurnal variability in the detection of Dunlin (*Calidris alpina*), Bird Study, 30:244-246.
- Reed, T. M., C. Barrett, J. C. Barrett, S. Hayhow, and B. Minshull, 1985. Diurnal variability in the detection of waders on their breeding grounds, *Bird Study*, 32:71-74.
- Scepan, J., F. Davis, and L. L. Blum, 1987. A Geographic Information System for managing California Condor habitat. GIS '87 Second Annual International Conference on GIS, San Francisco, California, 26-30 October.
- Smith, J. M., D. R. Miller, and J. G. Morrice, 1989. An evaluation of a low resolution DTM for use with satellite imagery for environmental mapping and analysis, *Remote Sensing for Operational Applications* (E. C. Barrett and K. A. Brown, editors), Proceedings of the 15th Annual Conference of the Remote Sensing Society, pp. 393-398.
- Stelfox, H. A., 1985. Wildlife resource evaluation and land-wildlife relationship models, *Land-Wildlife Integration No. 3* (H. A. Stelfox and G. R. Ironside, editors). Ecological Land Classification Series No. 22, Land Conservation Branch, Environment Canada, pp. 59-68.
- Stenback, J. M., C. B. Travlos, R. H. Barrett, and R. G. Congalton, 1987. Application of remotely sensed digital data and a GIS in

evaluating deer habitat suitability of the Tehema Deer winter range. GIS '87 Second Annual International Conference on GIS, San Francisco, California, 26-30 October.

- Stoms, D. M., F. W. Davis, and C. B. Cogan, 1982. Sensitivity of wildlife habitat models to uncertainties in GIS data, *Photogrammetric Engineering & Remote Sensing*, 58(6):843-850.
- Tommervik, H., and I. Lauknes, 1988. Inventory of reindeer winter pastures by use of LANDSAT-5 TM data, Proceedings of the International Geoscience and Remote Sensing Symposium 1988, Edinburgh, Scotland, p. 1223.
- Trodd, N. M., 1989. Approaches to mapping heathland vegetation. Remote Sensing for Operational Applications (E. C. Barrett and K. A. Brown, editors), Proceedings of the 15th Annual Conference of the Remote Sensing Society, pp. 507-508.
- Trodd, N. M., G. M. Foody, and T. F. Wood, 1989. Maximum likelihood and maximum information: mapping heathland with the aid of probabilities derived from remotely-sensed data, *Remote Sensing for Operational Applications* (E. C. Barrett and K. A. Brown, editors), Proceedings of the 15th Annual Conference of the Remote Sensing Society, pp. 421-426.
- Turner, M. G., and R. H. Gardner (editors), 1991. Quantitive Methods in Landscape Ecology, Ecological Studies No. 82. Springer–Verlag, New York, 536 p.
- Walker, A. D., C. G. B. Campbell, R. E. F. Heslop, J. H. Gauld, D. Laing, B. M. Shipley, and G. G. Wright, 1982. *Eastern Scotland: Soils and Land Capability for Agriculture*. Macaulay Institute for Soil Research, Aberdeen.
- Walker, P. A., 1990. Modelling wildlife distributions using a geographic information system: kangaroos in relation to climate, *Journal of Biogeography*, 17:279-289.
- 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.
- Wardley, N. W., E. J. Milton, and C. T. Hill, 1987. Remote sensing of structurally complex semi-natural vegetation – an example from heathland. International Journal of Remote Sensing, 8:31-42.
- Watson, J., D. R. Langslow, and S. R. Rae, 1987. The impact of landuse changes on Golden Eagles (Aquila chrysaetos) in the Scottish Highlands. Nature Conservancy Council, Chief Scientist Directorate Report No. 720.
- Wood, T. F., and G. M. Foody, 1989. Analysis and representation of vegetation continua from Landsat Thematic Mapper data for lowland heaths. *International Journal of Remote Sensing*, 10:181-191.

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# GIS VIDEOS: AN ANNOTATED BIBLIOGRAPHY

# **COMPILED BY AMY RUGGLES**

This text is intended to serve as a reference guide for individuals who are searching for the video that best meets their GIS education and training needs. Each bibliography includes information on the video's: publication date; format; length of play time; copyright date; price; source; a brief description; and keywords. Over 150 videos are covered.

The videos have been grouped under 6 general headings: Data Acquisition, Data Display and Analysis, GIS Applications and Context, GIS Principles, GIS Software and Hardware, and Video Series. However, video topics are not limited to GIS alone. Some videos from related fields such as cartography, remote sensing, and surveying are also included.

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