

Effects of landscape compositional and configurational heterogeneity
on biodiversity in eastern Ontario farmland

by

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Abstract

As agriculture intensifies worldwide, there is interest in determining ways to improve current farmland landscape heterogeneity in a manner that will benefit many different species. It has been previously established in eastern Ontario farmland that a decrease in mean field size would benefit biodiversity (Fahrig et al., 2015). This thesis aimed to determine whether other landscape heterogeneity characteristics are also related to biodiversity in a manner which could be applied to farmland management strategies. Landscape metrics were used in a random forest regression analysis, and were related to abundance and alpha, beta, and gamma diversity of bees, birds, butterflies, plants, syrphids, spiders and carabids sampled in 2011 and 2012 at 93 1 km by 1 km study landscapes, which were mapped with detailed field verification. In order to test the relevance of these findings when applied to readily available data on agricultural lands for eastern Ontario, the landscape metric calculation and random forest regression approach were also used with Agriculture and Agri-Food Canada Annual Crop Inventory maps. The AAFC Annual Crop Inventory had an overall accuracy of 71.3% when compared with the highly detailed data for this project. Both map sources were assessed in terms of metrics of importance to each taxon and important metrics across taxa. It was found that mean field size remained the most consistent predictor, with a negative biodiversity response. However, the percentage of like adjacencies (while less consistent) often had a stronger negative response. In addition, of the four landscape metrics found to have the most consistent biodiversity response, the percentage of like adjacencies was found to be the most important metric for 20 of the 27 biodiversity variables. If biodiversity conservation is a concern for farmland management in the region, fields should not only be smaller, but field cover types should also be variably distributed wherever possible.

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1.0 Introduction

The field of landscape ecology is centred on the study of pattern and process, with one main research interest focused on relating the effects of land cover change to biological diversity. Biodiversity can be defined as the variety of life from the genetic to the global level, and is most often assessed at the species level (Chapin et al., 2000). Over the past century, biodiversity levels worldwide have been in decline (Butchart et al., 2010). Among the major causes of this decline is land cover change, where semi-natural or natural areas are altered for human use. One of the most prominent types of land cover alteration is the transitioning of areas into agricultural regions (Chapin et al., 2000).

Observations at the landscape scale allow for an assessment of landscape structure effects over a larger extent than that of one farm, and this is often the scale at which species respond to their surroundings through interactions with habitat areas and resources. A landscape can be defined as a geographical area based on features of interest that are affected by spatial pattern (Singh et al., 2010). In landscape ecology, landscape heterogeneity is assessed in order to relate spatial patterns to ecological processes. Landscape heterogeneity comprises the size, shape, and arrangement of land cover patches (configuration) and the types and evenness of different land covers (composition) (Fahrig et al., 2015). The concept of landscape heterogeneity can be applied to agricultural areas in order to assess for its effects on biological indicators.

Intensification of agriculture in recent decades not only involves the alteration of lands, but also increases levels of production activity, which often leads to increased chemical use (Benjamin et al., 2008). To accommodate larger production and pest control machinery, fields become larger and linear features are removed (Baessler & Klotz, 2006). This process of field enlargement is one

of the most prominent forms of disturbance in agricultural areas, as semi-natural or natural vegetated strips and woody borders are removed, and replaced with farmland. To maximize production and reduce obstacles, in-field strips are also removed, and the diversity of species in fields becomes significantly reduced from surrounding populations (Rodríguez & Wiegand, 2009).

Given recent declines, it is important to emphasise the importance of biodiversity for farmland areas. Biodiversity contributes to many ecosystem services which are essential to successful agricultural production, the most prominent being pollination and pest control. Others include services such as improved soil composition, nutrient cycling, climate control and erosion and wind control (Pimentel et al., 1997). It is not only the presence of certain species that is required for these contributions, but also a diversity of species as many contribute to different aspects of ecosystem functioning. As an example, Isaacs et al. (2010) found that with increased diversity of bee species, bee individuals would move to more floral resources to avoid competitors, which contributed to more pollination overall. In addition, more species diversity contributes to increased stability in an ecosystem, especially in the face of climate change where many species are affected in different ways. This stabilizing role of biodiversity is referred to as the diversity stability hypothesis (Chapin et al., 2000). A wide range of species increases adaptability and resilience to change in the face of global disturbance. Moreover, a diversity of species controls pest outbreaks, since invasive species can dominate in degraded ecosystems where there is no competition or resistance to their presence (Chapin et al., 2000). It is clear that biodiversity is an essential component of ecosystem function in an agricultural context.

