

**Exploring the relative importance of satellite-derived descriptors of production, topography and land cover for predicting breeding bird species richness over Ontario, Canada**

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## **ABSTRACT**

In this paper we investigate the relative predictive power of a number of remote sensing-derived environmental descriptors of land cover and productivity to predict species richness of breeding birds in Ontario, Canada. Specifically, we first developed a suite of environmental descriptors (productivity, land cover, and elevation). These descriptors were based on readily available data, including the MODerate-resolution Imaging Spectroradiometer (MODIS) onboard the Terra and Aqua satellites and terrain data from Shuttle Radar Topography Mission (SRTM). We then assessed the capacity of the environmental descriptors, using a decision tree approach, to estimate species richness of all breeding birds, and of groups of bird species based on habitat and nesting groupings, using data summarized from the Ontario Breeding Bird Atlas. Results indicated that the variance in the distributions of total bird species richness, as well as richness of habitat and nesting groups, were well predicted by the environmental descriptors (with variance explained ranging between 47 to 75 %) with the predictions clearly related to both habitat (as modeled by land cover and land cover diversity) and vegetation productivity. Modeling demonstrates that initial partitioning is most often based on land cover class, indicating it may be the driving variable of bird species richness; however, information on vegetation productivity and energy were then critical in defining how many species occur in each habitat type. The results indicate that remotely sensed environmental descriptors can provide an effective tool for predicting breeding bird species richness at regional scales.

## 1. INTRODUCTION

Understanding the factors that drive patterns of species diversity across large areas is important for predicting how species will respond anthropogenic influences and changing climate (Orme *et al.* 2005). At the global scale, species richness is most commonly explained by a latitudinal gradient effect, which predicts richness of most taxa to increase towards the tropics (Rosenzweig 1995). At continental and regional spatial extents, however, it is more likely that a series of factors combine to influence species diversity (Kerr and Packer 1997). In cold or temperate terrestrial regions, such as Canada, the role of climate, in particular heat, becomes increasingly important (Currie and Paquin 1987). Additionally local factors such as topography, disturbance, water movement, and species competition have all been demonstrated as important drivers at finer grains and over smaller extents (Daubenmire 1974; Moore *et al.* 1993; Virkkala *et al.* 2005). Given likely changes in climate, and disturbance regimes, predicted to occur across Canada (Flannigan *et al.* 2005, Kurz *et al.* 2008), it is becoming critically important to better understand the link between these factors and species richness and map current patterns so any likely changes in species richness can be anticipated and where possible adapted for.

Understanding the factors which influence the species richness of breeding birds provides an excellent case study as avian species differ significantly in their migratory behavior, nesting requirements, feeding and mating habits, and other aspects of specific life histories. For example, permanent residents do not migrate at all, while Neotropical migrants nest in North America and then fly to wintering habitat in Mexico, Central or

South America (McLoughlin *et al.* 2000). These complexities make broad patterns of bird biodiversity difficult to predict and often necessitate datasets covering large spatial areas. Fortunately, data on breeding bird richness is common and often readily available with studies carried out at a national level in a number of countries such as on a 5-km (in the Netherlands) and 10-km grid (in the United Kingdom, Bibby *et al.* 1992), and across South Africa with a quarter degree grid (Githaiga-Mwici *et al.* 2002).

Within North America the breeding bird survey (BBS) and Christmas bird count (CBC) surveys are normally undertaken by thousands of amateur ornithologists (Venier *et al.* 2004). Similarly, the Ontario Breeding Bird Atlas (Cadman *et al.* 2007) is a volunteer-based project which gathers data on the breeding distribution of all the bird species in Ontario. The 10 x 10 km OBBA gridded dataset provides information on the distribution and relative abundance of 286 bird species throughout the province. Ontario offers an ideal study area to investigate the relationship between breeding bird species richness and physical and environmental conditions.

Larger than many nations, the Canadian province of Ontario occupies an area of approximately 1 million km<sup>2</sup> covering a wide range of land uses and ecological conditions. The terrestrial ecozones of Canada (Wiken 1986) define four broad ecozones that are encompassed by the province, ranging from wetland dominated lowlands through boreal forests to mixed forests dominated by anthropogenic activities.

The goal of this research is to explore the capacity of a number of remote sensing-derived environmental descriptors to predict the variance in bird diversity patterns over

the province of Ontario, Canada. To meet this goal we first gathered or calculated a number of descriptors (land cover, productivity, and topography) based on readily available satellite data acquired from either MODerate-resolution Imaging Spectroradiometer (MODIS) or the Shuttle RADAR Topography Mission (SRTM). We then assessed the predictive capacity of these descriptors, via a decision tree methodology, to estimate species richness of all breeding birds, and of groups of bird species aggregated by habitat associations and nesting behaviors using data summarized from the OBBA.

## **2. BACKGROUND**

MacArthur (1972) postulated that biodiversity patterns respond to three major descriptors; climatic stability, productivity, and habitat structure – with empirical evidence demonstrating that each of these descriptors plays an important role in biodiversity variations. As a result, bioclimatic models are often applied to estimate the distribution of species at broad scales (Guisan & Zimmermann 2000; Rahbek & Graves 2001; Willis & Whittaker 2002). At more local scales, however, bioclimatic models may produce poorer predictions due to the exclusion of important local factors (Iverson & Prasad 1998; Thuiller *et al.* 2003) such as land cover and disturbance, particularly those due to human influences (Thuiller *et al.* 2004). For example, Kerr *et al.* (2001) examined the relationship between butterfly species richness across Canada in 2 – 5 ° latitude grid with habitat heterogeneity data acquired from remote sensing and climate information from meteorological datasets. They found that habitat heterogeneity explained the most variability in species richness, with secondary contributions from climatic factors.

Likewise, Hurlbert and Haskell (2003), using remotely sensed estimates of productivity (through the normalized difference vegetation index (NDVI)) and spatial data describing biomes and topography to predict avian species richness. The authors found habitat heterogeneity was important for predicting avian species richness at coarse spatial grains with descriptors such as temperature, evapo-transpiration, or vegetation productivity important at finer spatial scales grains among species that specialize on different habitat types.

These, and other studies, demonstrate that remote sensing offers an ideal technology to develop a range of variables to not only predict species richness at a point of interest, but also to monitor and assess changes in biodiversity at a variety of spatial and temporal scales (Link & Sauer 1997). Monitoring these factors through time has the potential to provide for continental and/or national stratifications of biodiversity – indicating areas where potential changes impacting biotic diversity may be occurring. This type of information is critical for conservation planning, priority setting, designing future surveys and to facilitate monitoring (Venier *et al.*, 2004). In a recent review of the potential of remote sensing technology to provide explanatory variables to predict species richness, Duro *et al.* (2007) proposed broad categories which capture previous and current research trends. These categories, described in detail below, include measures of: (i) the physical environment, such as topography, (ii) indicators of vegetation productivity and (iii) habitat suitability, with respect to its spatial arrangement

and structure (Table 1). Importantly, all of these factors can be described at a similar grain (1 km) using remote sensing technology.

