

# Using the spatial and spectral precision of satellite imagery to predict wildlife occurrence patterns

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## Abstract

We investigated the potential of using unclassified spectral data for predicting the distribution of three bird species over a ~400,000 ha region of Michigan's Upper Peninsula using Landsat ETM+ imagery and 433 locations sampled for birds through point count surveys. These species, Black-throated Green Warbler, Nashville Warbler, and Ovenbird, were known to be associated with forest understory features during breeding. We examined the influences of varying two spatially explicit classification parameters on prediction accuracy: 1) the window size used to average spectral values in signature creation and 2) the threshold distance required for bird detections to be counted as present. Two accuracy measurements, proportion correctly classified (PCC) and Kappa, of maps predicting species' occurrences were calculated with ground data not used during classification. Maps were validated for all three species with Kappa values >0.3 and PCC >0.6. However, PCC provided little information other than a summary of sample plot frequencies used to classify species' presence and absence. Comparisons with rule-based maps created using the approach of Gap Analysis showed that spectral information predicted the occurrence of these species that use forest subcanopy components better than could be done using known land cover associations (Kappa values 0.1 to 0.3 higher than Gap Analysis maps). Accuracy statistics for each species were affected in different ways by the detection distance of point count surveys used to stratify plots into presence and absence classes. Moderate-to-large detection distances (100 m and 180 m) best classified maps of Black-throated Green Warbler and Nashville Warbler occurrences, while moderate detection distances (50 m and 100 m), which ignored remote observations, provided the best source of information for classification of Ovenbird occurrence. Window sizes used in signature creation also influenced accuracy statistics but to a lesser extent. Highest Kappa values of majority maps were typically obtained using moderate window sizes of 9 to 13 pixels (0.8 to 1.2 ha), which are representative of the study species territory sizes. The accuracy of wildlife occurrence maps classified from spectral data will therefore differ given the species of interest, the spatial precision of occurrence records used as ground references and the number of pixels included in spectral signatures. For these reasons, a quantitative examination is warranted to determine how subjective decisions made during image classifications affect prediction accuracies.

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## 1. Introduction

One of the greatest impediments to accurate mapping of the Earth's resources is a paucity of spatially referenced

information (Franklin, 2001). Remote sensing technologies could improve this situation for objects detectable at the spectral frequencies and grain, or smallest spatial sampling unit, of the sensor. In the case of wildlife habitat studies, the Landsat Thematic Mapper series of sensors are often used due to their relatively low price, short repeat-time (16 days), spatial resolution (approximately 30 m × 30 m), and spectral

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resolution capable of detecting differences in vegetation (Lillesand & Kiefer, 1999).

Landsat imagery is often used to map wildlife distribution patterns indirectly. This is accomplished by first classifying images into land cover categories and then reclassifying land cover categories for wildlife occurrence by using known vegetation affinities of each species (e.g., Morrison et al., 1992; Scott et al., 1993). In order to characterize land cover, however, a classification scheme must be used to instruct image processing software how to aggregate pixels of remotely sensed imagery into discrete categories.

Land cover classification schemes divide continuous ecological gradients (Austin, 1985; Whittaker, 1956) into compositionally distinct features to achieve an objective (Foody, 1999; Townsend, 2000; Zube, 1987). While this allows large regions to be divided in ways that humans can understand, wildlife often perceive and respond to landscape heterogeneity in substantially different ways (Johnson et al., 1992; Tang & Gustafson, 1997). For example, rather than choosing habitat based on a particular forest type or age class, some bird species select for understory vegetation or forest structure (Anders et al., 1998; Probst et al., 1992; Stouffer & Bierregaard, 1995). Thus, most land cover classifications have limited utility for predicting patterns of these species' occurrences. Similarly, when classification schemes do not include key habitat features under selection by target species, investigations into the dependence of wildlife species' occurrences on land cover classes are not likely to identify causal mechanisms underlying the observed distributions (Wiens et al., 2002). Thus, the disparity between human and wildlife perceptions of and responses to landscape heterogeneity can add substantial error into statistical analyses and management prescriptions.

In attempts to minimize predictive errors potentially fostered by inappropriate or inaccurate land cover maps, a logical approach to extrapolating patterns of wildlife distributions across large areas is to directly classify imagery for an individual species' occurrence using raw spectral reflectance data. Using this approach, spectral characteristics of locations where species are known to occur are employed when extrapolating their distributions. The underlying assumption is that species' occurrences can be predicted by spectrally detectable components of their habitat. A benefit to this approach is that distribution maps are classified using all occurrence locations separately yet simultaneously, therefore no global model relating spectral variables to occurrence sites need be assumed.

This direct approach to mapping wildlife distributions is growing in popularity (e.g., Conner, 2002; Hepinstall & Sader, 1997; Jenkins et al., 2003a; Laurent et al., 2002). While such studies indicate the potential for bypassing a land cover map, they have not yet provided a strong methodological test of raw satellite imagery's capability to map species' distributions. Some of the choices made by the authors during classification were arbitrary and no framework was established for investigating the influence of these

choices, or the range of possible choices on prediction accuracy.

Several decisions must be made during image analyses in order to extrapolate the results of presence/absence surveys across a landscape using spectral information. Some options include the type of imagery, the classification scheme, the method of classification, the choice of pixels used to represent classes, and the parameter values (both spatial and spectral) used to classify maps. While these choices could be described as the "art" of image processing, it is also possible to place them within a hypothesis-testing framework to quantify their effects on prediction accuracy.

To investigate the influence different choices in classification options have on predicting wildlife occurrence maps, we have created a software program (PHASE1) as the first phase in the development of a **Habitat Analysis By Iterative CLASSification** procedure (HABICLASS). The purpose of HABICLASS is to minimize anthropocentric classification bias when predicting wildlife distribution patterns (first phase) and to determine causes of the predicted patterns (second phases). PHASE1 was created to make the prediction phase methodologically rigorous through the use of statistical models. This is accomplished by creating maps of species' occurrence patterns, iteratively modifying classification methods used to create the maps, and evaluating divergences in prediction accuracies of maps created in different ways. The goal therefore is to identify better means of improving prediction accuracy within a strong inference framework. Here we use PHASE1 of HABICLASS to predict forest bird occurrence with the spatial precision of Landsat imagery. Although these analyses are conducted using spectral data, PHASE1 may be used in combination with any raster dataset.

PHASE1 is superficially similar to other image classification software. It is used to create a spectral signature for each field plot describing grid values at that location. These signatures are then used to identify spectrally similar pixels and classify them into categories to create a thematic map. PHASE1 differs from many other image classification software through its application of cross-validation to stratify and repeatedly sample random subsets of signatures. As a result, a group of maps, rather than a single map, are created from a set of reference plots. The accuracy of the group of maps can then be summarized to describe a statistical distribution of accuracy for comparisons with maps made through other methods. However, reference data for this approach need to be spatially compatible to deny the introduction of scale or aggregation effects (Dutilleul, 1998; Dutilleul & Legendre, 1993) that could influence class descriptions. Reference data used in signature creation should therefore describe the same size area, or grain, for proper use within the PHASE1 classification framework.