As the demand for agricultural production grows, biodiversity concerns must be balanced with needs and demands of the current human population (Brandon et al., 2011). This involves landscape management in agricultural regions that addresses the need for biodiversity, without

taking lands out of production. While some individual species are benefitting from agricultural intensification (e.g. ring-billed gull, *Larus delawarensis*), biodiversity conservation overall is an integral goal for management (Barbaro & van Halder, 2009). This involves considering changes in the diversity of species in a region, in addition to how different groups contribute to ecosystem services and function (Blaum et al., 2011). Assessments conducted at the landscape scale are needed in order to observe components of landscape structure that are important to local biodiversity levels, and thereby recommend solutions for meaningful farmland management action.

1.1 Biodiversity and landscape metrics

Implementing effective solutions to the effects of land alteration in farmland from landscape heterogeneity assessments requires selecting appropriate scales of observation and recommendation. While improvements can be made at the farm scale, often landscape heterogeneity is found to have stronger effects on biodiversity levels than farming practice (e.g. Weibull et al., 2003). For this reason, evaluating landscape heterogeneity at the scale of study landscapes can provide valuable information for improving spatial organization of farmland field cover types.

In addition to evaluations at a relevant scale, appropriate tools for landscape pattern quantification are required. One widely used approach is the calculation of landscape metrics, which allow for the quantification of landscape pattern to be later evaluated in terms of ecological process (Tischendorf, 2001). A high correlation between landscape and biodiversity variables can inform on species' response to landscape structure, and this understanding can be used to shape management action (Tischendorf, 2001). Many metrics are available for this purpose, and require

evaluation for regional applicability. There are many ways to select landscape metrics, and Schindler et al. (2015) found statistical selection approaches to be better than random or expert choice of metrics. Landscape metrics are also often highly correlated, as they describe similar aspects of landscape structure in different ways, and thus parsimony is required when selecting the best metrics to use for a given region (Cunningham & Johnson, 2011). Selection of appropriate metrics, therefore, becomes a central focus of studies that aim to use this information for regional landscape heterogeneity improvements.

Landscape metrics are increasingly accessible for the purpose of evaluating regions for the best courses of management action. The availability of geographic information system (GIS) resources in recent decades has facilitated the availability of data for the calculation of landscape metrics for a variety of applications. Metric outputs can also be easy to communicate to non-experts, and allow for transparency when reporting the results of metric analyses (Leitao & Ahern, 2002). There are also programs available for quick and repeatable calculations, which makes landscape metrics attractive for repeated use to follow up on regional change and the effects on biodiversity indicators (Marks & McGarigal, 1994).

Landscape heterogeneity and species distributions vary greatly from region to region, which not only stresses the importance of a landscape scale of observation, but also a regional assessment of effects. Findings from one region will not necessarily be applicable in another, which highlights the importance of evaluations that consider regional attributes in order to provide meaningful recommendations for future action and land cover planning.

1.2 Context and aims

This study forms part of a project in the Geomatics and Landscape Ecology Lab at Carleton University. The NSERC Strategic Project entitled, “Landscape Indicators and agri-environmental policies for biodiversity enhancement on agricultural lands” aimed to determine policies and practices that would enhance biodiversity in agricultural lands, while sustaining agricultural output (Fahrig et al., 2009). This project was funded by an NSERC program called “Strategic Project Grants”, and will therefore be referred to as the Strategic Project throughout the thesis. A main goal of this project was to evaluate measures of biodiversity in farmland, in addition to measures of landscape heterogeneity (which were hypothesized to be related). Initial findings (Fahrig et al. 2015) indicated that mean field size had an overall negative effect on biodiversity. That study concluded that if conserving biodiversity is a goal for eastern Ontario farmland, smaller field sizes should be considered as a course of management action.

The research reported here was designed to further the findings of Fahrig et al. (2015) through an analysis of alternative measures of heterogeneity, using landscape metrics which evaluate composition, configuration, and elements of both. This broader range of metrics was hypothesized to be able to add insight into which components of landscape structure most affect the seven taxa for which biodiversity data were obtained in the broader project. Metrics were calculated from very detailed field-based landscape maps of land cover. However, such data are not always feasible to collect in terms of time or cost. As an alternative, publicly-available land cover maps were also used to calculate metrics and tested in biodiversity modelling to gauge whether such data could be used in place of highly-detailed land cover data.