**Table 1: Description of the remotely sensed datasets used in this study.**

	<b>Topography</b>	<b>Productivity</b>	<b>Land cover</b>
Image spatial resolution / grain	90 m < 60° N 1000 m > 60°N	1000 m	1000m
Image extent	Canada Wide	All vegetated areas	Global
Type of remotely sensed data	RADAR	MODIS fPAR	AVHRR Land cover
Platform	Shuttle	Terra / Aqua	AVHRR / MODIS
Temporal Capacity	Single	Monthly / Annual	Once
Ownership / cost	Free	Free	Free
Size of Dataset	250 MB	100 MB	300 MB
Processing strategy	Coefficient of Variation (COE)	Dynamic Habitat Index (DHI)	Image classification, Pattern indices
Processing strategy references	Wilson and Gallant (2000)	Mackey et al. (2004), Coops et al. (2008)	Hansen et al. (2000)

## 2.1 Topography

While elevation is a relatively static variable compared to other biophysical factors such as climate, its function as a key driver of biodiversity has been well documented (Rosenzweig 1995). For example, in the tropics, unimodal shaped patterns have been developed to explain species diversity, with the highest species diversity often occurring at mid-elevations (as summarized in Rosenzweig 1995) partially explained by mid-domain effects. Similarly Patterson *et al.* (1998) showed a decreasing trend in bat and bird species richness as elevation increased.

## 2.2 Vegetation productivity

A number of hypotheses have been suggested to explain the positive correlation between species richness and productivity (Evans *et al.* 2005). Theories such as "more trophic levels" (Evans *et al.* 2005) hypothesize a direct correlation between productivity and species richness whereby areas of high productivity have more resources to partition among competing species, thus supporting a greater number of species and larger populations than areas with lower productivity (Walker *et al.* 1992). Contemporary thought is that the "more individual hypothesis" (Wright 1983) explains the positive correlations between species richness and productivity. This is due to the availability of more resources resulting in more individuals with the subsequent larger populations reducing the extinction risk, therefore increasing the number of species present in an area at any one time. However direct evidence to support this hypothesis is difficult to develop (Mason *et al.* 2008).



Remotely sensed data offers a capacity to estimate vegetation productivity through relationships with standing biomass, leaf area index (LAI), tree volume, or canopy light absorption which can be associated with species richness. The relationship between avian species diversity and annual vegetative biomass for example, was successfully applied in Senegal using broad scale information on vegetation greenness (Jorgensen & Nohr 1996). Skidmore *et al.* (2003) predicted mammalian and avian species richness using 1-km scale predictions of vegetation greenness, however they noted that, in general, climatic layers were better predictors of richness than the greenness observations alone. Bonn *et al.* (2004) applied a similar approach to study the relationship between the species richness of birds in Southern Africa and productivity, and found that increased productivity lead to increased species richness. More recently Nilsen *et al.* (2005) linked landscape greenness with fauna diversity to test the hypothesis of Harestad and Bunnell (1979) that species home ranges should be inversely related to productivity. The results indicated that the inclusion of satellite data increased the predictive accuracy of 8 of the 12 examined carnivore species. Waring *et al.* (2006) utilized satellite data over the conterminous United States to predict woody species richness, as measured using Forest Inventory and Analysis data (of the United States Department of Agriculture Forest Service) and found significant relationships between total species richness at the ecosystem level and maximum annual greenness.

### 2.3 Land cover

While climate and productivity have been linked to broad global patterns of biodiversity (Willig *et al.* 2003; Hawkins *et al.* 2003), finer scale spatial patterns such as land use

and land cover, forest structural stage, and their associated spatial patterns, are increasingly being investigated as potential predictors of species diversity (Fahrig 2003). Land cover maps, in particular, depicting individual or assemblages of land cover types or species are critical to biodiversity assessments as they represent a “first-order” analysis of species occurrence (Turner *et al.* 2003). Luoto *et al.* (2004) used land cover type, fragmentation and topographic metrics, at 30 m spatial resolution, to predict bird species richness in the boreal agricultural-forest mosaics in Finland. Their habitat-composition model explained 61 % of the variation in species richness, but the variance explained decreased to 48 % when applied to the model test area. In contrast, the habitat-structure model explained 59 % of the variation in species richness, which then increased to 62 % when applied more broadly. In Ontario, Smith (2007) found that vegetation type was the best explainer of winter bird species richness in urban environments with natural vegetation and size of area more important than similarly sized patches of managed, horticultural parkland, within urban natural areas.

### **3. METHODS**

#### *3.1 Study area and data*

##### 3.11 Breeding bird surveys

To quantify avian biodiversity we used atlas data provided by the OBBA (version 2; available at: [www.birdsOntario.org](http://www.birdsOntario.org); described at: Bird Studies Canada, 2006a, 2006b).

For atlas data collection, the province was tessellated into a grid of 10 km cells on a Universal Transverse Mercator (UTM) projection. In southern areas of the province the tessellation was surveyed in a spatially continuous manner; in northern areas with

limited population base and road access, a minimum of one 10 x 10 km cell for every 100 x 100 km area was surveyed resulting in a total of 5555 surveyed cells. Point counts by experienced birders were collected to generate estimates of abundance. Additional information was collected through the use of nest record cards detailing information for any nests found. For our analysis, we calculated total bird species richness and richness for six species groupings based on nesting and habitat preferences: woodland species, successional-scrub species, wetland, urban, and grassland species, with remaining species grouped as non-specialists. Our species group definitions followed those of the Canadian Wildlife Service Canadian bird trends species habitat groups (Downes & Collins 2007).

### 3.12 Remotely Sensed Data: Topography

In 2000, NASA and the United States National Imagery and Mapping Agency (NIMA) launched the SRTM on the Space Shuttle. The SRTM mission obtained data for 80 % of the land surface between  $\pm 60^\circ$  latitude which provides previously unavailable consistent elevation data over the global land base at 90 m spatial resolution, with vertical resolution of  $\approx 5$  m (Farr & Kobrick 2000). We obtained SRTM version 2 data for Ontario and, in order to describe variation in topography at the OBBA scale, we computed the topographic coefficient of variation as the mean of the elevation within a 10 km window divided by its standard deviation.

