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RESEARCH ARTICLE

Optimizing landscape selection for estimating relative effects of landscape variables on ecological responses

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Abstract Empirical studies of the relative effects of landscape variables may compromise inferential strength with common approaches to landscape selection. We propose a methodology for landscape sample selection that is designed to overcome some common statistical pitfalls that may hamper estimates of relative effects of landscape variables on ecological responses. We illustrate our proposed methodology through an application aimed at quantifying the relationships between farmland heterogeneity and biodiversity. For this project, we required 100 study landscapes that represented the widest possible ranges of compositional and configurational farmland heterogeneity, where these two aspects of heterogeneity were quantified as crop cover diversity (Shannon diversity index) and mean crop field size, respectively. These were calculated at multiple spatial extents from a detailed map of the region derived through satellite image segmentation and classification. Potential study landscapes were then selected in a structured approach such that: (1) they represented the widest possible range of both heterogeneity variables, (2) they were not spatially autocorrelated, and (3) there was independence (no correlation) between the two heterogeneity variables, allowing for more precise estimates of the regression coefficients that reflect their independent effects. All selection criteria were satisfied at multiple extents surrounding the study landscapes, to allow for multi-scale analysis. Our approach to landscape selection should improve the inferential strength of studies estimating the relative effects of landscape variables, particularly those with a view to developing land management guidelines.

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Introduction

Practical limits to landscape selection during study design can have large effects on results, particularly for quantifying the relative effects of different measures of landscape structure on biodiversity for the development of land management guidelines (Brennan et al. 2002; McGarigal and Cushman 2002; Smith et al. 2009; Eigenbrod et al. 2011). Appropriate selection of the set of study landscapes is a critical element in the design of such observational studies, which draw conclusions on the relative effects of managing landscape factors from estimates of the parameters in a statistical model (e.g., standardized regression coefficients, Smith et al. 2009). Problematic shortcomings in landscape selection include using only a portion of the potential range of a landscape variable, using landscapes that overlap in space or proximal landscapes for which the variables of interest are spatially autocorrelated, and failing to account for correlations among the landscape variables of interest. These issues or "common statistical pitfalls", can affect the strength, significance, and even direction of the estimated relationships (Eigenbrod et al. 2011).

It has been well demonstrated that using only a portion of the potential range of a landscape variable (e.g. forest cover, fragmentation, or road density) not only reduces the chance of detecting an effect of the predictor variable (Brennan et al. 2002) but, in the presence of non-monotonic effects, can also lead to contradictory findings (Eigenbrod et al. 2011). The use of overlapping or proximal landscapes is quite common in landscape ecology studies as a result of logistical constraints imposed by landscape size, the size of the study region (i.e., the area encompassing all the sample landscapes), and the number of landscapes required. Using non-spatially independent landscapes effectively results in a reduction in the number of independent study units (landscapes) and can greatly increase the chance of Type I errors (Legendre 1993). Finally, there are often "natural" correlations among predictor variables of interest in ecological studies, particularly in landscape ecology studies. For example, landscapes with high road density typically have low forest cover (Findlay and Houlahan 1997). Although such correlations do not affect the expected value of the parameter estimates, they greatly increase the uncertainty associated with them (Smith et al. 2009). Minimizing these correlations at the site selection stage of a study increases the precision of the estimates, thus increasing the statistical power to detect effects of the landscape predictors (McGarigal and Cushman 2002; Fahrig et al. 2011).

To overcome these pitfalls and draw clear and useful recommendations for land management, landscape studies should apply a "pseudo-experimental" approach (Brennan et al. 2002; Fahrig et al. 2011; Eigenbrod et al. 2011, also called "mensurative experiments" sensu Hurlbert 1984): "experimental" because the ultimate goal is to control potentially confounding factors and select statistically independent study units that approximate a balanced sample across all landscape factors (i.e., the treatments), and "pseudo" because no actual manipulations are performed. This approach is, in many ways, analogous to the balancing of potentially confounding variables in observational studies in epidemiology and medicine (e.g., cohort studies, Armitage et al. 2002), in which a non-random sample of subjects are selected to estimate the effects of particular treatments or exposures, while controlling for potentially confounding factors such as age, sex, income level, etc. In this analogy, each of the main landscape predictors acts as both the treatment and a potentially confounding factor that is also part of the main focus of the study, and the balancing is done simultaneously for both predictors, creating a factorial design. While these types of observational studies have lower inferential strength than manipulative experiments, they do have greater inferential strength than more descriptive studies (those that involve a random selection of available landscapes) and therefore should be preferred whenever the results of the study are to be used in decision-making.

In addition, practical considerations will often limit the degree to which these criteria can be met. Selecting landscapes that are not spatially autocorrelated for the variables of interest, that represent the whole range of each landscape variable, and that provide uncorrelated landscape metrics is not a simple task and may not be completely feasible based on conditions and constraints of a study or study region. Some combinations of landscape metrics (e.g., large mean patch size with high patch type diversity), may be very rare or even non-existent. However, in order to maximize inferential strength of a study, an attempt should be made to meet these criteria, as nearly as possible, through a strategic, multi-stage approach such as we propose in this paper. It is important to note that the goal here is not to characterize the landscape patterns of a given region but, rather, to conduct a study which is expected increase inferential strength in relation to a study that does not consider these factors, and thereby improve the potential for application of the methods and findings in development of reliable guidelines for land management.