The overall study aims were threefold:

(1) evaluate whether other metrics (besides mean field size) that represent landscape pattern and heterogeneity are related to farmland biodiversity and whether they have potential viability for future use (both in eastern Ontario and elsewhere) with respect to landscape planning and management;

(2) compare biodiversity models derived using landscape metrics calculated from detailed field-based land cover maps to models derived using metrics calculated from coarser, publicly available land cover data; and

(3) evaluate the findings with respect to potential in designing best practices for eastern Ontario farmers and biodiversity conservation.

1.3 Research questions

Based on the aims described in Section 1.2, the following research questions and sub-questions were addressed in this study:

(1) Can we find better metrics of composition and configuration to represent landscape effects on biodiversity in eastern Ontario?

- Do metrics that represent elements of both composition and configuration perform better than those that represent one or the other?
- Is there a spatial extent which best captures the effects of landscape structure for each taxon (1, 2, 3 km)?

- Can coarser spatial resolution land cover data be used to calculate landscape metrics and uncover the same overall direction of biodiversity effects?

(2) What are potential biological reasons behind the findings of the above analyses?

- Would bird variables respond more consistently in groupings of farmland specialists, generalists, and other species?
- Are bird species groups responding at different spatial extents than other taxa?

(3) What are the implications for management in eastern Ontario farmland?

- What do these findings mean in terms of application for overall biodiversity improvement?

1.4 Thesis structure

The thesis is divided into seven chapters. Chapter 1 provides the context and need for the research, and the study aims and research questions. Chapter 2 provides background information on the issue of biodiversity decline, the use of landscape metrics for land cover change analysis (and alternative approaches), the definition and concept of heterogeneity, ways of calculating species diversity and heterogeneity, individual taxon responses to landscape structure, and current management practices and goals. Chapter 3 describes the study area and data, including the preceding analyses (Fahrig et al. 2015) this research builds on, field work conducted in 2015, preparation of data for landscape metric analysis, and data processing for the comparison of findings with coarser, publicly available data. Chapter 4 describes the methods of the study, including calculation of landscape metrics, analysis of response to metrics within and across taxa groups, analyses in bird farmland specialist and generalist groups, and the comparison of the

detailed field-based land cover maps to the coarser land cover maps in terms of direct correspondence of land cover classes in both datasets and biodiversity models derived using metrics calculated from each source. Chapter 5 provides the results, including which metrics had consistent relationships with biodiversity, and the results of the detailed and coarser land cover data comparison. Chapter 6 provides a discussion of the results, including hypothesized biological reasoning for metric importance for each taxon, and links to findings by other studies. There is also a discussion of the implications of the main landscape metrics found to be of importance across taxa. This chapter also discusses the ability of coarser data to be used as a substitute for the highly detailed data used in this analysis, and the implications of these findings. Finally, implications for land cover policies and planning are discussed, in addition to future areas for study and recommendations. Chapter 7 concludes the thesis with the main message and findings of the study, and implications for eastern Ontario farmland management and future research.

2.0 Background

Biodiversity levels worldwide have declined rapidly over the last half-century. Some drivers of this decline are invasive species, greenhouse gas emissions, and land use change (Chapin et al., 2000). While regional effects vary, land use change is projected to have the strongest negative effect on biodiversity over the next century (Singh et al., 2010).

One of the most significant forms of landscape alteration has been the conversion of natural areas into farmland. Agriculture was estimated to occupy 40% of land cover worldwide at the end of last century (Ramankutty & Foley, 1999). This large area, combined with increasing demand for agricultural production as the world population grows, has contributed to increased intensity in farming practices and efficiency. Agricultural intensification involves fields becoming larger as linear features are removed from the landscape to increase crop areas (Baessler & Klotz, 2006). In addition, landscapes become simplified, non-fertile areas are converted from developed forest areas into shrubs (lowering landscape heterogeneity), and chemical use typically increases (Benjamin et al., 2008). Studies have predicted that current food production areas will be able to address the food demand until 2050, which underlines the importance of reconciling current land use practices with biodiversity and ecosystem services to continue to produce food for decades to come (Barral et al., 2015).

In the larger project this research contributes to, a primary objective was to determine “which measure(s) of landscape heterogeneity are the best indicators (i.e., best predictors) of biodiversity in agricultural landscapes” (Fahrig et al., 2009). Here, I address this objective through assessing alternative measures of heterogeneity of eastern Ontario agricultural landscapes, and

their effects on biodiversity levels. This chapter presents the background and literature review of landscape effects on biodiversity, heterogeneity, and current farmland management practices.