To ensure grain equivalency within datasets used in PHASE1, we developed a **Grain Representative Assessment and INventory** protocol (GRAIN). GRAIN permits a per-pixel extrapolation of spatially referenced survey data across large areas with the spatial and spectral precision of satellite

imagery. For bird point count surveys, GRAIN requires the surveyor's location be georeferenced and the distance between the surveyor and each bird recorded. The georeferenced position is employed to identify the pixel used for signature development in PHASE1. Species presence and absence at those locations define classes used in supervised image classification. However, proximity thresholds (hereafter referred to as detection distances) can be set to exclude species detected beyond specified distances from observers, effectively converting a presence location into an absence. In addition to pixels overlapping georeferenced locations, signatures may also contain values for pixels surrounding the georeferenced position if they meet specified spatial and spectral criteria. Such decisions made during image classification can be iteratively modified, allowing the analyst to repeatedly tune the classification parameters and create a series of maps for investigating the influence of these choices on map accuracies.

The goal of this study was to identify methods of image classification that could predict the regional occurrence of Neotropical migrant warblers with the spectral and spatial precision of Landsat 7 ETM+ imagery and independent from any other system for categorizing the landscape (e.g., land cover maps). Furthermore, we were interested in whether this method could obtain results comparable to Gap Analysis (Donovan et al., 2004; Scott et al., 1993). Gap Analysis is used to classify maps representing species' fundamental niches (Hepinstall et al., 2002, Gap maps), or areas of potential but not necessarily occupied habitat, using known species-habitat associations, land cover data and expert knowledge within a geographic information system. Land cover maps provide the foundation for most predictions within the Gap framework. Thus, comparisons of spectrally derived species' occurrence maps with Gap maps provide a useful and contemporary reference for how well Landsat imagery can be used to directly predict species' occurrences.

Our specific questions were 1) do individual pixels of Landsat 7 ETM+ imagery contain some of the information needed to predict the occurrence of forest bird species, especially those that select for understory conditions during the breeding season? If the answer to question (1) is yes, then 2) can we identify the influence of detection distances for categorizing species occurrence and alternative classification options on prediction accuracy, and 3) how does the accuracy of spectrally derived maps compare to those created from land cover maps using the methods of Gap Analysis?

We used the GRAIN protocol to collect ground reference data of bird occurrence over a large forested region. PHASE1 was employed to automate signature creation describing surveyed plots and classify maps predicting species occurrence. We also examined the influence of varying two spatially explicit classification parameters on prediction accuracy: 1) the window size used to average spectral values in signature creation, and 2) the threshold distance required for bird detections to be counted as

present. The accuracy of maps predicting species' occurrences was validated with ground data not used during classification and compared with the accuracy of recent Gap maps. Accuracy was assessed using two common measures, and the information content of these measures was compared.

## 2. Methods

### 2.1. Study region

The study region is located in Michigan's Upper Peninsula, USA and includes parts of five counties (Baraga, Dickinson, Iron, Menominee, and Marquette; Fig. 1A). This

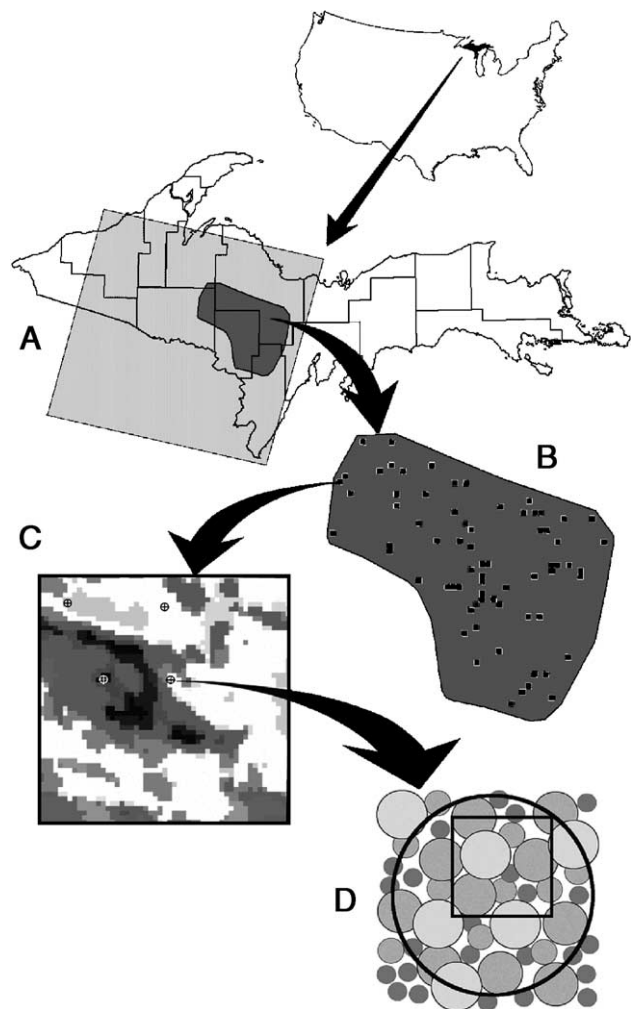


Fig. 1. The study region lies within a single Landsat 7 ETM+ scene and contains parts of five counties in Michigan's Upper Peninsula (A). Within the study region (B), randomly selected landscape units (C; township sections or USGS QQs with coarse land cover classes within landscape units shown as shades of gray) define areas for the selection of specific plots (D; overview showing different tree species) for bird occurrence surveys. Plots were sampled with a minimum 30-m radius from plot centers (D; large circle), so that a single Landsat 7 ETM+ pixel (D; square) falling within this area could be precisely characterized.

region covers ~400,000 ha or approximately 11% of a single Landsat 7 ETM+ scene (Path 24 Row 28). A majority of the land is owned by state government and industry with management primarily focused on wood production. The study region is an ecologically diverse landscape characterized by a spatial mosaic of forest stands that include upland hardwoods (sugar maple (*Acer saccharum*), quaking aspen (*Populus tremuloides*), yellow birch (*Betula alleghaniensis*), basswood (*Tilia americana*)), lowland hardwoods (black ash (*Fraxinus nigra*), red maple (*Acer rubrum*)), lowland conifers (northern white cedar (*Thuja occidentalis*), black and white spruce (*Picea mariana* and *Picea glauca*), tamarack (*Larix laricina*)) and upland conifers (European larch (*Larix deciduosa*), eastern hemlock (*Tsuga canadensis*), red and jack pine (*Pinus resinosa* and *Pinus banksiana*)). Besides the influence of glacial topography and other edaphic factors, the composition and structure of canopy and understory vegetation has high spatial variability due to differences in forest management practices and gradients of deer browsing pressure (Albert, 1995; Van Deelen et al., 1996).