Objectives

Our objective is to describe a protocol for landscape selection that overcomes the statistical pitfalls described above and to illustrate it with a case study. In this case study, the ultimate goal of the research is to quantify relationships between farmland heterogeneity and biodiversity, to inform the development of guidelines for future farmland management policies. An initial set of at least 100 landscapes was desired, providing a wide range of values of farmland compositional and configurational heterogeneity, while keeping the variables representing these two aspects of heterogeneity independent of one another, and avoiding spatial autocorrelation.

Landscape selection approach and case study

Figure 1 presents the general method, which involves a step by step strategic refinement of potential study landscapes, with the number of suitable sites being reduced at each step in order to satisfy a specific criterion. Below we describe each step in detail and how the methods were applied to our case study on farmland heterogeneity-biodiversity interactions. The study is focused specifically on the production areas of agricultural landscapes (hereafter referred to as "farmland") including cover types (hereafter referred to as "crops" such as row crops, hay, pasture, and forage), and thus farmland "heterogeneity" refers to spatial variation in farm field and crop metrics. We therefore did not include natural or semi-natural cover types in our metrics of farmland heterogeneity. We divided farmland heterogeneity into compositional heterogeneity based on diversity of crop types and configurational heterogeneity based on mean field sizes.

Step 1: study region

The case study was carried out within the region delineated by the Eastern Ontario Model Forest in Canada (Fig. 2). This $\sim$15,500 km^2 management region is primarily made up of agricultural areas and is bordered by the St. Lawrence River to the south, the Ottawa River to the north, the Ontario–Québec provincial border to the east and the Canadian Shield to the west. According to the 2006 agricultural census, $\sim$7,800 km^2 ($\sim$50 %) within the region was in crop or pasture (Statistics Canada 2007), while forests covered $\sim$38 % of the region, although predominantly in the northwest towards the Canadian Shield (Pasher and King 2006). We used this region because it was the largest continuous agricultural area in proximity to our research centre and it is the location of the biodiversity study described here as well as other ongoing research studies on landscape-species interactions.

We aimed to select a sample of at least 100 agricultural landscapes where intensive field-based sampling and inventory will be carried out to provide the biodiversity response variables. The sample landscapes were selected to be 100 ha each to match the approximate average farm size in the region, thus matching the spatial unit at which farming policies resulting from the research would be developed and implemented. Square landscapes were used to simplify GIS processing. To select landscapes dominated by agriculture and reduce effects of forest or other natural vegetation, we set a range of 60–90 % agricultural land cover. We initially desired a smaller range (e.g., 60–70 % agriculture) to avoid introducing the amount of landscape not in agriculture as an additional confounding variable that was not the primary interest or focus of our study, but this constraint proved too limiting to produce enough landscapes that would satisfy the three statistical criteria (as presented in later sections). Our upper limit of 90 % agriculture avoided landscapes with very little or no natural cover, which would likely produce overriding effects on biodiversity (e.g., Freemark and Kirk 2001; Ökinger and Smith 2006; Kirk et al. 2011; Mortelliti et al. 2011) and potentially obscure our ability to detect effects of farmland heterogeneity on biodiversity.

To find these agricultural landscapes, the most detailed existing land cover map for the region was initially acquired (SOLRIS v1.2, OMNR 2008). This dataset comprised general land cover attributes and although it did not provide details on crop type it contained an 'undifferentiated' class, which included both field and forage crops. A moving window analysis, with extents from 1 km × 1 km to