2.1 Landscape effects on biodiversity

Habitat and resources to support wildlife in agricultural landscapes have declined over the past two decades (Javorek & Grant, 2010). One means for assessing the causes of this decline is to assess levels of landscape and land cover heterogeneity (hereafter referred to simply as heterogeneity) in agricultural areas and effects on organisms. Land cover heterogeneity in farmland is comprised of both the types of fields (composition) and the size, shape, and arrangement of fields (configuration) (Fahrig et al., 2015). The overall notion is that such spatial and temporal heterogeneity may affect ecological processes, so understanding both landscape features and ecological processes can inform management and planning (Li & Reynolds, 1994). For this purpose, relevant biological indicators must be selected that are both sensitive to landscape change and can be monitored over long periods of time (Cain et al., 1997). From these assessments, management recommendations can be implemented based on the known effects on biodiversity, derived through studying diversity measures (Sheffield et al., 2013).

Assessment of farmland has established that biodiversity typically decreases when habitat quality is degraded, and landscape heterogeneity is reduced (Moreira et al., 2015). Landscape heterogeneity is expected to have positive effects on biodiversity due to increased availability of a variety of resources, and improved access of resources for species with low mobility (Burel et al., 1998). The level of importance of landscape heterogeneity effects is suspected to depend on the geographic ranges of species in question (Katayama et al., 2014). With a loss of landscape heterogeneity and the expansion of field sizes comes a loss of semi-natural or natural areas between

fields. These areas have been found to increase habitat area and quality, as well as landscape heterogeneity (Hopfenmüller et al., 2014). Again, the effectiveness of the presence of natural and semi-natural cover on species distributions depends on taxon-specific requirements for traversing over and surviving in the landscape.

Two management techniques have been proposed for aiding in biodiversity conservation in farmland: land sharing and land sparing. Land sparing is defined as setting aside areas that will not be affected by human impacts, while land sharing requires developing innovative solutions in existing agricultural systems (Barral et al., 2015). Typically, it is not practical to revert agricultural lands to natural areas, and Barral et al. (2015) found the rate of biodiversity recovery to be the same for both land sharing and land sparing. This finding asserts that agricultural areas need not be reversed to natural areas in order to conserve or enhance biodiversity. Nonetheless, maintaining remaining natural areas has become a conservation goal in some agricultural remediation strategies (Scherr & McNeely, 2008).

Many studies have outlined the positive effects on biodiversity of natural and semi-natural areas (areas with minimal human impacts), since when they are removed, habitat area and quality are degraded, and heterogeneity is decreased (e.g. Steffan-Dewenter et al., 2003; Sheffield et al., 2013; Hopfenmüller et al., 2014). While these positive effects are known, it has also been found that semi-natural areas can influence species diversity in smaller categorical groups (grassland, wooded areas, and cereal land cover types), and heterogeneity in habitat or crop diversity can also have positive effects (Dufлот et al., 2014b). This implies that having more overall heterogeneous areas can be considered more important than trying to re-integrate small strips or patches of semi-natural areas (Dufлот et al., 2014b).

For this reason, while natural and semi-natural areas can have positive effects, it remains integral to consider overall landscape structure. In addition, it is of interest to study whether there are solutions that can be implemented in farming regions that have already eliminated many natural areas, without taking converted lands out of production (Fahrig et al., 2015).

2.1.1 Ways of calculating diversity

From genes to landscapes, relative variability of biological diversity can be assessed in order to determine areas that have been degraded by anthropogenic impacts over time (Burel et al., 1998). Typically, biodiversity is measured as species diversity, which is the most widely documented measure of affected groups. Species diversity has a cascading effect in ecosystems, particularly in terms of plant diversity and microorganisms (Chapin et al., 2000). Given the connectedness of effects, species diversity can inform on areas of concern for a myriad of ecological impacts.

While research on one (or a few) indicator species is still conducted for gathering information on organisms of interest, in some cases, it is of interest to assess biodiversity with the use of multiple indicator species (or taxa) to evaluate management options that would benefit all groups (Blaum et al., 2011). Although many species respond positively to increased heterogeneity and availability of habitats and resources, there may be underlying mechanisms affecting each differently (Ekroos et al., 2013). Assessing multiple taxa at multiple scales can aid in informing on which actions may be most effective for biodiversity conservation.