## 2.2. Study species

We chose three bird species for analysis (Latin name and American Ornithologists' Union four-letter code): Black-throated Green Warbler (*Dendroica virens*; BTNW), Nashville Warbler (*Vermivora ruficapilla*; NAWA), and Ovenbird (*Seiurus aurocapillus*; OVEN). All three of our study species commonly breed in deciduous and mixed forests of northern North America and select territories on the basis of subcanopy composition and structure in addition to dominant overstory components (Collins, 1981; Collins, et al., 1982; Dunn & Garrett 1997; Morse, 1976). These birds perceive and respond to landscapes at a small spatial grain for many functional reasons including those related to niche partitioning and territory delineation (MacArthur & Pianka 1966; Robinson & Holmes, 1982; Schoener, 1968). Predicting the occurrences of these warblers therefore provides a strong test for assessing the information embedded in Landsat 7 ETM+ imagery.

Although the study species are included in the same family and have all shown a general affinity for breeding in forested areas, they have markedly different habitat associations. BTNW nest in a wide variety of mature coniferous, deciduous and mixed forests (Brewer et al., 1991; Dunn & Garrett, 1997; Morse, 1976). Most foraging and nesting take place in the midlevels of vegetation, therefore requiring a multi-storied layering of vegetation, often with a shrub or coniferous understory component (Collins, 1983; Norton, 1999). NAWA nest within dense ground cover in a variety of wet and dry open woodlands (Brewer et al., 1991; Dunn & Garrett, 1997) and often near ecotones (Williams, 1996). In drier areas, they commonly select early successional forests that arise following fires or deforestation. OVEN nest on the ground and often in large stands of mature

deciduous and mixed forests (Brewer et al., 1991; Smith & Shugart, 1987; Zach & Falls, 1979). Dry upland areas are most commonly used but they sometimes are found in lowland forests and swamps. In all OVEN breeding habitat, however, leaf litter is essential for foraging and nest construction (Van Horne & Donovan, 1994). Males of all three species are territorial and vociferous during the breeding period and have distinctive songs that make them easy to distinguish from other species in the study region. In addition, they have characteristic plumages that can be identified by trained observers.

## 2.3. The GRAIN protocol for field sampling

The GRAIN protocol was used to select and characterize locations for BTNW, NAWA and OVEN occurrence surveys. GRAIN uses the random sampling method described by Lillesand et al. (1998) for the Upper Midwest Gap project but modified to incorporate the field data collection approach of Liu et al. (2001). In 2001, random United States Geological Survey (USGS) quarter quarter quads (QQQs;  $n=28$ ) served as landscape sampling units (LUs). In 2002 and 2003, random township sections ( $n=36$  and 32, respectively) served as LUs (Fig. 1B). This switch between roughly equal area QQQs and township sections (1000 ha vs. 1037 ha, respectively) was made in order to allow our data to be more easily integrated with public and private databases such as Michigan's atlas of breeding birds (Brewer et al., 1991).

Within each LU, between 2 and 8 plots (Fig. 1C) were selected for bird surveys for a total of 433 plots surveyed over the course of the study. These plots were a minimum of 90-m apart with the mean minimum distance of 240-m (194-m standard deviation) from the next closest plot. Survey plots encompassed a 30-m radius area so that a single pixel of Landsat 7 ETM+ imagery sensed over plot centers could be precisely characterized by data collected within this area (Fig. 1D). The specific plot selection criterion was that a hypothetical 30-m  $\times$  30-m square could be placed anywhere within the plot and perceived by the field crews as having the same vegetation structure and composition as a similar square placed anywhere else within the plot.

Plot selection in general was dependent on two criteria: 1) permission to access the property and 2) maximizing the biotic and abiotic differences among plots to sample the spatial and spectral heterogeneity of the study region. Preference was given to at least one northern hardwood plot in each LU to satisfy collaborative research priorities if northern hardwood plots could be located in the field. Locations of plot centers were georeferenced using a minimum of 80 global positioning system (GPS) point locations collected at 5-s intervals with a Trimble Geo-Explorer 3 (Trimble Navigation Ltd.) and later differentially corrected to a precision of  $\pm 5$  m using Coast Guard base station data. Site centers were flagged, as were 30-m distances in the 4 cardinal directions (sensu Huff et al.,

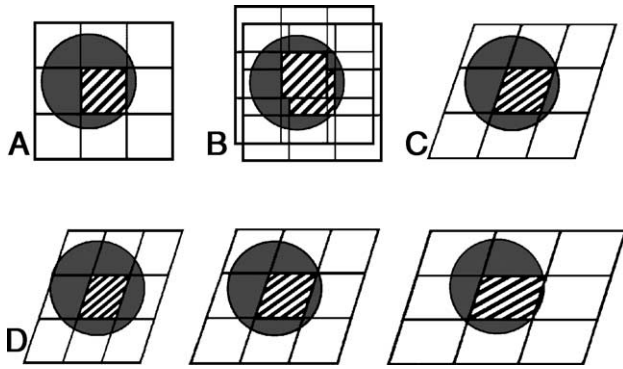


Fig. 2. Factors affecting the ground instantaneous field of view captured by pixels in Landsat imagery include: A) unknown pixel location, B) non-overlapping pixels of multiple images, C) effects of Earth rotation, and D) inclusion of increasing ground coverage within pixels increasingly farther from nadir. Gray circles represent 30-m radius field plots. Each grid represents the ground information contained within a nine-pixel window. The hashed center cell represents the ground area used to describe the sampling plot.

2000). Accuracy of plot center locations was determined to be within the precision of Garmin III+ GPS receivers (15 m; Garmin Corporation) used to navigate to these locations during repeated point count surveys.

There were several reasons why we used a 30-m radius circle for selecting survey locations. First, many of our ground surveys were conducted prior to image acquisition so the exact pixel location was unknown (Fig. 2A). Also, we used multiple season imagery for analysis (see Section 2.4) and pixels from different images do not always overlap (Fig. 2B). Third, the ground information attributed to a pixel is actually a parallelogram that is not square due to the rotation of the Earth as the Landsat 7 satellite travels in a circumpolar orbit (Fig. 2C). Fourth, the Landsat satellites have sensors that sweep back-and-forth past a central point called nadir. The ground instantaneous field of view attributed to pixels farther from nadir is therefore larger than that of pixels closer to nadir (Fig. 2D). Although geometric correction during level 1G processing of Landsat 7 imagery makes adjustments for the last two factors, the resulting image values are still dependent on the geometric limitations of the sensor and the influence of reflective features adjacent to the ground area contained in the pixel (Cracknell, 1998). Finally, circular plots are easier to inventory for birds than parallelograms.