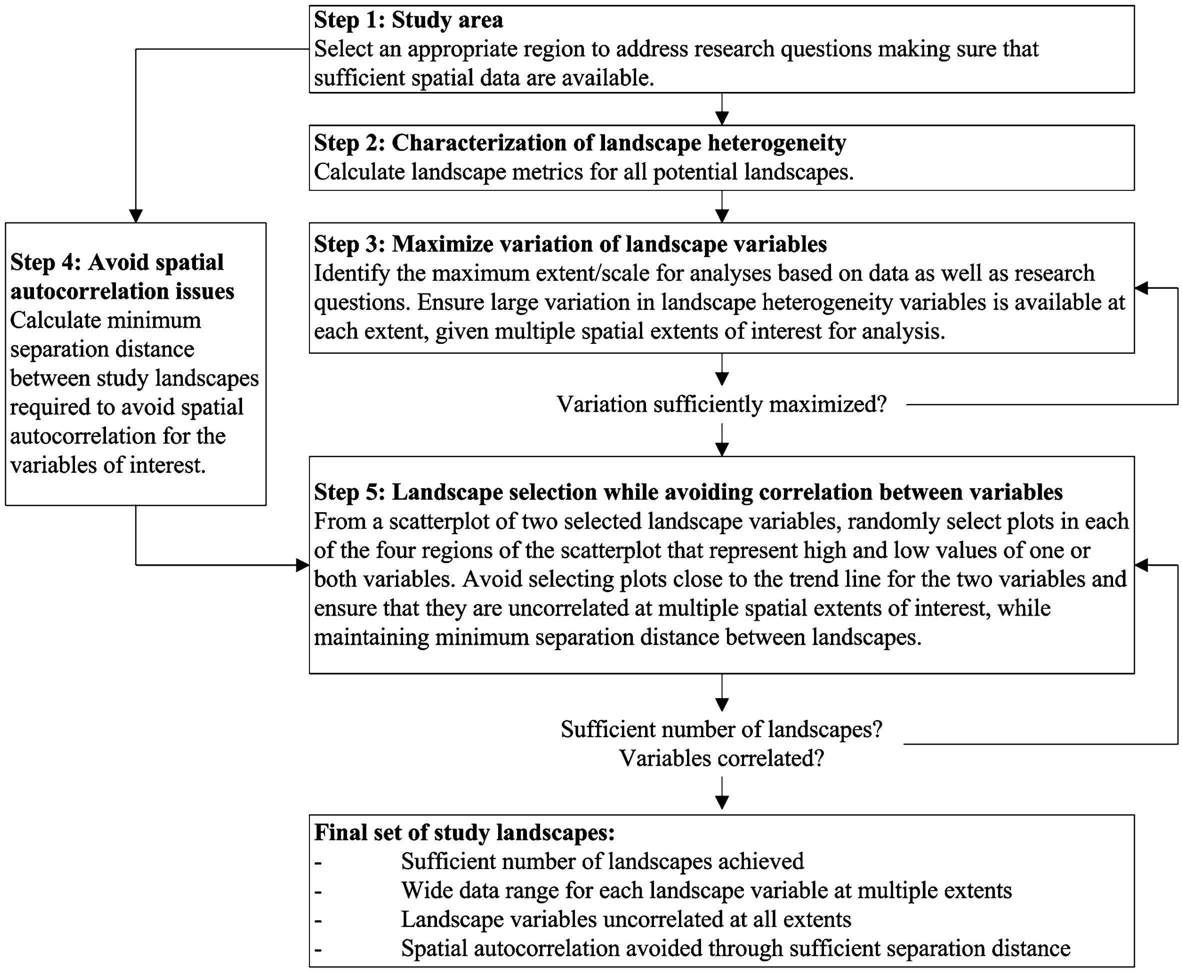

Fig. 1 General overview of landscape selection process

7.5 km × 7.5 km, was implemented to identify individual pixels that were centred in landscapes with between 60 and 90 % 'undifferentiated' agriculture at each extent. These pixels were identified as candidates for the set of sample landscapes subject to the remaining criteria below. GIS and statistical analyses were carried out using ArcGIS10 (ESRI Inc. 2011), Geomatica 10 (PCI Geomatics Inc. 2011), Microsoft Excel (Microsoft Corporation 2003), SPSS 12 (SPSS Inc. 2003), and Statistica 9 (Statsoft Inc. 2009).

Step 2: characterization of landscape heterogeneity

Compositional heterogeneity of each landscape was characterized by the Shannon diversity index of the crop types, and configurational heterogeneity was represented by the mean size of all crop fields in the landscape, where landscapes with smaller crop fields were considered more heterogeneous. The eventual analysis to be conducted with data acquired for these landscapes will investigate a range of pattern metrics to evaluate which have the strongest relationships with biodiversity, but in absence of a priori knowledge of this, we chose these two simple and common metrics, with relatively well-known statistical properties. To calculate these variables, the geo-spatial data for landscape selection needed to: (1) distinguish among different crop types, and (2) have individual fields delineated so their sizes could be determined. No existing land cover product provided these for the entire study region. Therefore, we created our own map through supervised classification of satellite

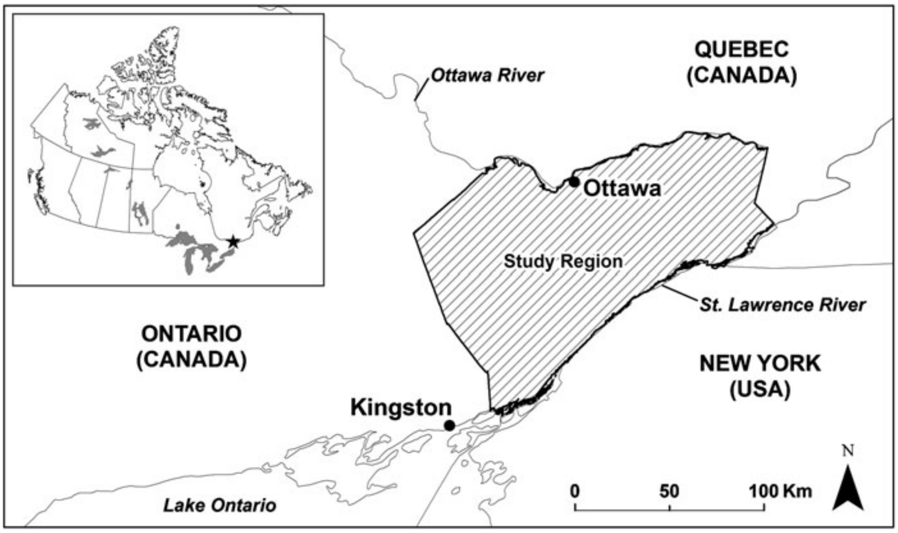

Fig. 2 Location of study region coinciding with the Eastern Ontario Model Forest boundary

images to identify crop types, combined with an image segmentation process to delineate field boundaries. Multiple Landsat-5 images (30 × 30 m pixels) from the 2007 growing season were used along with ground data provided by Agriculture and Agri-Food Canada AAFC (2007) to produce a detailed land cover map. The main crop classes discernible in the region were cereals (winter and spring wheat/oats/barley/mixed grains), corn, soybeans, and hay/pasture.