To calculate diversity metrics, sample values can be averaged across sampling sites, with assessments of differences between sampling sites, and at the level of the entire landscape. For this purpose, measures of alpha, beta, and gamma diversity can be employed. Alpha diversity is defined

as the mean number of species per sample site, gamma is the total number of species across all sample sites in the landscape, and beta diversity is the ratio between mean alpha and gamma (Whittaker, 1960). Conceptually, these measures provide not only a comparative value between study landscapes, but also averaged across sample sites within a landscape (alpha), at the scale of the study landscape (gamma) and the ratio between the sampled sites and sampled landscape (beta) (Tylianakis et al., 2006). Alpha diversity provides the average number of species at a given site, or species richness of a given location. Beta diversity measures the “degree of species turnover or compositional change” by evaluating the ratio of the total number of species across all samples and the average value of the species per sample site (Whittaker, 1972). Ecologically, beta diversity values provide measures of two elements that contribute to a change in species composition between sample locations: spatial turnover between sites (or replacement of some species with others) and nestedness (having a differing subsets of species contributing to the overall list of species present at a sampled site) (Baselga, 2010). Beta diversity can be calculated in the classical sense (by subtracting alpha diversity from beta, or using a ratio value), but can also be calculated using multivariate approaches that consider the distance between sites. Measures of beta diversity that consider distance-based interactions can be useful for comparing beta values between regions (Bennett & Gilbert, 2015). Therefore, diversity for study landscapes can be assessed in three detailed ways, the number of species, different spatial scales of observation at each site, and the differences between sites. Thus, alpha, beta and gamma provide more information than simply using a count of observed individual organisms, and can be used in conjunction with this traditional measure to provide detailed information on regional diversity.

It is likely that a relationship could be found between the number of species and landscape arrangement, but it is expected that more effects would be found on population processes, as the

threat to biodiversity arises inherently through disruption of these processes (Burel et al., 1998). Studying groups that behave similarly or require similar resources allows for these processes to be assessed. For this purpose, core traits must be identified, clustered, and scrutinized to ensure they are indicative of the process they intend to describe (Blaum et al., 2011). As an example of possible functional traits, body size of butterflies has previously been used as a proxy for dispersal ability (Stevens et al., 2010).

There are many ways in which species can be categorized in order to calculate diversity of groups of interest. Measures such as body size for dispersal ability are called soft traits, as they are not always directly linked to all abilities (such as flight, in this case), but are often the only universally available information about a taxon (Blaum et al., 2011). Guilds can also be used, which are groupings of species based on resource use. Functional groups describe assemblages that function or contribute to processes in the ecosystem in similar ways (Blondel, 2003). Overall, complex functioning, especially in terms of trophic levels, is more stable in terms of ecosystem cycling (i.e. nutrients) and resource regeneration, meaning that the system is less likely to collapse when there is damage to the ecosystem (Blondel, 2003). Biodiversity, therefore, is not only considered a measure of the diversity of species, but can also represent a measure of the diversity of ways in which species contribute to overall ecosystem function.

2.1.2 Impacts of biodiversity loss on farmland

Biodiversity in agricultural areas is important for a number of reasons. While it may seem as though agricultural productivity in the face of growing food needs outweighs the ability to consider biodiversity as a primary management component, this notion is countered by several examples of benefits of biodiversity and necessary ecosystem services. The most prominent

anthropogenic reasons for maintaining and improving biodiversity can be categorized as ecosystem stability, ecosystem function, and economic contributions.

Ecosystem stability is defined as resilience to change. The diversity stability hypothesis states that diversity minimizes the risk of detrimental ecosystem change in response to disturbances (such as climate change and pest outbreaks) (Chapin et al., 2000). Another component of ecosystem stability is the continued provision of services and materials from farmland areas, including food, fuel, genetic resources, and clean and accessible water systems (Chapin et al., 2000). Maintaining biodiversity allows a level of insurance for stability in agricultural regions to defend against effects of short-term adversities such as natural disasters, and longer-term effects such as global climate change.

Ecosystem function is aided by a complementation of species and cycling of elements, in other words, a variety of organisms that support others complementarily. Maintaining biodiversity can not only contribute to cultural, aesthetic, and economic benefits, but also provides services such as nutrient cycling and pest control (Squire & Ward, 2003). Although high levels of biodiversity most prominently contribute to pest control and pollination, other benefits include rich soil composition, carbon sequestration, and climate control (Belfrage, Björklund, & Salomonsson, 2014). It is clear that high levels of biodiversity form either very large, or small but essential parts of ecosystem function that are required for human livelihoods.