In addition to detections within the 30-m sampling radius, species were also recorded if detected within larger radii circles surrounding plot centers. These radii included 50 m and unlimited distance during all three years. During 2002 and 2003, an additional detection distance of 100 m was used. These larger spatial thresholds are commonly employed during point count surveys for birds (e.g., Ralph et al., 1993; Ralph et al., 1995). Bird detectability was assumed to be consistent among plots and all detections were assumed to be made within approximately 180 m from plot centers (see Wolf et al., 1995).

LUs were divided into 7 (2001), 6 (2002), and 12 (2003) groups for daily bird surveys to minimize travel time (not necessarily minimizing distances) among LUs surveyed during any day. The surveyed order of LU groups, plots among LUs, and survey timing was randomized, as was the selection of observer for each survey. Beginning at sunrise, observers conducted surveys within a 5-h period when weather conditions did not preclude birds from singing (Ralph et al., 1993; Ralph et al. 1995). Observers had been trained to detect the three species in this study and other species in the region by song and sight using tapes, field guides and practice prior to data collection.

Bird species were counted as present if detected by song, call or sight within each detection distance over an 11-min period. Timing of surveys began immediately when observers reached the center of the plot. After 10 min an additional 1 min was spent walking around the plot center to flush elusive individuals within 30 m. The distance of flushed individuals detected <180 m from plot centers by surveyors walking in or out of the plots was also recorded. Each plot was visited three times during the breeding period for these species between June 4 and July 3 in either 2001, 2002, or 2003. At least two observers surveyed each site to account for possible differences in observer's physical abilities to detect the study species (Ramsey & Scott, 1981). A total of 8 observers collected data over the 3 years of this study.

In all, 433 plots ( $n=112$ , 86 and 235 for years 2001, 2002 and 2003, respectively) were surveyed for bird species' occurrences 3 times during the breeding period (Table 1). Survey plots were placed in a wide variety of land cover classes (see Space Imaging Solutions, 2001 for land cover descriptions) including aspen associations ( $n=85$ ), herbaceous openland ( $n=10$ ), lowland coniferous forest ( $n=35$ ), lowland deciduous forest ( $n=14$ ), lowland shrub ( $n=2$ ), mixed upland conifers ( $n=4$ ), mixed upland deciduous ( $n=6$ ), northern hardwood associations ( $n=190$ ), pines ( $n=23$ ), other upland conifers ( $n=15$ ), upland mixed forest ( $n=36$ ), and upland shrub / low-density trees ( $n=10$ ). Within these land cover classes, surveys were conducted over a wide variety of size classes (non-forest, sapling, pole, mature), management histories (clear cuts, selective cuts, no cuts) and ranges of vertical

Table 1

The number of plots where species were observed within each detection distance

Species	Detection Distance			
	30 m $n=433$	50 m $n=433$	100 m $n=321$	180 m $n=433$
Black-throated Green Warbler	44	175	196	271
Nashville Warbler	88	208	208	271
Ovenbird	150	309	297	409

All 433 plots were surveyed using 30-m, 50-m, and 180-m detection distances and 321 plots were surveyed using the 100-m detection distance.

structure (homogeneous to diverse). Survey plots were placed at varying distances from hard and soft vegetation edges as long as specific plot selection criteria were met (see Fig. 1D).

#### 2.4. Image processing

We used Normalized Difference Vegetation Index values (NDVI, Jensen, 2000) derived from bands 3 and 4) and short-wave infrared values (SWIR, band 5) from multiple seasons of Landsat 7 ETM+ imagery to create spectral signatures describing survey plots and to create maps predicting bird species' occurrences. Multiple season images have been found useful in distinguishing among forest classes with differing phenological leaf canopy trajectories (Mickelson et al., 1998; Wolter et al., 1995). NDVI is often used for vegetation classification because plants reflect or absorb different amounts of red (band 3) and near-infrared (band 4) light depending on biophysical factors such as chlorophyll content and leaf area (Jensen, 2000). The longer SWIR wavelengths are also functional for vegetation discrimination because they are influenced by leaf moisture content and canopy cover (Asner & Lobell, 2000; Ceccato et al., 2001) as well as coniferous timber volume (Gammel, 1995). Multiple seasons of NDVI and SWIR values can therefore be useful in distinguishing among differences in overstory composition. Leaf-off images can also be helpful in separating deciduous woodlands by non-deciduous components under the canopy (Mickelson et al., 1998). Subcanopy factors of deciduous and mixed forests that may be influential to the warbler species in this study include leaf litter, coarse woody debris, and the presence of balsam firs, among others.

Two Landsat 7 ETM+ level 1G images of Path 24 Row 28 were obtained from the USGS. Because the study area is very cloudy due to the influence of Lake Superior and Lake Michigan, we were limited in our choices for contemporary, cloud-free imagery. An April 27, 2001 image was selected to describe early spring leaf-off conditions just after snowmelt. Photosynthesizing species during this time included conifers, grasses and early spring ephemeral herbs and forbs (personal observation). A May 29, 2001 image was chosen to represent early leaf-on conditions. During late May in Michigan's Upper Peninsula, most deciduous species have small, young leaves (personal observation) which likely allow some vegetation under the canopy to contribute to reflectance values.

All image processing was conducted using Imagine 8.7 software (Leica Geosystems GIS and Mapping LLC). The two images were converted to at-sensor reflectance using the import utility. At-sensor reflectance was converted to surface reflectance through a dark object subtraction (sensu McDonald et al., 1998). Each image was georectified (RMSE <8 m) using 200 road intersections within and around the study area. A nearest neighbor transformation was employed during georectification to maintain the

information content within pixels. Road intersections were identified using a digital road map obtained from the state of Michigan's Center for Geographical Information (<http://www.mcgi.state.mi.us/mgdl/>). This road map is a level 3b product, originally created from Census Bureau TIGER line files and most recently repositioned using USGS 1:12,000 Digital Ortho Quarter Quad aerial photography.

Visual inspection of the resulting images revealed overlap of the two images and 50 ground control road intersections independently georeferenced in the study region, hence indicating accurate georectification. Two to four corners of the ground control road intersections were georeferenced using a minimum of 100 GPS point locations collected at 5-s intervals with a Trimble GeoExplorer 3 (Trimble Navigation Ltd.) and later differentially corrected to a precision of  $\pm 2$  m using Coast Guard base station data. A lack of canopy at these intersections permitted greater spatial precision than could be obtained at many of the forested plots where bird surveys were conducted.

After georectification, the spectral data were relativized (see McCune & Grace 2002). Relativization of spectral values is necessary when using simple distance measures in spectral space during classification. In this way, the values within bands are modified so that equal weight can be given to a similar increment of difference in any band (see Section 2.5.3). For these analyses, we rescaled the image bands to unsigned 8-bit integer values. This conversion type is an artifact of an earlier PHASE1-type analysis conducted with scripts written for proprietary software. The PHASE1 software can use long integers and floating point values, however the use of integers substantially reduces computer processing time.