Delineation of individual fields was accomplished using a semi-automated method involving segmentation (Definiens Professional 5.0; Definiens 2006) of higher resolution SPOT panchromatic imagery (10 × 10 m pixels) into individual objects, based on maximizing between-object variance and minimizing within-object variance (Flanders et al. 2003; Dingle Robertson and King 2011). To maintain a clear distinction between adjacent fields of the same crop class through the conversion from vector to raster representations, an 8 m internal buffer was applied to all segmented objects, yielding a final raster-based five class thematic map (cereals, corn, soybean, hay/pasture, and unclassified/non-agriculture), which was used to calculate metrics of compositional and configurational farmland heterogeneity.

We calculated Shannon diversity and mean field size from this thematic map (Fig. 3) using moving window analyses in FRAGSTATS v3.3 (McGarigal et al. 2002), with window sizes corresponding to the potential analysis extents, i.e., square areas of 1, 2, 3, 4, 5, 6, and 7.5 km on a side. Calculations of metrics within the moving window were based on the 8 cell neighbours to the centre cell to avoid potential alignment affects, which could occur due to row crops if using a four neighbouring cell rule. From this, we obtained heterogeneity values for multiple extents at all possible landscapes in the portion of the study region that had 60–90 % agriculture, with every pixel being the potential centre of a landscape. The unclassified/non-agricultural areas in the map were treated as background and not included in calculating the heterogeneity variables.

Step 3: maximizing variation of landscape variables

Effects of landscape structure on ecological responses are often found to be strongest at a specific extent surrounding the focal area where the response is measured. Therefore, analyses are often conducted at multiple extents to determine the “scale of effect” (e.g., Dunford and Freemark 2004; Holland et al. 2004; Eigenbrod et al. 2008). However, there are limits to the maximum extent that can be analyzed in any particular project, for two reasons. First, given a limited study region, larger extents reduce the potential to select non-overlapping, spatially- independent landscapes. Second, as the analysis extent increases, variability among potential sample landscapes declines to the point that the landscapes are almost identical to one another and

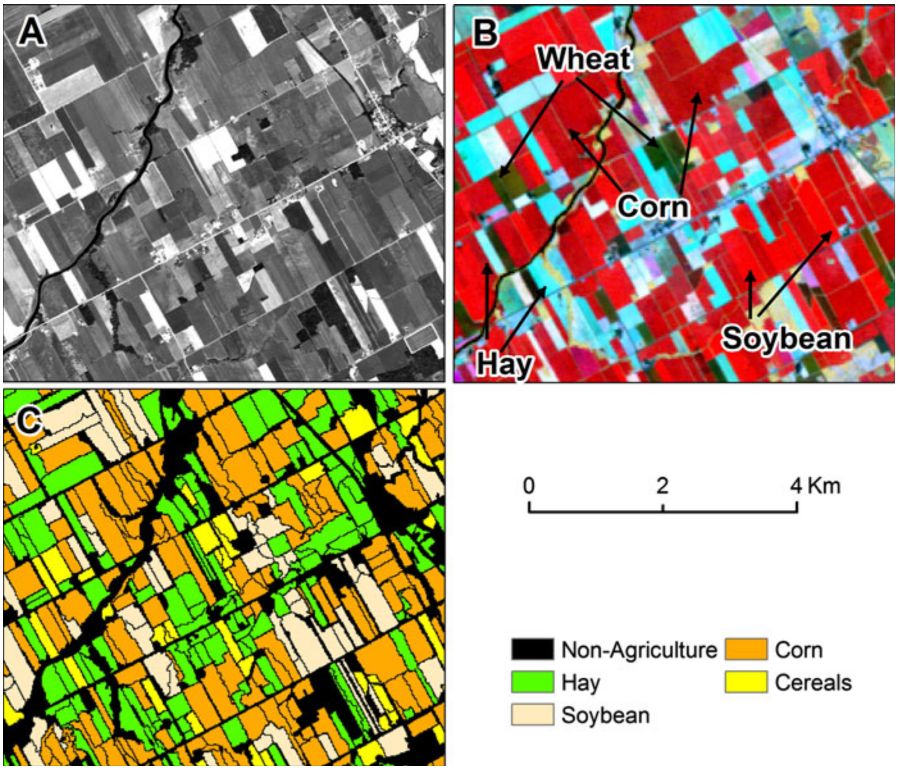

Fig. 3 Example subarea of the SPOT panchromatic image (**A**), Landsat 3-date NDVI composite (**B**), and the final land cover map produced from classification of Landsat imagery followed by segmentation of fields from the SPOT panchromatic image and field object buffering (**C**)

landscape metric values derived from each represent the global average. This reduction in variability across landscapes greatly reduces the chance of detecting an effect of a landscape variable on the ecological response (e.g., biodiversity in our study) (Brennan et al. 2002; Eigenbrod et al. 2011).

For each heterogeneity metric and for each extent (1 km × 1 km up to 7.5 km × 7.5 km), we calculated the coefficient of variation (CV) across all potential study landscapes. Based on a plot of CV versus landscape extent, we selected a threshold extent beyond which insufficient variability existed among potential sample landscapes. Then, by applying the mask representing 60–90 % agriculture at each of these extents, we ensured that all landscapes selected in the following steps would contain 60–90 % agriculture at all spatial extents up to this threshold.

Step 4: avoiding spatial autocorrelation among study landscapes

To assess potential spatial autocorrelation of the heterogeneity metrics for the landscapes selected to this point, we calculated Moran's I (Moran 1950) using Idrisi GIS (Clark Labs 2011), with increasing lag distances from 30 m (1 pixel) to 5 km for both metrics at all selected spatial extents (moving window sizes). This analysis provided information to help select the minimum distance between study landscapes that would avoid high spatial autocorrelation, which could reduce the power of statistical analyses relating landscape heterogeneity and biodiversity (Fortin and Dale 2005).