### 3.13 Remotely Sensed Data: Productivity

A key metric of vegetation productivity from satellite imagery is the prediction of the fraction of photosynthetically active radiation (fPAR) intercepted by vegetation, which is analogous to greenness cover (Knyazikhin *et al.* 1998) and ranges from zero (on barren land) to one (for dense vegetation cover). In theory, the higher the average fPAR level observed over the course of a seasonal plant growing cycle, the more dense the green leaf cover, the higher the productivity, and the less disturbed the vegetation cover. In order to condense the time series of fPAR we implemented a Dynamic Habitat Index (DHI) proposed by Mackey *et al.* (2004) and Berry *et al.* (2007) and applied to Canada by Coops *et al.* (2008), which utilizes time series of satellite observations of greenness to derive three descriptors of the underlying vegetation dynamics: the total annual productivity, the minimum level of perennial cover, and the degree of vegetation seasonality. We utilized data from both MODIS sensors TERRA and AQUA, launched in 2000 and 2002 respectively, which provided imagery at 1 km spatial resolution in 36 spectral bands (Heinsch *et al.* 2006). To minimize the influence of cloud cover, atmospheric variation, and other confounding environmental conditions, the maximum daily fPAR was selected for each 8-day period. These 8-day composites were combined into monthly maximum fPAR products and mapped at a spatial resolution of 1 km. Global fPAR monthly images from 2000 – 2005 were accessed from Boston University (<http://cliveg.bu.edu>). From these data we computed the three DHI components: (i) annual primary productivity, (ii) seasonal greenness, and (iii) annual minimum cover.

Annual primary productivity can be expressed as the integrated (or summed) greenness over an entire year. This annual index of productivity has a strong theoretical base

(Goward *et al.* 1985), as well as empirical justification for forests (Coops *et al.* 1999), grasslands (Wang *et al.* 2004), and crops (Groten 1993).

In this study annual primary productivity was derived by summing monthly fPAR observations for each year, from 2000-2005 and then averaged over the 6 years.

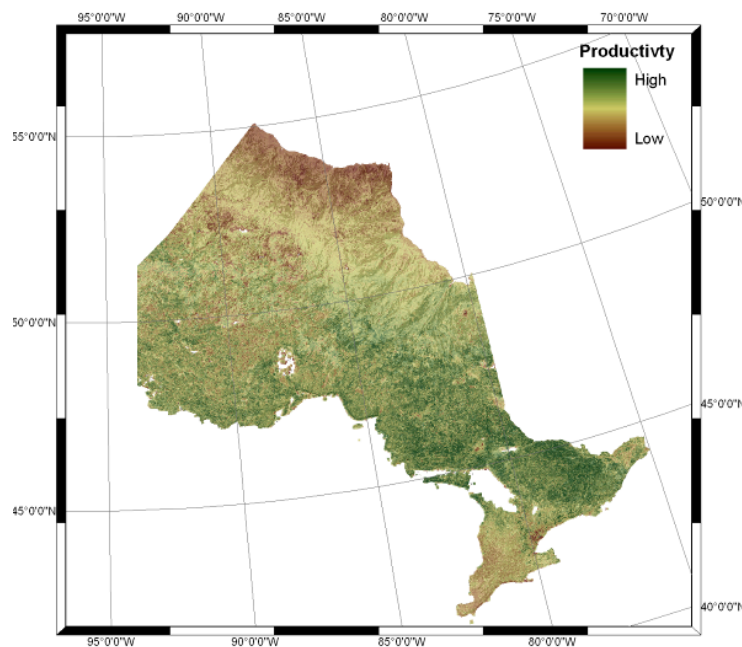
Annual minimum cover relates the potential of the landscape to support populations throughout the year (Schwartz *et al.* 2006). Locations bereft of significant snow cover following summer often maintain greenness into winter, and fPAR remains above 0. In areas where snow covers the vegetation, fPAR equals or approaches 0. The annual minimum value of fPAR was therefore derived by calculating the annual minimum monthly fPAR observation for each year, from 2000-2005 and averaged over the 6 years .

Seasonal variation in greenness is an integrated measure of climate, topography, and land use. To assess variation in the fPAR throughout the year, we computed the standard deviation of monthly values for each cell, and then divided that value by the mean annual fPAR to attain the coefficient of variation (CV). High CV values signified seasonal extremes in climatic conditions or limited periods with agricultural productivity, whereas sites with low coefficient of variation typically represented irrigated pasture, barren land, or evergreen forests (with additional trends and distribution detailed in Coops *et al.* 2008). The three annual DHI composite were then averaged over the 6 years to provide a long term average DHI descriptor for this study.

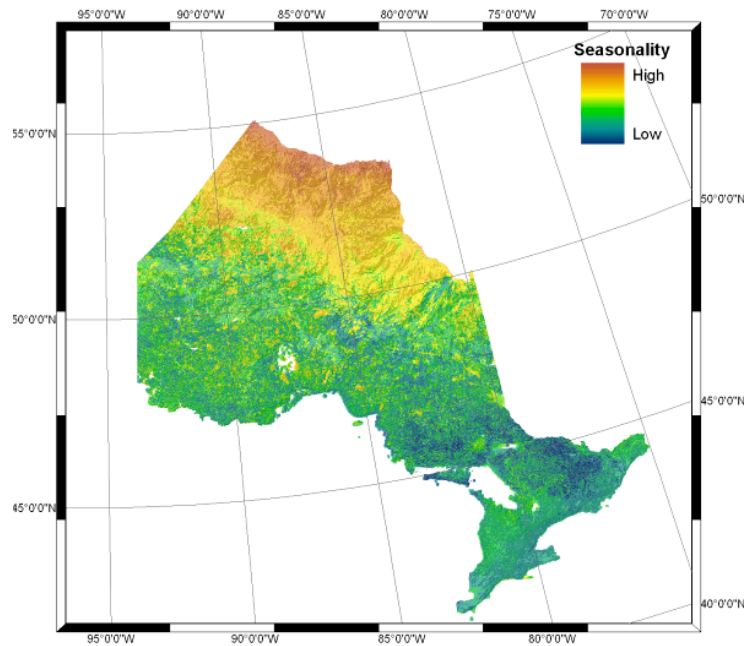
As befitting such a large and geographically diverse region, Ontario has marked differences in productivity largely expressed along a latitudinal gradient. The highest annual seasonality in Ontario is found in the northern portions of the province where the vegetation is largely characterized by open fens and bogs with dry ground cover dominated by lichens. Some forest species exist in small patches, including trembling aspen (*Populus tremuloides*), poplar (*Populus sp*), and white birch (*Betula papyrifera*). This region experiences extensive snow cover in the winter months resulting in significant phenological change with greening of the fens and bogs in summer. The combined DHI response in this region therefore shows a highly seasonal landscape, low in productivity, and low apparent minimum cover. Moving southward into more central Ontario, the landscape has an increasingly variable topography with coniferous and evergreen boreal forest species and a mosaic of forest conditions resulting from harvesting activities (Wulder *et al.* 2007). The area also experiences less snow cover, persisting for a shorter time, and is combined with evergreen vegetation. The result is the seasonality component of the DHI being low, with higher productivity and minimum cover components. In the southern areas of Ontario, greater land cover diversity is found over mild topography and warmer temperatures making the area suitable for agriculture that has reduced forests to small isolated woodlots. The combined DHI indicates higher vegetation productivity, low seasonality, and high levels of minimum cover. The intensive agriculture practices throughout this mosaic act to create patches of higher seasonality and low minimum cover.