Finally, in terms of economic benefits, it was estimated that the profits derived from biodiversity in the United States could be valued at \$300 billion a year almost two decades ago, and this estimate is likely to have increased since then (Pimentel et al., 1997). These economic benefits manifest in the form of soil formation, nutrient cycling, pest control, and nitrogen fixing.

Not only are benefits directly applicable to current agricultural practices, but biodiversity has also led to advances in biotechnology (presenting alternatives for fertilizer and fossil fuels), genetic breeding benefits (breeding between diverse groups for resilience), and perennial crop alternatives (such as perennial corn found in Mexico) (Pimentel et al., 1997). These contributions and advancements would not be possible without areas with high levels of biodiversity.

While these three main categories of benefits of biodiversity have been outlined, there are many studies which outline the complexities associated with productivity, stability, and diversity. One example is Hautier et al. (2015), which highlights biodiversity as a main determinant of productivity. It is important to note that the interactions between biodiversity and other ecological processes (as well as economic benefits which can arise from productive systems) are a very complex and active topic of discussion in the literature.

Bees and plants are well suited to illustrate the importance of diversity in cases of specific taxa. Worldwide, an estimated 35% of crops rely on pollinators for production (Klein et al., 2007), and 70% of the world's leading crops require pollination services for improved quality, size, or stability of the growing system (Ricketts et al., 2008). A maximal diversity of pollinators is needed in order to maintain required levels of pollination, which primarily includes diversity of bees, and also syrphids (hoverflies) (which are less well studied overall, but have been found to contribute to pollination services) (Jauker & Wolters, 2008). Not only are bees required for pollination services, but it has also been found that as bees are lost, crop yields are lowered (Colla & Packer, 2008). A higher level of bee diversity leads to higher seed production, and although syrphids contribute to pollination, they cannot offset the negative impacts were bees to become extinct. For this reason, species which contribute to services complementarily are important for ecosystem functioning in agricultural areas (Frund et al., 2013).

Plant diversity is also integral to biodiversity contributions in agricultural areas. More money is spent on weed control than crop inputs, which can be considered an unnecessary or excessive expense given that maintaining high levels of plant diversity provides a naturally occurring invasive species control service (Squire & Ward, 2003). Plant diversity contributes to ecosystem functioning as it is linked to pollinator needs, and increases resilience of regional plant systems to disturbance and climate change (José-María et al., 2011). While measures such as maintaining habitat areas and plant diversity are often seen as a luxury in developing countries, this is not the case when ecosystem goods and services are considered. As biodiversity declines, so too does agricultural output, and actions supporting biodiversity must be considered a priority in order to maintain functioning ecosystems that support agricultural areas (Brandon et al., 2011).

2.2 Taxonomic responses to landscape structure

Taxa (and groups within taxa) respond to landscape heterogeneity differently. A multi-taxon approach is one method of assessing a span of groups of interest in order to see whether there are patterns across groups (Alaruikka et al., 2003). It is interesting to note that although studies generally find low correlations between taxa, and all are responding to different aspects of landscape structure, most benefit from an increase in heterogeneity (e.g. Ekroos et al., 2013; Fahrig et al., 2015). Regional studies are still required to identify local trends, which can then be situated in a larger context. In one European study by Weibull et al. (2003), higher levels of diversity were found for butterflies, plants, spiders, and beetles in more heterogeneous areas. In this case, farming practice was less important for these taxa compared to the effects of landscape structure (Weibull et al., 2003). The following sections will outline taxon-specific effects of landscape structure, and previous studies' recommendations for improvements to cropland management.

2.2.1 Bees

Bee diversity is declining in many regions (Colla & Packer, 2008; Henriksen & Langer, 2013). Due to their essential service of pollination, bees are often considered a keystone species in terrestrial ecosystems that depend on this service for reproductive success of plant species (Sheffield et al., 2015). Generally, bees in human-disturbed habitats have lower overall diversity than those in natural habitats. Those that are able to remain in altered landscapes (such as farmland) benefit from heterogeneity (Sheffield et al., 2013).