Step 5: avoiding correlations between the landscape variables

Since the two heterogeneity metrics will eventually serve as predictors of biodiversity, and since correlations between predictor variables (i.e., confounding) can lead to weak inferences (McGarigal and Cushman 2002; Smith et al. 2009; Eigenbrod et al. 2011), independence between predictor variables was the third criterion for landscape selection. Over the entire study region we expected a correlation between the two farmland heterogeneity metrics: landscapes with higher crop diversity would generally be comprised of smaller fields. We expected this correlation to be stronger across landscapes of larger spatial extents, as variability among larger landscapes is lower as they approach the global average. Therefore, we started with heterogeneity variables calculated using the largest extent of interest (determined in "Step 3: maximizing variation of landscape variables" section) to find a set of landscapes for which the two heterogeneity metrics (Shannon diversity and mean field size) were uncorrelated. We plotted the two metrics against each other and clipped the tails of the distributions (2.5 % from each end) to remove processing errors and extremely rare landscape conditions. Instead of randomly selecting landscapes from the whole data distribution, which would have resulted in a correlation between the heterogeneity variables, we strategically selected landscapes that lay towards the four corners of the scatterplot. This selection represents a 2 × 2 factorial design where each landscape represents one of the following: low crop diversity and low mean field size, low crop diversity and high mean field size, high crop diversity and low mean field size, or high crop diversity and high mean field size. To accomplish this, the plot axes were divided into deciles to provide hard thresholds and 2-dimensional 'selection windows' were manually grown across the scatterplot, increasing in size in an iterative process to create 'selection windows' incorporating enough variability to generate 30 spatially independent landscapes representative of each of the four identified conditions ($N_{\text{total}} = 120$). Note this includes five "extra" landscapes from each selection window, bringing the total number of selected landscapes to 120 rather than our objective of 100. This was done in anticipation that, for some landscapes, we may not be able to obtain permission from landowners to conduct the biodiversity sampling or the crop cover characteristics may have changed over time. Note also that in other studies with fewer logistical constraints, it may be possible to study a larger number of landscapes to create a 3 × 3 factorial design—high, medium, and low values of each heterogeneity variable—which would allow modeling of non-linear relationships.

At each iteration of this process, using a stratified random sampling tool (Hawth's Tools for ArcGIS; Beyer 2004), we repeatedly identified 30 candidate landscapes within each of the four categories (selection windows). For each attempt, we maintained a minimum separation distance between all points based on the results of the tests of spatial autocorrelation ("Step 4: avoiding spatial autocorrelation among study landscapes" section). Finally, we selected a set of landscapes that were distributed such that similar landscapes were not clumped within the study region, and no major regional trend was visible.

Results

Maximizing variation of heterogeneity variables

Figure 4 shows how CV of the two heterogeneity metrics (Shannon diversity and mean field size) decreases with increasing landscape extent. By the 5 km extent CV levels off almost to the point of homogeneity across landscapes, suggesting that this extent was the maximum possible for useful analysis across the study region based on these heterogeneity metrics. In addition, an examination of Fig. 4 showed little difference between CV of the metrics calculated at 5 km and those calculated at 4 km and even 3 km. Correlations of 0.95 and 0.94 for Shannon diversity and average patch size, respectively, were found between the 5 and 4 km metrics. Similarly, correlations between the 4 and 3 km extents for each metric were 0.91 and 0.92, respectively. While still relatively high, the correlations dropped to 0.87 and 0.85, respectively between the 3 and 2 km extents, suggesting that heterogeneity calculated with the 3 km extent was representative of heterogeneity out to at least 5 km. Based on this, we chose to limit the maximum spatial extent to 3 km × 3 km for the landscape selection process and because selecting at least 100 landscapes that are spatially non-overlapping would have become infeasible for larger landscape extents.

With the extent threshold established, we created a single map representing pixels that contained 60–90 % agriculture in the surrounding 1 km × 1 km, 2 km × 2 km, and 3 km × 3 km areas (Fig. 5). This map was then used to refine landscape selection based on the criteria below.

Avoiding spatial autocorrelation

As expected, we found a negative relationship between spatial autocorrelation and lag distance for both heterogeneity metrics at all three spatial extents (Fig. 6). We selected a minimum distance of 3.5 km between landscape centres. There was no obvious

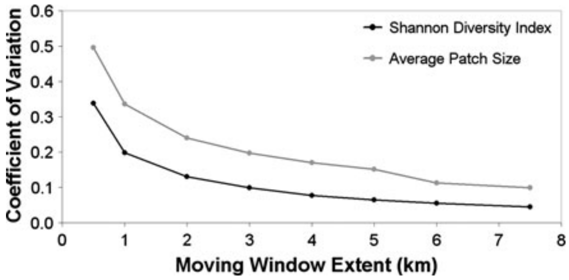

Fig. 4 Coefficient of variation for heterogeneity metrics with increasing landscape spatial extent

threshold in the relationship and all values remained significant, presumably due to the large number of samples involved, therefore an evaluation of the level of autocorrelation that we considered tolerable was used to choose our cut-off. This distance was a compromise between maximizing the number of landscapes that would fit within our study area and limiting the spatial autocorrelation. As well, it ensured that Moran's I was <0.4 for all landscape extents, and there was at least 500 m between all landscape borders in both the horizontal and vertical directions for the largest landscape extent of 3 km. In theory, a small amount of overlap (<2.8 %) could occur between diagonally adjacent 3 km landscapes but this was rare.