Visualizing the three components of the DHI in a single combined color composite

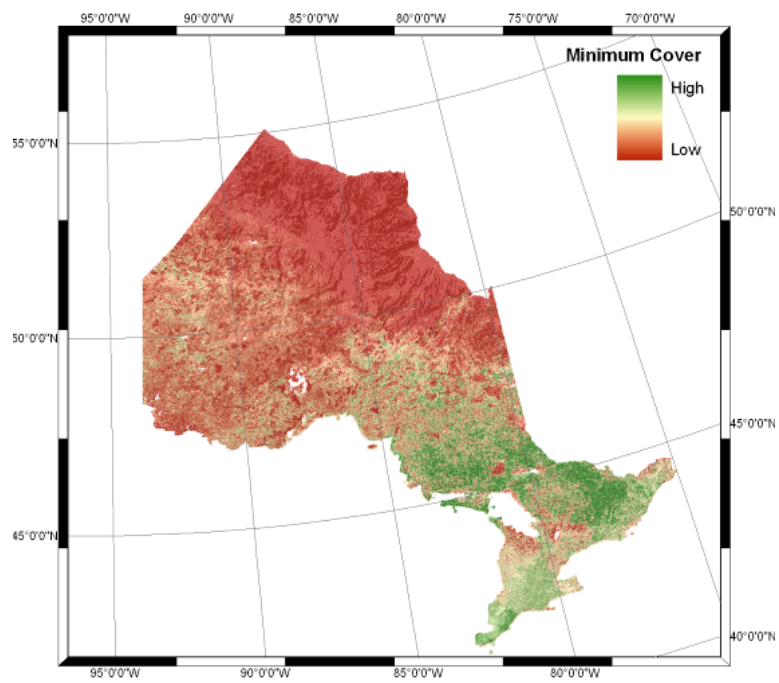
highlights locations where the environmental descriptors are correlated or otherwise (Figure 1, a-d). Figure 1(d) was created by assigning the annual integrated greenness to the green band, the minimum cover to the blue band, and the seasonality to the red band. Bright red areas have low annual mean fPAR, low annual minimum fPAR and high seasonal variability. Thus, bright red areas indicate locations where the small amount of primary productivity was evident for only part of the year. Bright cyan areas have a high mean, a high minimum and low variability, which represent locations with vegetation that was consistently productive throughout the year. Darker blue indicates landscapes with a low mean, a high minimum, and low variability. Orange areas indicate moderately productive vegetation that varied in productivity throughout the year. Green areas are high annual productivity, a high annual minimum productivity and low seasonality.



**A**

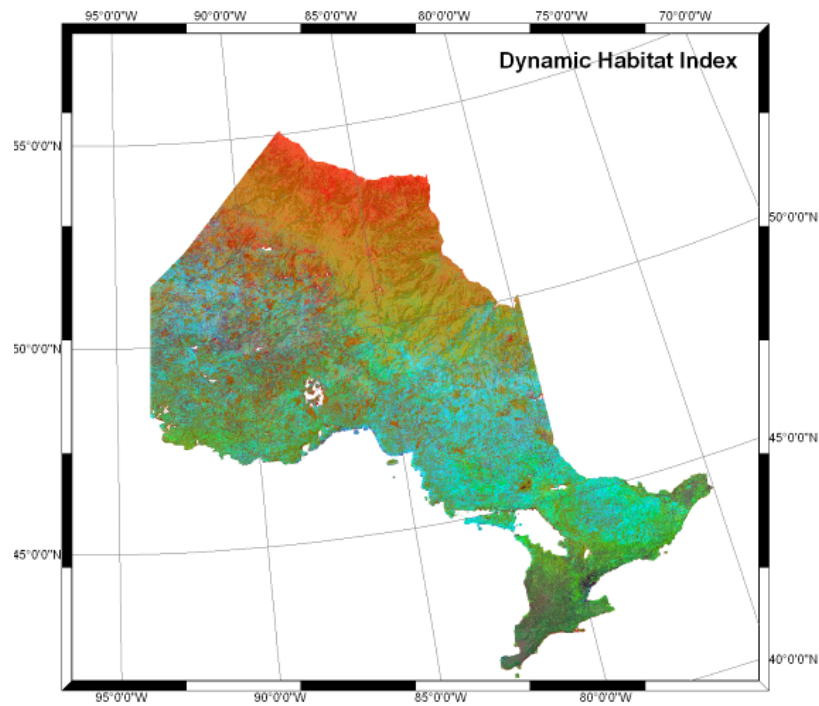


**B**



**C**





**D**

**Figure 1: Individual components of the Dynamic Habitat Index (DHI): (a) annual production, (b) seasonality, (c) annual minimum cover averaged over the 6 years of observations and the combined dynamic habitat index derived from 2000 – 2005 MODIS data.**

### 3.14 Remotely Sensed Data: Land Cover

Information on current land cover is available at a 1 km grain from the University of Maryland (UMD) land cover classification (Hansen *et al.* 2000). The classification allows a comparison of the behavior of the DHI components stratified by land cover class. The dataset was derived using MODIS and AVHRR satellite data and was developed using a classification tree approach based on individual spectral bands as well as spectral indices that enhance vegetation greenness. The UMD classification utilizes a hierarchy of vegetation forms similar to that discussed by Running *et al.* (1994) and defines 14

land cover classes, including evergreen needle leaf, evergreen broadleaf, deciduous needle-leaf forest, deciduous broadleaf forest, and a mixed forest. The remaining classes include 2 classes each for shrub and woodland complexes grassland, cropland, bare ground, urban, and water. For our analysis we used information on the land cover of individual pixels as well as changes in the pattern of the UMD land cover classification assessed at the 10 km grain size. Within each 10 km window, the dominant land cover class, the land cover dominance (calculated as the proportion of the area covered by the dominant land cover class), and the richness of land cover classes (calculated as the total number of land cover classes within the 1 km cell) were calculated following methods of Hill and Smith (2005).

### 3.15 Statistical Analysis

The environmental descriptors were re-sampled to a 10 x 10 km cell to match the OBBA using simple averaging in the case of continuous input variables or using a majority filter for the land cover classification. A suite of regression trees (developed in Decision Tree Regression (DTREG, Sherrod, 2008) were then developed by relating the OBBA species richness with the coincident remotely sensed descriptors of each sampled cell.