The NDVI values were calculated from surface reflectance values of the April and May images. Surface reflectance SWIR values of these images were range shifted to have minimum values of 0. For each image, SWIR values and NDVI values greater than zero were multiplied by 600. The multiplication constant of 600 was chosen because it allowed us to take advantage of the full 256-value range of an 8-bit integer. The 4 grid layers (2 NDVI and 2 SWIR) were exported as ASCII files for use in PHASE1.

#### 2.5. HABICLASS PHASE1

##### 2.5.1. Validation data

Before each classification procedure, a subset of survey plots was randomly selected to evaluate the accuracy of derived occurrence maps (validation data). Detections of a species within a specified distance of the plot center were stratified into presence and absence (e.g., Ovenbird detections within 30 m). One-third of the plots from each of these strata were randomly selected for validation. The remaining plots were used to classify maps of species occurrence within that detection distance using cross-validation (classification data). The detection distance was then iteratively modified, all the occurrence data were re-stratified, and the

process was repeated for each species and detection distance.

### 2.5.2. Signature creation for multiple window sizes

Signature creation, as well as image classification (Section 2.5.3), cross-validation (Section 2.5.4) and majority map generation (Section 2.5.5) were automated by means of the PHASE1 program created with the C++ programming language. Points indicating plot centers were overlaid with the processed imagery to identify focal pixels. A window size was specified around each focal pixel, and within that window, all pixel values were averaged for each grid layer (2 NDVI and 2 SWIR). These 4 values served as a multivariate spectral signature describing each plot. Four sets of signatures were created using 4 different window sizes. They included 0 (per-pixel classification), 1 ( $3 \times 3$  square of 9 pixels), 2 (2 pixel radius containing 13 pixels), and 3 (3 pixel radius containing 29 pixels).

### 2.5.3. Image classification

The following classification procedure was followed for each window size, bird species, and detection distance. The set of signatures was stratified by species presence and absence. Two-thirds of the signatures within each species occurrence stratum were randomly selected. The signatures were then used to classify all the pixels in the image based on their minimum spectral Euclidean distance to sampled plots. Spectral Euclidean distance is a relatively simple, non-parametric method of image classification. Images were classified using the following discriminant function (Richards & Jia, 1999):

$$\min [d(\mathbf{x}, \mathbf{s}_i)^2] = (\mathbf{x} - \mathbf{s}_i)^t (\mathbf{x} - \mathbf{s}_i) \quad (1)$$

where  $\mathbf{s}_i$ ,  $i=1, \dots, M$  are the signature values,  $\mathbf{x}$  is a  $4 \times 1$  vector of values of the pixel to be classified, and  $t$  indicates that the vector is transposed. In other words, each of the 4 grid values for any given pixel was evaluated for its distance to the respective grid values described in the signatures. The squared distances for each grid were summed, and the signature with the smallest square root summed distance to the pixel was used to classify that pixel. In cases where two or more signatures had equal distances from the pixel in question, a random signature from among the alternatives was assigned.

### 2.5.4. Cross-validation

PHASE1 implements a cross-validation procedure to quantify the statistical distribution of accuracy for the maps it generates in each combination of window size, species and detection distance. We generated eleven maps during each combination. Each map was generated from two-thirds of the signatures randomly selected from both occurrence strata. The remaining one third of the classification data were used to test the accuracy of the map. Accuracy statistics of proportion correctly classified (PCC) and Kappa

were calculated for each of the 11 maps. The distribution moments from the 11 instances for each combination were then calculated.

Like PCC, the Kappa coefficient (Cohen, 1960) generally ranges from 1 for perfect agreement to 0 for no agreement (negative values indicating less than chance agreement are dependent on marginal distributions (Rosenfield & Fitzpatrick-Lins, 1986)). Unlike PCC, Kappa removes chance agreement from consideration in accuracy assessment. Kappa uses all the cells in the error matrix and therefore includes a measure of overall thematic classification accuracy as well as omission and commission error for each class. While other accuracy measures such as sensitivity and specificity (e.g., Hepinstall et al., 2002) can be calculated from the error matrix, for simplicity we compare only PCC and Kappa.

### 2.5.5. Majority map validation

A majority classification was implemented in PHASE1 to summarize the 11 maps created during cross-validation. The majority classification created a new map whereby each pixel in the majority map was labeled using the most common occurrence class for that pixel from the 11 maps created during the cross-validation procedure. Accuracy statistics for this map was assessed using the 1/3 of plots reserved for validation (see Section 2.5.1). Because the validation data were randomly selected for each species and detection distance but not window size used in signature development, differences in classification accuracy within species and detection distances were solely due to differences in window sizes.

## 2.6. Gap Analysis

The Michigan Gap Analysis Program (MI-GAP) was recently instituted and initial maps predicting the occurrence of bird species across the state were released in 2004 (Donovan et al., 2004). These maps were developed based on known habitat associations (e.g., Brewer et al., 1991) and expert opinion (J. Skillen, personal communication). Using a recently derived land cover map (Space Imaging Solutions, 2001), land cover classes considered to be habitat for each species (Table 2) were classified as presence while all others were classified as absence. The spatial precision of Gap maps was presented to the public at a 90-m resolution. The maps, however, represented resampled versions of the original 30-m resolution Landsat imagery-derived maps, which we obtained and used in this study.

The accuracies of Gap maps were assessed in several ways using the entire set of field data. Pixels overlapping plot centers were assessed for their ability to predict species' occurrences using PCC and Kappa for each detection distance. For example, a  $30\text{-m} \times 30\text{-m}$  pixel overlapping a survey plot and classified by MI-GAP for Ovenbird occurrence (using known land cover associations) was assessed for its accuracy in predicting whether

Table 2  
Land cover classes used to classify species presence in Gap Analysis

Black-throated Green Warbler	Nashville Warbler	Ovenbird
N. hardwood assoc.	N. hardwood assoc.	N. hardwood assoc.
Mixed upland deciduous	Oak assoc.	Oak assoc.
Pines	Aspen assoc.	Aspen assoc.
Other upland conifers	Mixed upland deciduous	Mixed upland deciduous
Mixed upland conifers	Pines	Pines
Upland mixed forest	Other upland conifers	Upland mixed forest
	Mixed upland conifers	
	Upland mixed forest	
	Lowland deciduous forest	
	Lowland coniferous forest	
	Lowland mixed forest	
	Lowland shrub	

Ovenbirds were present or absent within 30 m, 50 m, 100 m, and 180 m. We also assessed whether pixels in regions surrounding the plot centers accurately predicted species' occurrences using the other window sizes employed during signature creation (see Section 2.5.3). If the Gap maps predicted species' presence within any pixels contained within each window size then the plot was labeled present. Otherwise, it was labeled as absent. The accuracies of MI-GAP predictions were thus compared with field observations over all combinations of detection distances and window sizes.