Avoiding correlations between the landscape variables

Figure 7 shows the bivariate plot of Shannon diversity and mean field size. We focussed the landscape selection on the four corners of this plot in order to avoid a correlation between Shannon diversity and mean patch size in the selected landscapes, and to maintain high variance within both variables. We attempted to select 30 landscapes from each corner, and we iteratively increased the sizes of the areas in the corners towards the centre of the bivariate distribution, until we obtained 30 sample landscapes in each, such that all other criteria were also satisfied.

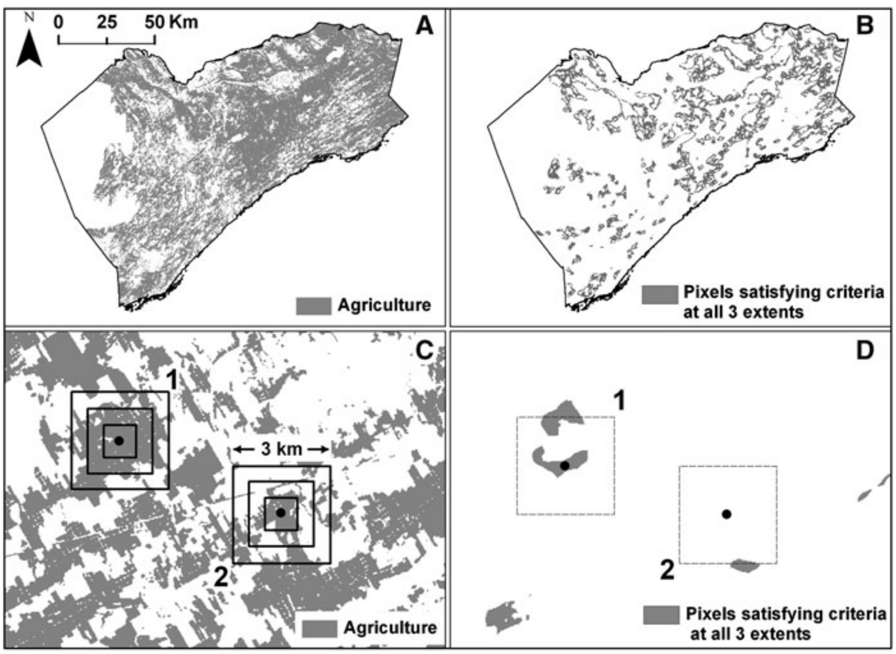

Fig. 5 **A** Agriculture in eastern Ontario defined by SOLRIS 'undifferentiated' class. **B** Initial areas for potential study landscapes had 60–90 % agriculture in the area surrounding each grey pixel at all extents: 1 km × 1 km, 2 km × 2 km, and 3 km × 3 km. **C** Zoomed-in example of *panel A*, showing two simulated potential landscape centres (*black dots*) with surrounding extents indicated. **D** Zoomed-in landscapes from *panel B* showing pixels satisfying the 60–90 % criterion at all three extents. Landscape 1 meets the criterion at all extents while Landscape 2 does not, since there is too little agricultural land at the larger extents (see *panel C*). Any landscape centre located in the shaded regions of *panel D* was considered a potential study landscape at this step of the landscape selection process

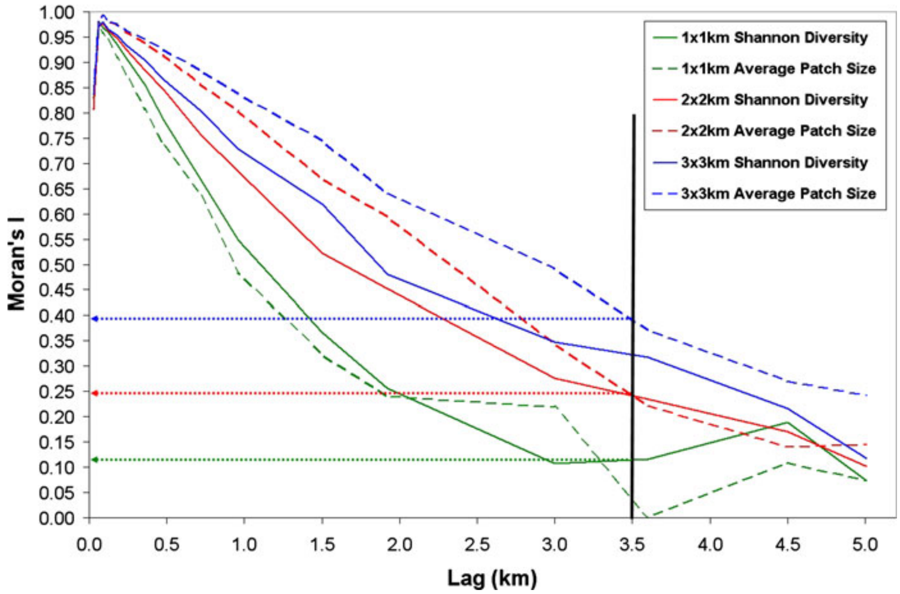

Fig. 6 Moran's I for the two heterogeneity metrics at the three landscape extents over lag distances up to 5 km. A lag threshold of 3.5 km is shown, which was selected as the minimum separation distance between study landscape centres

The resulting 120 candidate landscapes were well distributed across the region (Fig. 8). The correlations between the two heterogeneity metrics for these 120 landscapes were $r = 0.01$, 0.04, and 0.08 for extents of 1, 2, and 3 km, respectively.