Before model development we assessed the inter-correlations of the DHI components to ensure that unique information was being provided by model co-variates. We then examined the variation in the productivity related remote sensed descriptors in relation to land cover class. In order to assess the utility of the remotely sensed descriptors to

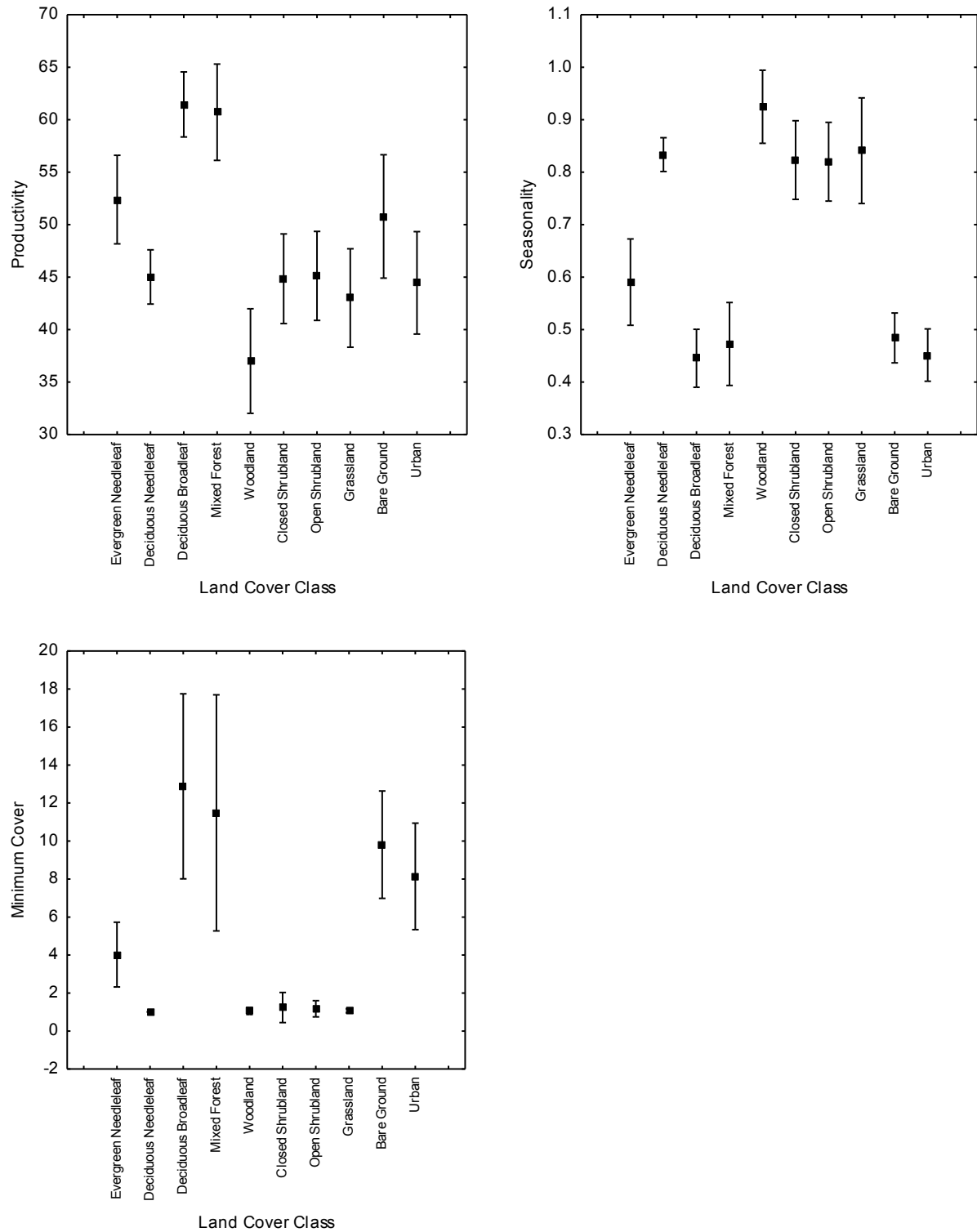
explain the variance observed in the total bird species richness data and richness of the six focus species groups, we utilized a non-parametric data-mining approach using regression trees. Regression tree analysis is a modelling technique that splits dependent variables using optimal predictor variables based on least squares (Melendez *et al.* 2006) and can be considered as a sequence of binary queries partitioning a dependent variable into homogeneous sets of responses. Each node in the tree branches to two other nodes or to a final response which corresponds to a labeled predictor variable (terminal node). Regression trees are increasingly applied in ecological research (e.g., De'ath *et al.* 2000; Schwalm *et al.* 2006) as they can be applied independent of statistical distributions and are suitable for dealing with collinear datasets, potentially insignificant predictors, and outliers (Melendez *et al.* 2006; Schwalm *et al.* 2006, Goetz *et al.* 2007). Single trees for the total bird species richness, and the focus species groups were developed using a 10 fold cross validation technique, similar to a "jackknifing" procedure, which randomly partitions the dataset into 10 equally sized groups (or folds). One set is held in reserve, while the other nine are pooled and a model developed. The accuracy of the model is assessed using the remaining 10 % of the data which was not used in model development. This process is then repeated 10 times, resulting in ten different test trees and ten different accuracy assessments determined in reference to success in predicting species richness using the remaining 10 % of the referenced dataset. The decision rules of the 10 models were then merged and pruned to produce a final classification tree with the optimum number of nodes and an overall accuracy accessed by averaging the independent results of the 10 simulations (Breiman *et al.* 1984).

In addition to the models for the total bird species richness and the focus group species richness, we assessed the relative importance of land cover and productivity related remote sensed descriptors when predicting species richness.

#### **4. RESULTS**

Correlation analysis confirmed that the three DHI components were providing redundant data with  $R \leq 0.80$  in all cases. The highest observed correlation was between DHI productivity and seasonality, with the lowest correlation between layer productivity and minimum apparent cover. The variation in the three DHI components stratified by land cover class is shown in Figure 2.

The DHI productivity related remotely sensed descriptors, when stratified by land cover, indicate deciduous broadleaf and mixed forest in Ontario typically had the highest levels of productivity, followed by evergreen needle leaf forest. Grass and shrub dominated land cover had the highest seasonality and forest land cover, apart from the deciduous needleleaf class, had the lowest levels of seasonality. Grass and shrub land cover also had low levels of apparent minimum cover.