Heterogeneity in farmland means more cover types, which translates into increased ability for more uses by differing bee species. Proximity of these essential land cover types is also important for accessibility of necessary resources (Colla & Packer, 2008). Distributions of bee populations are limited by floral preferences, hosts (for cleptoparasitic bees) and habitat availability (Colla & Packer, 2008). For instance, long tongued bees are more specialized because they need flowers with long corollas (Colla & Packer, 2008), while short tongued bees are not able to benefit from flowers with deeper corollas at all (Evans et al., 2008). For ground nesting bees, more heterogeneity means more availability of resources and potential nesting sites, and less opportunity for risk of tilling damage (Evans et al., 2008). It is evident that a wide variety of cover types distributed at accessible distances is crucial for bee survival.

Wild bees are also an overlooked component of pollination services, but they represent half of all pollinators contributing services in an agricultural context worldwide (Martins et al., 2015). A southern Quebec study found that meadow and forest areas adjacent to agricultural areas enriched bee diversity overall (both wild and managed) (Martins et al., 2015). While such natural areas are not always feasible to develop or maintain, heterogeneity of cover types enables access of habitats. Wild bees have to commute between nesting and foraging sites when they have

offspring, which limits them spatially (Jauker et al., 2009). Overall, pollinator behaviour ecology and status for wild bees are understudied in conservation biology, but it is apparent that they would benefit from increased heterogeneity. Bees are an important component of agricultural systems, and ensuring resource and habitat availability is essential for maintaining both abundance and diversity of this taxon.

2.2.2 Butterflies

Butterflies need breeding, foraging, and roosting habitats which makes them good candidates for heterogeneity analyses (Flick et al., 2012). One approach that has been used to address their need for a variety of floral resources is the use of green lanes, which are shrubby vegetated areas that border machinery tracks in farmland areas (Dover et al., 2000). Butterflies get the benefit of the resources on the outer walls of the lanes, but also in the two strips of greenery (which is often an area of reduced disturbance and increased nectar sources). These areas have been found to be superior to most land cover types for butterfly resource use with the exception of wooded areas (Dover et al., 2000). Green lanes, hedgerows, and ditches provide resources, while field margins can also be used as breeding habitat. There are many different species of butterfly that benefit from different combinations of these land cover types, so higher configurational heterogeneity (for access to habitat areas) and increased levels of butterfly habitat are recommended as a means to provide for many species at once (Flick et al., 2012).

In addition to beneficial cover types, some studies have found links between behaviour and dispersal ability of butterflies and landscape structure. For instance, Perović et al. (2015) studied landscape effects on butterflies in terms of functional traits related to size, feeding habits, and migration traits. It was found that butterfly diversity increased with more field cover types, while effects related to the traits of interest were positively affected by smaller fields. For instance,

specialist species benefitted from smaller fields when their larvae fed on specialized plant types, or were limited by low dispersal distances. The positive effect of smaller field sizes even outweighed the effects of farming practices (machinery, pesticide use, etc.) (Perović et al., 2015). This case study underlines the importance of providing not only essential cover types, but access to these through maintaining and creating smaller fields. The main finding of the benefit of smaller field sizes is also aligned well with the Fahrig et al. (2015) finding of the negative effects of increased mean field size on butterfly alpha, beta, and gamma diversity, and abundance.

2.2.3 Syrphids

Syrphids (or hoverflies) require the use of many varied resources, which makes them sensitive to land cover change – and thus good indicators of the effects of landscape heterogeneity. There are also many keys for easy identification of species, and syrphids are widespread and present in many regions (Sommaggio, 1999). As pollinators, they are an integral part of agricultural systems.

Complex landscapes have been found to enhance the abundance and species richness of syrphids. This is likely due to their need to access many resource types to complete their life cycles (Bommarco et al., 2012). In terms of management, Haenke et al. (2009) found that the implementation of flower resources for syrphids is more effective than increasing heterogeneity in simple landscapes, while maintaining heterogeneity in complex landscapes is recommended. These recommendations have been found to increase pest control services of syrphids, due to the fact that when floral resources are adjacent to wheat fields, it was found that more syrphids were consuming aphids in the fields (Haenke et al., 2009). It is evident (similar to butterflies) that syrphids benefit from a variety of cover types at accessible distances that allow them to complete their life cycle requirements, while also providing valuable services to farmland function.

2.2.4 Spiders

Spiders in agricultural areas tend to benefit from edges between fields. In one European study, most spider species were found in field edges and heterogeneous areas (Clough et al., 2005). While field management and regional elements did not have an effect on spider diversity, landscape heterogeneity (or lack thereof) affected species distributions, and increased heterogeneity was recommended to improve spider diversity (Clough et al., 2005).