Discussion and conclusions

This study arose from our need to select landscapes for research on the impacts of farmland heterogeneity on biodiversity, with the results intended to inform development of agricultural policy and practice for conservation and restoration of biodiversity in agricultural regions. In considering where to sample and inventory biodiversity, we recognized that without a landscape selection design that avoided the "common statistical pitfalls" we would not be able to independently estimate the effects of farmland compositional and configurational heterogeneity on biodiversity.

Aspects of the approach presented here have been applied in previous studies. For example, in a study of landscape effects on forest birds, Trzcinski et al. (1999) estimated the independent effects of forest

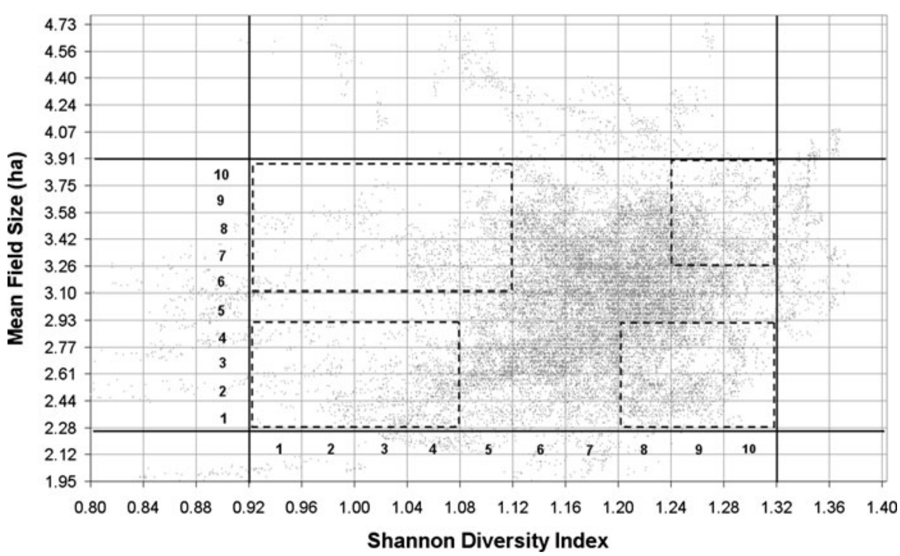

Fig. 7 Scatterplot of Shannon diversity index against mean field size (both metrics calculated using 3 km × 3 km extents). The four corners of the 95 % distribution 'selection window' are shown, within which study landscapes were selected, with the deciles of the window labelled from 1 to 10 on each axis for reference

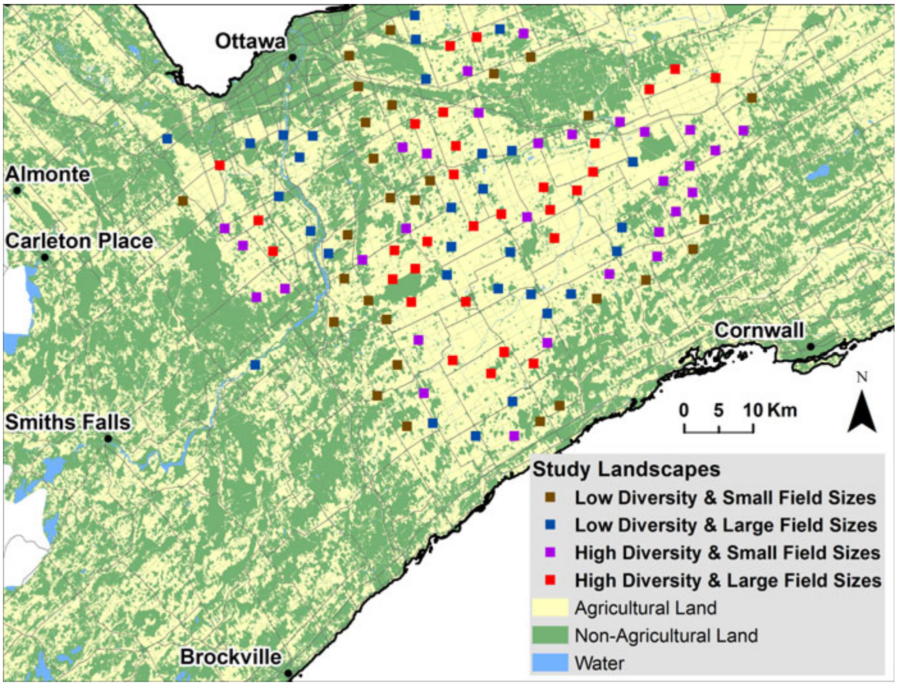

Fig. 8 Final set of study landscape centres that satisfied all selection criteria. They are colour coded by heterogeneity condition category (corners of selection window in Fig. 7) and displayed over simplified SOLRIS land cover classes. Note that "undifferentiated" includes all crop types

amount and fragmentation on forest birds by selecting replicate landscapes in each of the four combinations of low and high levels of each of two landscape variables. Eigenbrod et al. (2008) used a similar approach for selecting landscapes such that forest amount and road traffic were uncorrelated, allowing estimation of their independent effects on amphibians. Avoidance of regional trends in landscape variables has been accomplished in previous studies by finding "replicate" landscapes of one type distributed widely over the region, and then for each of these landscapes locating the nearest landscape of each of the other types. Carr and Fahrig (2001) used this approach to select a set of landscapes such that low and high road density landscapes were intermixed across the region. Holzschuh et al. (2007) used a similar approach to selecting crop fields for insect surveys such that organic and conventional fields were intermixed through the study region. Previous studies have also attempted to control effects of confounding variables that were not the focus of the study by limiting potential sites to a small range of values of the potential confounding variables; here we used this approach to limit the proportion of farmland variation across landscapes. For example, a study of road effects on mammal distributions limited potential landscapes to those with 20–35 % forest, to remove its potential confounding effect on mammals (Rytwinski and Fahrig 2011).