**Figure 2: Mean and standard deviation of DHI cells stratified by dominant land cover class.**

#### 4.1 Breeding Bird Habitat Groups

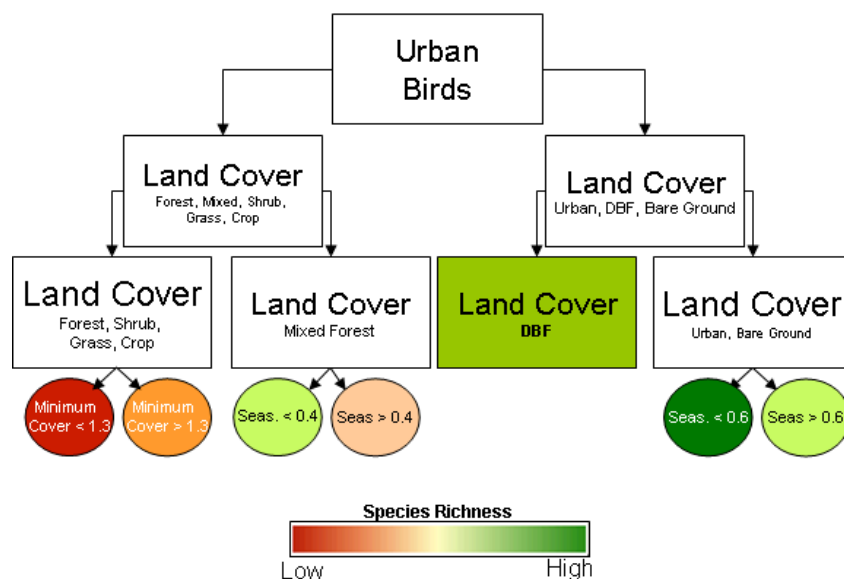
The grassland species decision tree explained 75 % of the variance observed in the dataset (original variance = 11.8, with unexplained 2.8) (Table 2). The model also ranks input descriptors based on the variance explained and in this particular model the highest ranked descriptor was dominant land cover. The second most significant explanatory descriptor of grassland birds was the apparent minimum cover derived as part of the DHI (annual minimum fPAR), which provided 15 % of the total explanatory power. The other descriptor in the final model was DHI seasonality. The terrain and DHI productivity descriptors explained no additional variance in the grassland bird species richness model.

**Table 2: Description of the developed decision tree models for total species richness and the groupings based on nesting and habitat preferences.**

<b>BBS Grouping</b>	<b>% Variance Explained</b>	<b>Nodes</b>
Grassland birds	<b>75</b>	24
Succession or Scrub birds	<b>61</b>	25
Woodland birds	<b>47</b>	31
Non-Specialists	<b>66</b>	29
Urban birds	<b>74</b>	25
Wetland birds	<b>49</b>	31
All birds	<b>61</b>	24

The model for urban bird species richness produced similar results to that of the grassland model with a large amount of the total variance (74 %) explained by the

decision tree model and the dominant land cover class explaining the majority of the variance in the model. The second most significant descriptor was DHI seasonality, followed by DHI minimum cover. Again, the remaining variables offered no additional explanation of variance. Figure 3 provides a basic schematic of the upper levels of the decision tree model for the urban bird species richness and shows that cells dominated by the land cover classes: forest, shrubs, grass, and crops, had the lowest levels of urban bird species richness. By comparison, cells with land cover dominant by bare ground, urban, and deciduous broadleaf vegetation had the highest species richness of urban bird species. Overall, the model indicated that land cover explained the majority of the variation, and DHI seasonality explained some additional variance within each land cover type.



**Figure 3**

Generally, models for wetland and woodland bird species richness explained less variance than the other models, explaining 47 and 49 % of the variance in the total

dataset respectively. In both of these cases, land cover explained the most variance, followed by DHI minimum cover and DHI seasonality explaining between 20 and 40 % of the variance in the case of woodland and wetland bird species richness, respectively. The model for total bird species richness explained 61% of the observed variance, and like the other models, land cover described the most variance in species richness.

Figure 4 provides a schematic of the upper levels of the total bird species richness tree and shows that most forest (except deciduous broadleaf), shrub, grass and crop land cover types had lower levels of bird species richness when compared to the other land cover types. DHI minimum cover and DHI seasonality played secondary roles providing a stratification within each land cover class to refine the total bird species richness. Overall, land cover was the most utilized descriptor with land cover dominance, rather than richness, the second most important land cover descriptor. Maps of the observed total, and grassland, species richness, and that predicted using the decision tree models, are shown in Figure 5.