### 3. Results

#### 3.1. Information content of imagery

Presence and absence were accurately predicted better than chance using unclassified imagery for all species within most detection distances (Fig. 3A). However, there were large differences between accuracy statistics. Comparisons between PCC and Kappa showed that PCC was greatly influenced by the proportion of plots where the species were detected, independent of which species, detection distance, or window size were used in map classification (Fig. 3A). For example, in situations where a species was rarely detected (e.g., BTNW within 30-m radius; Table 1), classification of the entire landscape as absent for that species would yield high PCC values. Alternatively, in situations where a species was nearly ubiquitous (e.g., OVEN within 180 m; Table 1), classification of the entire landscape as presence would yield high PCC values. Such classifications, however, do not yield predictions better than could be made with a random assignment of pixels to classes. The Kappa coefficient accounts for this problem by including row and column totals of the error matrix in its calculation and therefore provided a measure of prediction accuracy that was less dependent on the proportion of plots

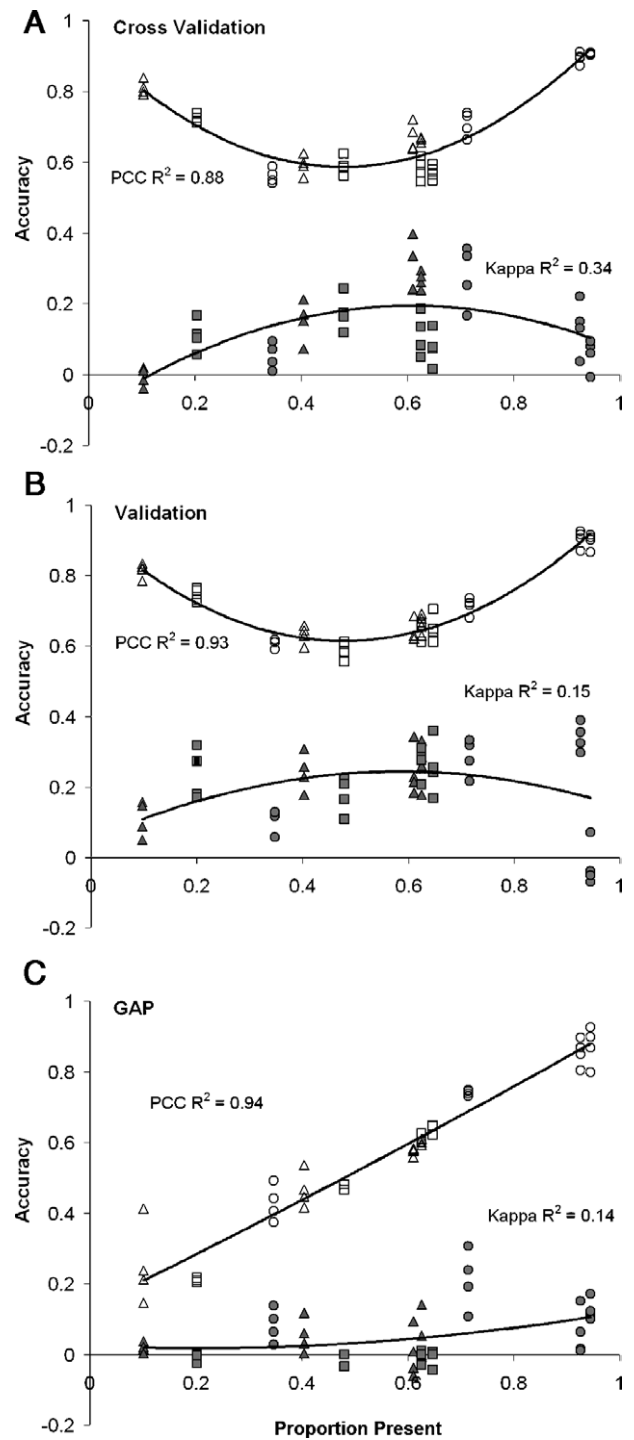


Fig. 3. Relationships between the proportion of plots where species were detected and accuracy measures of proportion correctly classified (PCC; open symbols) and Kappa (filled symbols) values for (A) cross-validation, (B) validation, and (C) Gap Analysis maps. Each symbol represents the results of a single analysis for a given species (Black-throated Green Warbler=triangle; Nashville Warbler=square; Ovenbird=circle), detection distances and window size. First-order polynomial model fit is provided only as a descriptive measure of dependence as each point represents accuracy statistics from random subsets of the same pool of plots classified in different ways.



where species were detected (as indicated by lower  $R^2$  values in Fig. 3).

The accuracy of maps differed among species. However, both accuracy measures were most affected by the detection distance used to separate sites into species occurrence strata. For BTNW, Kappa increased and PCC decreased with detection distance (Fig. 4A). Maps classified for NAWA occurrence show a similar, although less distinct relationship between the two accuracy measures (Fig. 4B). OVEN occurrence maps on the other hand, had a unimodal relationship between the Kappa coefficient and detection distance (Fig. 4C). PCC values for these maps increased with detection distance.

Window sizes used in signature creation had less of an effect than detection distances on Kappa values of BTNW and OVEN maps. For example, the difference between mean Kappa values for BTNW predictions at detection distances of 30 m and 180 m was larger than the range of mean Kappa values for any window size within those detection distances (Fig. 4A). However, window size appears to have a larger effect on Kappa values within detection distances where Kappa was highest. For example, highest mean Kappa values were obtained for BTNW at a detection distance of 100 m but also showed a greater range of variability over window sizes within this detection distance (Fig. 4A). Similar results were obtained for OVEN within a detection distance of 50 m (Fig. 4C). Kappa values for NAWA were affected primarily by window size (Fig. 4B).

In summary, differences in Kappa values allowed insight into factors affecting the predictive accuracy of species occurrence maps. While Kappa had a weak dependence on the proportion of presence or absence plots used as signatures during classification (i.e., small  $R^2$  values in Fig. 3), both the detection distance used to separate plots among occurrence strata and the window size used to create spectral signatures caused most of the variation in Kappa values (Fig. 4). However, the relative influence of these factors was species dependent. PCC on the other hand, was almost completely dependent on the proportion of presence or absence plots used as signatures (i.e., large  $R^2$  values in Fig. 3). PCC therefore summarized the relative number of plots per signature category and provided little information about the influence of detection distance or window size on classification accuracy.

### 3.2. Majority map validation

Majority maps accurately predicted species' occurrences from validation data better than chance for most detection distances and window sizes (Fig. 3B). Similar to the maps created via cross-validation, PCC provided little information. In fact, majority classification increased the dependence of PCC and reduced the dependence of Kappa on the distribution of plots among occurrence strata (increased and decreased  $R^2$  values, respectively; Fig. 3B).