Although individual aspects of our approach to landscape selection have been used previously, this is the first comprehensive and systematic description and application of an integrated multi-step methodology. It is generally applicable to studies requiring development of inferences about the effects of individual landscape variables on ecological responses. Of course, in any real study region there will be limits to the minimum attainable correlation between landscape variables, the maximum distance that can be maintained between sample landscapes, and the degree to which different "treatment" levels can be intermixed across the region. However, these are not limitations of the method itself, which aims to optimize landscape selection within the constraints of the particular study region. Given the cost of collecting high-quality field data across multiple landscapes, it is prudent to apply such a landscape selection design to maximize, to the extent possible, the inferential strength of the study for the given sample size (number of landscapes).

Any landscape selection protocol, including this one, will include errors due to the quality of the land cover data used to generate class objects and attributes (e.g., field size and crop types, respectively, in this study). There are two primary effects of these errors that may result in landscape sample selection error. First, error in the land cover map attributes and object delineation will be propagated through each of the stages of landscape selection. For example, in this study, errors of omission and commission in the agricultural classes probably affected the mask of 60–90 % agriculture that was first extracted. The heterogeneity metrics extracted from that agriculture mask also included errors from mislabelled land cover classes and these errors were propagated through processing in determination of CV and spatial autocorrelation of the metrics as well as the correlations between metrics. More research is needed to evaluate the net effects of these errors on the resulting landscape sample set. Secondly, changes in land cover between the time the land cover data are created and the time that the ecological response data (here, for biodiversity) are collected will produce additional error in landscape selection. By definition, the data used for selecting landscapes cannot be collected at the same time that the ecological response variables are actually surveyed in the field. Once the set of landscapes is selected and field work begins, the maps will need to be corrected for actual ground conditions during the field sampling time period, and landscape metrics will need to be recalculated using the corrected maps. The corrected landscape variables will then be used in testing for relationships, in our case, between biodiversity and farmland heterogeneity at extents from 1 to 3 km. In our initial field season, to facilitate this process, we selected landscapes that could be moved in any direction by several pixels without violating the initial criteria of landscape selection. When field work was conducted, where land cover map errors were evident or landowner permission was not forthcoming, the landscape position was changed to minimize or correct for these factors.

Our range of potential sites in eastern Ontario was limited by two key constraints: availability of sufficient existing land cover maps and remotely sensed data; and efforts to avoid a correlation between compositional and configurational heterogeneity and spatial autocorrelation within metrics. These constraints could result in a set of landscapes that does not cover the full range of agricultural heterogeneity in the region. However, by selecting sites in the windows placed at the corners of the 95 % bounds of the data distribution, almost all of the data range was sampled.

The temporal lag between creation of a suitable land cover map and collection of field data that was discussed above can lead to a different actual distribution of landscape variables than was targeted by the sampling scheme. In our case, we aimed to minimize the potential impacts of such a mismatch by selecting a large number (120) of landscapes. We evaluated the possibility of using more recent remote-sensing data (1 year before the field season) for landscape selection, but as this would have involved a large amount of data processing, we concluded the extra expense was unwarranted. Given the crop rotation regime in our area, the error involved in using land cover data that were 3 years out of date would not be much different from the error involved in using data that were 1 year out of date, due to the dynamic nature of cropping decisions.

Differences between the actual distributions of land cover compared to the specific conditions important to our particular research questions also limited to some extent our ability to follow our initial idealized approach. For example, we had initially hoped to select landscapes within a very narrow range of agricultural land cover (initially targeted at 60–70 %), to minimize confounding effects of the amount of natural or semi-natural cover, which is already known to have a strong positive correlation with biodiversity. However, in eastern Ontario we could not meet that condition at the same time as all the other constraints outlined above. Therefore, we compromised by allowing 60–90 % agricultural cover, and we will need to control for the amount of natural cover in subsequent statistical analyses.

In the example here, we selected landscapes with the goal of removing the correlation between two variables. This approach can be extended to situations with n variables by imagining the four quadrants of the 2-dimensional bivariate plot from which we selected landscapes (four combinations of high and low values of diversity and field size; Fig. 7) as the "corners" of an n-dimensional space. The goal of our approach is to select a balanced sample of landscapes that includes high and low values of each variable, in all possible combinations, and while this is perhaps not easily visualized, it is certainly theoretically possible in more than two dimensions. Within the 2-dimensional plot of our example, it would also be possible to create a 3×3 (or an $n \times n$) factorial design that could be used to model non-linear effects (e.g., quadratic or unimodal responses to each predictor), given sufficient sample sizes of landscapes.

In summary, our approach to landscape selection should be applicable to a wide range of empirical landscape ecology studies. It overcomes a range of common statistical pitfalls and should increase the inferential strength of landscape ecology studies intended to contribute to development of land management policy and practice. For this type of inference, our pseudo-experimental approach has numerous advantages over selection methods that are effectively ad-hoc and those that generate samples that are representative of a given region (e.g., random sampling).

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