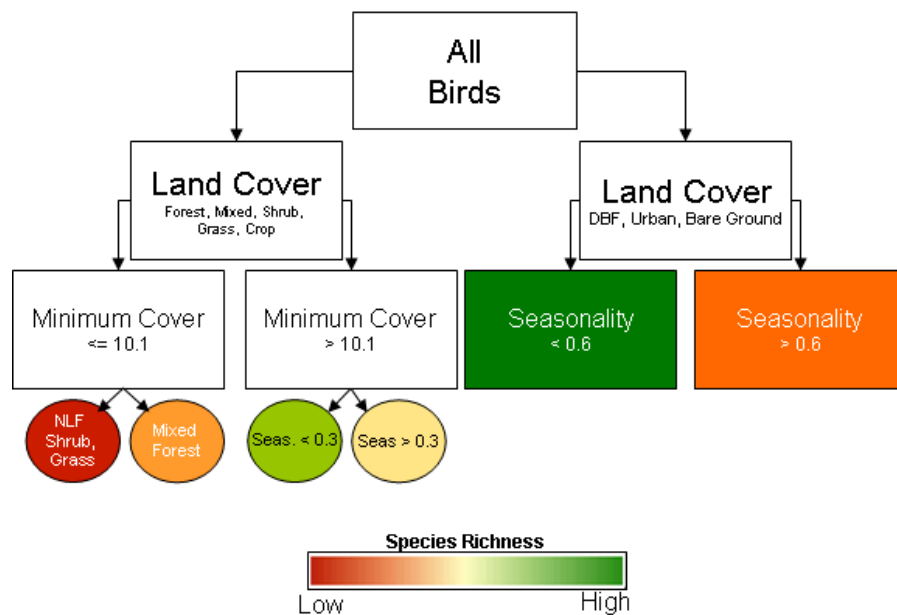
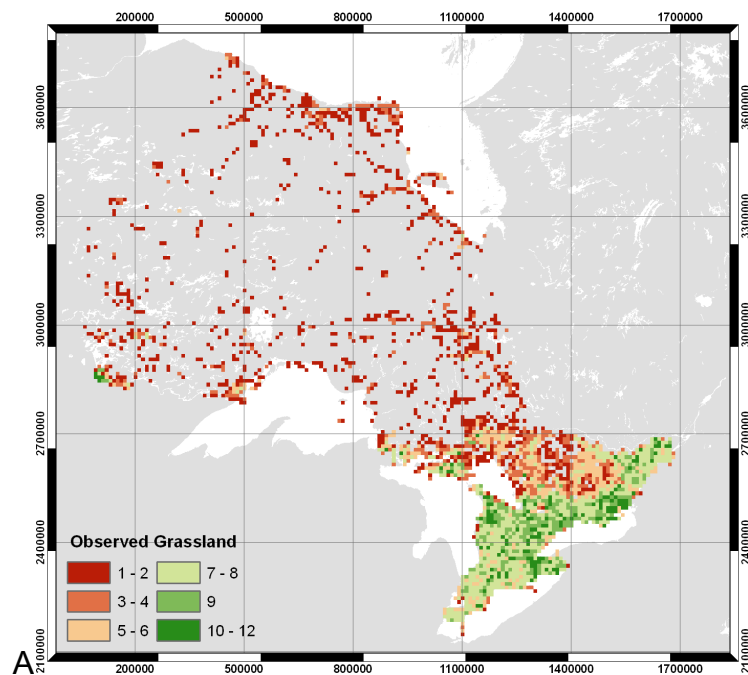
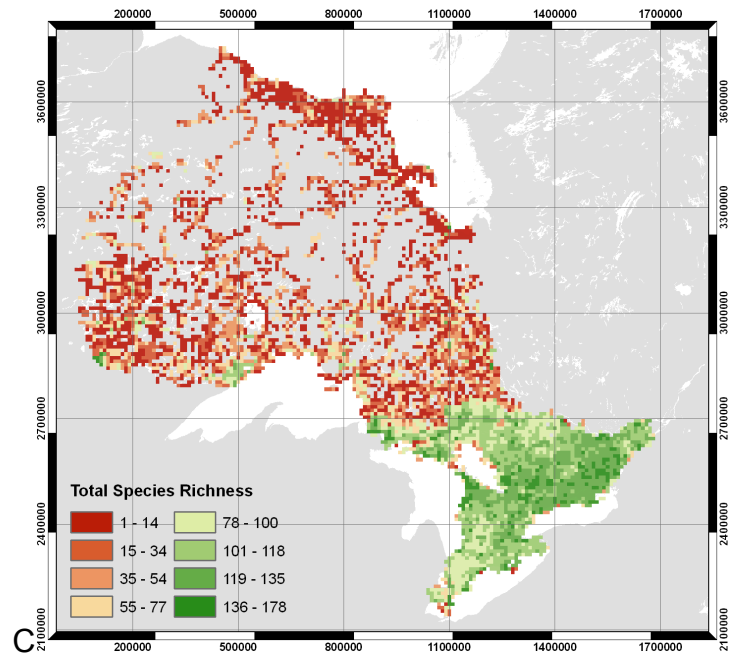
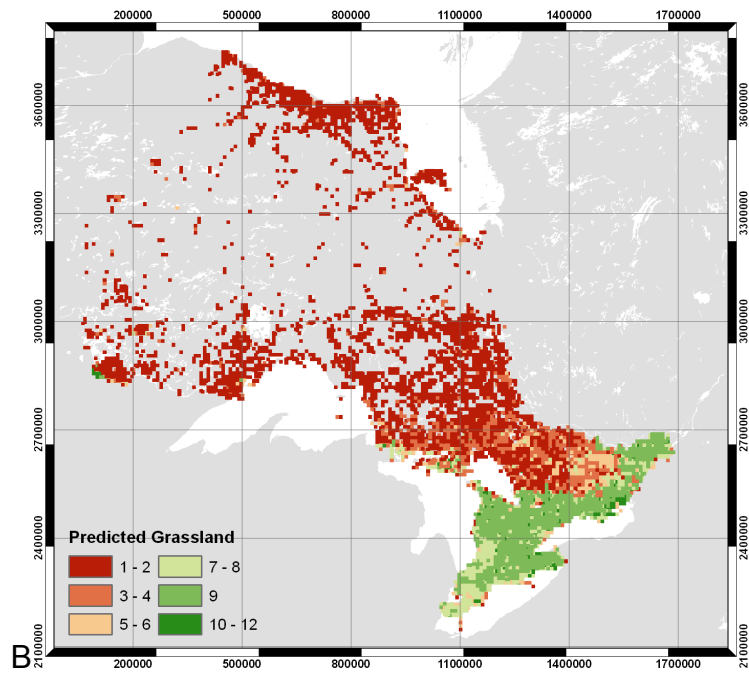
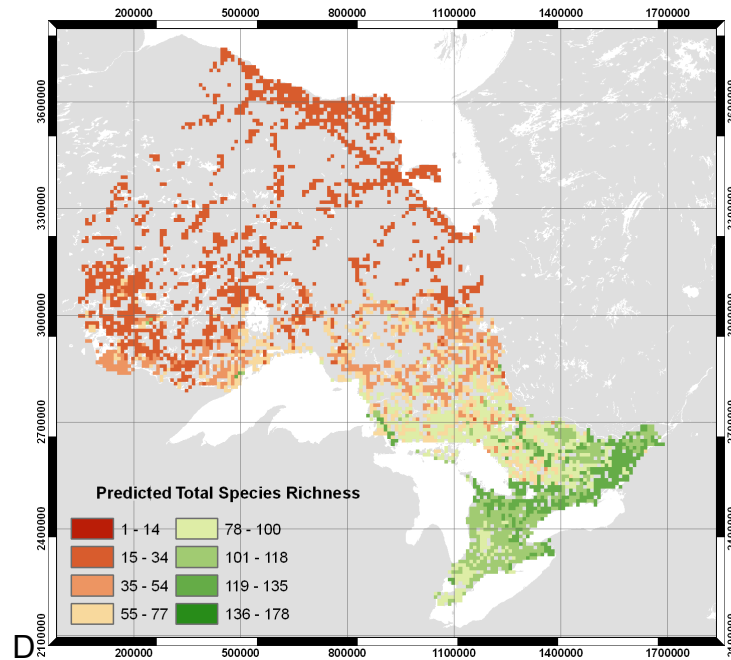


Figure 4: Upper levels of the total bird species richness decision. Forest land cover classes (except deciduous broadleaf forest (DBF), shrub, grass, and crop land cover types in general had lower levels of bird species richness than the other land cover classes.