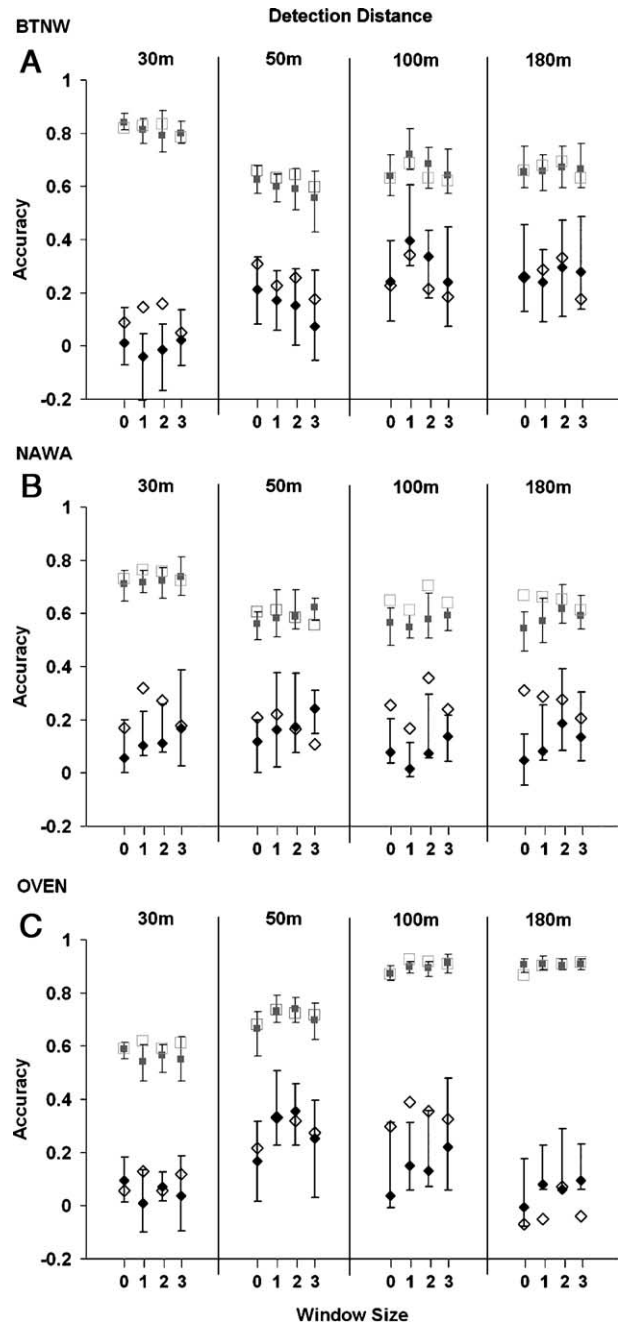


Fig. 4. Proportion correctly classified (gray squares) and Kappa values (black diamonds) for maps predicting the occurrence of A) Black-throated Green Warbler, B) Nashville Warbler, and C) Ovenbird using different detection distances and window sizes. Filled symbols represent mean values of accuracy statistics for 11 cross-validation iterations with error bars indicating minimum and maximum values. Open symbols represent accuracy statistics of a majority map summarizing the cross-validation runs and tested with a subset of data reserved for validation.

Majority maps classified validation data better than any of the cross-validation runs for some detection distances and window sizes (Fig. 4). Like the cross-validation maps, detection distance had a strong effect on Kappa values of majority maps. However, window size had a stronger influence on Kappa than detection distance for NAWA (Fig. 4B).

### 3.3. Gap maps

Gap maps yielded a linear relationship between PCC and the proportion of plots where species were detected regardless of species, detection distance or window size (Fig. 3C). As the proportion of detections increased within the dataset (e.g., via larger detection distances), PCC increased. Kappa values for Gap maps, like those for spectrally derived species' occurrence maps, were less dependent on the proportion of plots where species were

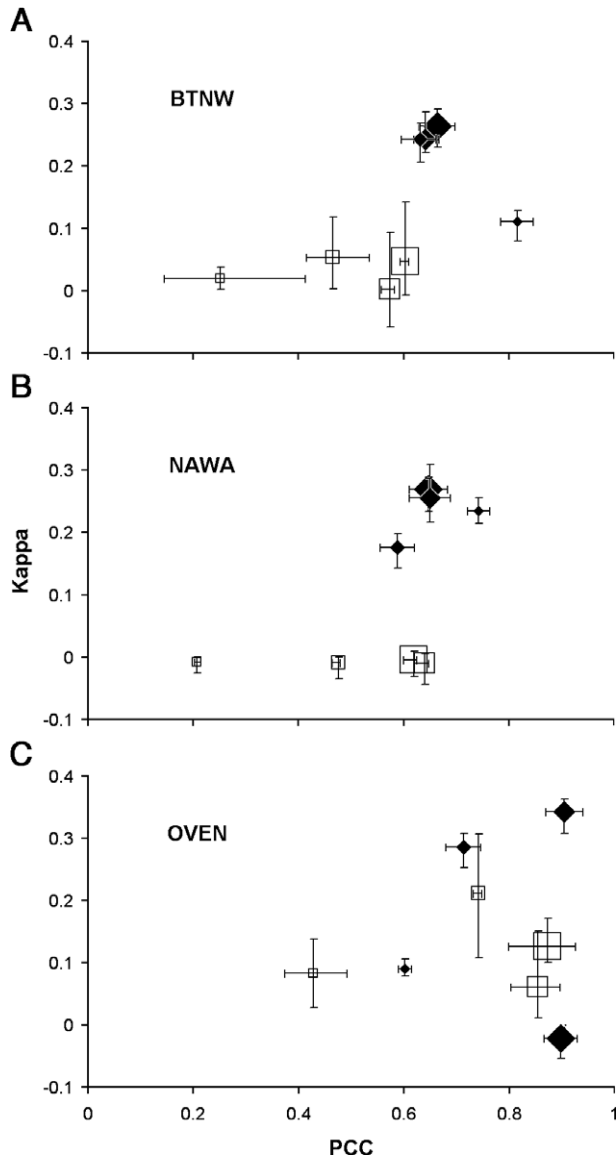


Fig. 5. Distribution of accuracy statistics (proportion correctly classified and Kappa values) for majority maps created from the 11 cross-validation runs and tested with a subset of data reserved for validation (filled diamonds) and for Gap Analysis maps (open squares) tested with data from all 433 plots. Statistics are shown for A) Black-throated Green Warbler, B) Nashville Warbler, and C) Ovenbird. Larger symbols represent larger detection distances. Symbol location indicates mean values for all window sizes used to classify maps for each detection distance, with error bars indicating minimum and maximum values.

detected and therefore provided a better measure than PCC of how detection distance and window size affected prediction accuracy. Detection distance (Fig. 5 symbol sizes) had little effect on Gap map Kappa values. Most of the variation in these values was due to the window size used to assess prediction accuracy (Fig. 5 error bars). Only the 50-m detection data of OVEN (Fig. 5C) were comparable to maps created using PHASE1. However, window size also had a very strong impact on these values.