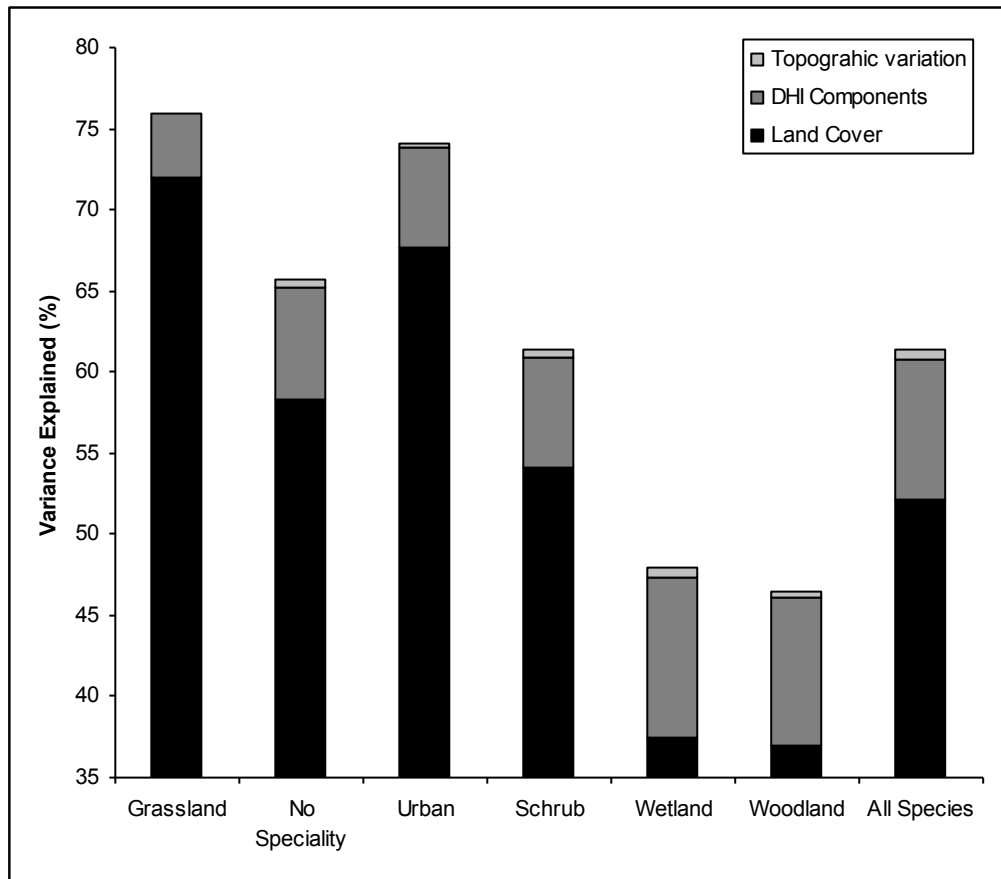






**Figure 5: Maps of the observed and predicted (a, b) grassland, and (c, d) total species.**

Figure 6 provides a summary of the variance explained by the environmental descriptors in the respective datasets. The addition of topographic variation into the models explained less than 1 % of the model variance. The addition of the DHI components, however, explained between 3 % and 10 % of the model variance. Models where the inclusion of the DHI information explained the greatest amount of variance were wetland, woodland, and total bird species. Grassland bird species richness, in particular, did not benefit from the inclusion of DHI information.



**Figure 6: Percent cumulative variance explained by the remote sensing derived environmental descriptors.**

## 5. DISCUSSION

Our results indicate that a combination of remote sensing-derived environmental descriptors can explain, in most cases, a major proportion of the variance in bird species richness over the Province of Ontario. The models of total species richness and richness for six species groupings based on nesting and habitat preferences all made initial splits of variance based on land cover followed by more refined splits principally based on one of the three remote sensing-derived environmental descriptors contained in the DHI. These results follow the observations of Hurlbert and Haskell (2003), who postulated that broad scale patterns of habitat heterogeneity are responsible for the

distribution of species that specialize on different habitat types, with climatic and productivity changes affecting how many species occur in each habitat type.

It is important to note that breeding bird surveys do contain biases, including observer experience, which may cause a positive bias in the estimation of population changes over time (Link & Sauer 1997). One advantage of the approach used in this study however is that total species richness, rather than numbers of individuals are used.

Our results demonstrate that out of the three DHI descriptors apparent minimum cover was selected most often. This index is highly related to the presence of snow or exposed soil on the landscape for some period of the year due to either a phenological responses (such as deciduous vegetation, grass and crops) or cold climates. The second most often used DHI descriptor was seasonality, which captures the change in the vegetation phenology signal throughout the year. Stands of evergreen boreal forest maintain a lower seasonality than deciduous vegetation which varies from leaf-off to leaf-on conditions through the year. The use of seasonality, which is designed to capture this variation, as opposed to long term climate means, is an important benefit of the DHI approach.

Seasonality and minimum cover variables explained more variance in woodland and wetland species richness groups whereas land cover explained more variance in the grassland and shrub species models. The finding that both the DHI components and the dominant land cover class both figured highly in the decision tree models confirms that

these factors all convey different, and potentially complementary, information in relation to species richness. The small number of models which utilized the DHI productivity component may be due to its higher correlation with other DHI components.

Thuiller *et al.* (2004) found that within cell habitat heterogeneity was a crucial factor predicting species occurrences. In this research, and similar work of Virkkala *et al.* (2005), who used a 10 x 10 km window to calculate richness and evenness, neither of these variables provided any explanatory power.

All of the environmental descriptors used in this study were derived from remote sensing technology, are available to users at no cost, and are readily available at 1 km spatial resolution. The decision tree models used in this study could be applied to data at finer scales to produce finer scale models of bird species richness. Within Canada, for example there is fine spatial land cover information (25 m) derived from circa 2000 Landsat Enhanced Thematic Mapper (ETM+) imagery available over forested regions from the Canadian Forest Service and Canadian Space Agency Earth Observation for Sustainable Development of Forests (EOSD) project (Wulder *et al.* 2003, 2008). Likewise a number of global fPAR datasets are becoming available at finer spatial scales than 1km such as a 300m product from the MERIS sensor on Envisat. As a result finer spatial grain predictions should be possible in the future.

While satellite derived estimates of vegetation productivity have been shown to be useful indicators of species richness, we acknowledge that there are some limitations

to explaining the mechanisms behind these patterns. As discussed by Hurlbert and Haskell (2003) for example, resources available in areas with harsh winters (e.g., seeds, dead arthropods) are not specially related to winter foliage. The resources present during the winter likely reflect, to some extent, productivity earlier in the year. Such a "storage effect" would predict higher winter richness in areas with greater summer productivity given equal levels of winter productivity. The complexity of these types of interactions is not directly accounted for in the three DHI components.

The growing body of literature on the effect of climate variation on natural ecosystems confirms that future impacts on bird communities and distribution are likely (Lennon *et al.* 2000; Austin & Rehfisch 2003; Julliard *et al.* 2004). The fact that many of the developed models in this study utilized information of the DHI apparent minimum cover and seasonality highlights that bird species richness in Ontario may be additionally sensitive to these changes, as changes in snowfall and vegetation seasonality are predicted as likely to occur in this region of Canada.

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