Spectrally derived maps yielded larger Kappa values than Gap maps in most situations (Figs. 3 and 5). For all three species, highest Kappa values were obtained using spectral associations. In particular, NAWA occurrence was predicted better than chance only by using spectral associations (Fig. 5B). OVEN, on the other hand, was predicted better from spectral associations only when using moderate detection distances (Fig. 5C).

### 4. Discussion

Using a relatively simple, non-parametric method of image classification, we predicted the regional occurrences of three warbler species with the spatial and spectral precision of Landsat 7 ETM+ imagery and independent of a land cover map. Maps were validated for all three species with Kappa values  $>0.3$  and PCC  $>0.6$ . Furthermore, spectral information was used to predict the occurrence of these species that use forest subcanopy components, with Kappa values 0.1 to 0.3 higher than achieved by the Michigan Gap program.

Bypassing subjective land cover categorization thus avoided land cover classification errors and exploited a large range of information provided in six bands of imagery. For example, all three species are known to use areas of mixed pine species in Michigan (Brewer et al., 1991). Mixed pines, however, are included in the same land cover class as pine plantations. In the study region, none of the study species were found in pine plantations. Thus, Gap maps would err on the side of commission for these species in pine plantations. This explicit intent of Gap Analysis to err on the side of commission for purposes of mapping "potential" habitat (Hepinstall et al., 2002) also likely contributed to the linear relationship between PCC and the proportion of plots where species were detected (Fig. 3C). If subtle spectral differences among different combinations of pine in the study region are detectable within pixels of Landsat 7 ETM+ imagery, then occurrence maps created using spectral associations would not systematically incur this error.

Although classification methods differed between Gap maps and direct use of spectral associations, similar factors likely affected their predictions. Misclassification of both types of maps could have occurred via the influence of spectrally undetectable components of habitat

on prediction accuracy. These components include vegetation structure (Collins, 1983; Collins et al., 1982; Probst et al., 1992; Smith & Shugart, 1987) and landscape factors such as edge effects, patch sizes and patch isolation (Dijak & Thompson, 2000; Kotliar & Wiens, 1990; Sisk & Haddad, 2002). Future uses of PHASE1 and efforts by the Michigan Gap program need to integrate additional data types into predictive models to account for these habitat associations and improve prediction accuracy. For example, additional data sources such as digital elevation models (O'Neill et al., 1997), radar (Imhoff et al., 1997), and lidar (Lefsky et al., 1999) will likely provide some of the non-spectral information needed to improve species' occurrence prediction accuracy and land cover map precision. Indices of landscape configuration and context (Conner, 2002; Pearson, 1993; Saab, 1999), land use and other land owner activities (Boren et al. 1997; Lepczyk et al., 2004), and the connectivity of potential wildlife occurrence areas (Fahrig & Merriam, 1985) could provide additional sources of information for increased prediction accuracy and interpretation of results. Alternative parametric measures of spectral dissimilarity such as Mahalanobis distance (Richards & Jia, 1999) also show promise for mapping species' occurrences through spectral associations (see Conner, 2002).

Comparison of PCC and Kappa in this study emphasizes the importance of selecting a measure of prediction accuracy that can be interpreted in a meaningful way. PCC did not provide a valid measure of prediction accuracy for binary classification of species presence and absence using either spectral associations or the approach of Gap Analysis. For the three species in this study, PCC provided little information other than a summary of the distribution of samples among classes. These results were obtained regardless of species, detection distance or window size. In contrast, Kappa values were nearly independent of the distribution of plots among occurrence classes, especially after majority map classification. Thus, Kappa values provided a more complete picture of classification accuracy than PCC.

The range of Kappa values, however, varied given the species, detection distance and window size. Kappa values spanned 20% to 30% the scope of the index over any group of 11 cross-validation iterations. Majority classification helped hone in on the "true" predictability of occurrence maps. Furthermore, majority maps often predicted species' occurrences better than any of the maps created during cross-validation. Cross-validation followed by majority classification thus shows potential for improving the accuracy of any image classification method. However, no single measure, including Kappa, tells the entire story about the quality of classification accuracy. Other accuracy measures such as sensitivity and specificity (Hepinstall et al., 2002) can shed additional light on reasons for omission and commission errors.

Our results also indicated that the detection distance used to characterize each species' occurrence affected Kappa values substantially (Fig. 4). Moderate-to-large detection distances (100 and 180 m) best classified maps of BTNW and NAWA occurrences. However, moderate detection distances, which ignored remote observations, provided the best source of information for classification of OVEN. Unlimited distance point counts for this very loud and common species in the study region may consequently include detections unrepresentative of the vegetation described by pixels used in signature creation. These larger detection distances are also subject to increased bias from differences in observer's hearing abilities (Ramsey & Scott, 1981). Attention should therefore be given to using appropriate detection distances when creating occurrence maps through spectral associations.

Besides detection distances, window sizes used in signature creation also influenced accuracy statistics but to a lesser extent. Highest Kappa values of majority maps were typically obtained using moderate window sizes. These window sizes of 9 to 13 pixels (0.8 to 1.2 ha) used in our analyses are best representative of the study species territory sizes (Morse, 1976; Schoener, 1968). These results emphasize the importance of considering the species' natural history when choosing among alternative classification parameters. However, habitat features within their territory may be of the greatest importance for some species, while landscape factors may be more influential for others (Pearson, 1993; Saab, 1999). In our analyses, window size provided an indication of how averaging the spatial variability of pixels surrounding survey plots affected our results. Spatial variability is expected to affect prediction accuracy as a function of the feature being classified, the information content of the imagery, edge effects, the interspersed spatial autocorrelation from higher order edaphic gradients and landscape structure (Collins & Woodcock, 1999; Hurlbert, 1984; Legendre et al., 2002).

In addition to the influence of window size and detection distance investigated in this study, prediction accuracy is likely dependent on several other factors. Kappa values are expected to vary as a function of the extent of the study area, type and timing of imagery, grain of imagery, image processing methods, and image classification methods. The type of occurrence data used in supervised image classification will also affect prediction accuracy. This is because the occurrences of some species are expected to vary spatially as a function of ontogenic changes in life history strategies (Kolasa & Waltho, 1998; Polis, 1984; Temple, 1990) and temporal changes in habitat use (Morse, 1985). The influence of all these factors on prediction accuracy can be tested within a strong inference framework (sensu Jenkins et al., 2003b; Murphy & Noon, 1992) using maps generated with PHASE1.

Descriptions of landscape heterogeneity will therefore differ given the process of interest as well as the grain of

analysis, the classification system in use and the variability of spectral information employed. For these reasons, a quantitative examination of all possible factors affecting prediction accuracy is warranted. The GRAIN protocol and HABICLASS procedure introduced in this paper provide a general framework for such an examination. By controlling for scale and aggregation effects and permitting a strong inference approach for investigations into causal mechanisms behind the predicted occurrence patterns, GRAIN and HABICLASS provide a compelling complement to regional mapping efforts of wildlife occurrences such as GAP Analysis.

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