Similarly, in Japan, spiders were assessed in paddy fields, and landscape heterogeneity was again found to be the most important factor (more than local elements such as farming practice) (Miyashita et al., 2012). This was found to be the case at several scales, which indicated that there should be also heterogeneity across multiple scales. Interestingly, natural areas were not the only areas which contributed to resource availability, as harvestable grasslands were suspected to have prey available for spiders that had traveled from adjacent habitats (Miyashita et al., 2012).

Increased non-crop areas in a regional context has also been found to be beneficial for the number of spiders in agricultural areas, which may be due to how spiders traverse the landscape (Schmidt et al., 2005; Sunderland & Samu, 2000). For instance, a review article found that spiders are less likely to walk into a field from an edge unless the field is similar to the edge land cover type they had traveled from (they won't enter the field more than 5 metres before returning to the edge) (Sunderland & Samu, 2000). The same article found that diversification of land cover types increased spider abundance in over half of the studies analyzed (Sunderland & Samu, 2000).

It is clear that spiders' ability to traverse agricultural landscapes and access resources is limited by connectivity of areas that can be used as habitat. Spiders are valuable predators in this context, and contribute to natural pest control. Increased regional studies that integrate the effect

of landscape heterogeneity on spider diversity are required to discern the ability of agricultural management to accommodate the varied needs of regional spider species (Clough et al., 2005).

2.2.5 Carabids

The effects of agriculture on carabids (beetles) have previously been studied based on the body size of specimens in study landscapes (on a gradient from urbanized areas into more rural areas) (Alaruikka et al., 2003). It was found that larger specimens tended to be present in more rural areas, which is expected to be due to their improved flight abilities. In a different but related study, size was also linked to dispersal ability based on wing length and flight (Fischer et al., 2013). Studies in agricultural regions with a specific focus on compositional and configurational heterogeneity (exclusive of natural areas) appear to be understudied for carabids.

However, the effects of farming practices on carabids have been studied, and abundance was found to be species specific (approximately half were more abundant with organic management, and approximately half were more abundant with conventional management) (Purtauf et al., 2005). The same study also concluded that landscape features were more important than farming practice for determining carabid diversity.

Duflot et al. (2015) found that heterogeneity in farmland provided benefits to carabid species, as it increased access and movement between woody borders and maize (corn) and winter wheat fields at different times throughout the year. This study asserted the importance of adjacencies to woody habitats as well as overall landscape heterogeneity in order to maintain carabid populations, and ease between-field movement (Duflot et al., 2015).

Carabids are an important part of farmland, particularly as they are food for bird species, and they prey on crop pests such as aphids (Östman et al, 2001; Benjamin et al., 2008). In farmland

areas, carabid populations have been affected by a rapid rate of change in landscape heterogeneity, but have adapted in many cases as evidenced by landscape preferences for carabids with specific traits. For instance, carabids which are good fliers prefer open landscapes, while those that cannot travel great distances are not found in these settings (Duflot et al., 2014a). Larger carabidae species do not survive as well in simplified landscapes (Kohler et al., 2014). In this way, landscape heterogeneity “filters” species traits as only species that survive in simplified landscapes are found in those areas.

2.2.6 Birds

Farmland birds are widely accepted as indicators of biodiversity in many regions in North America and Europe (Greenwood, 2003). In terms of response to landscape structure, smaller fields have been found to have a positive effect on bird diversity (Belfrage et al., 2014). In addition, it has been found that annual crops may be less attractive for most bird species than permanent crops (Ahnström et al., 2008). In spite of this knowledge, and many subsidies and policies in Europe to enhance farmland biodiversity, bird populations are still in decline overall (Belfrage et al., 2014).

As birds are varied in terms of their resource needs and habits, examining effects on different species can inform on the effects of landscape heterogeneity. For instance, Devictor et al. (2008) found that the more specialized a bird was, the more affected it was by landscape heterogeneity change. Bird specialist species decline in areas where landscape heterogeneity has decreased, and over time only generalists remain, and some generalist species even benefit from agricultural intensification (e.g. ring-billed gull) (Devictor et al., 2008). Observing effects in groups of species (i.e. specialists) is important to inform conservation decisions that address a wide

variety of species' needs. Overall, a variety of cover types (many of them permanent) are required in order to sustain diverse groups of birds in farmland.

2.2.7 Plants

An increase in landscape heterogeneity contributes to more plant diversity in agricultural regions (Honnay et al., 2003). Plant diversity is important to maintain as it may affect biodiversity of other taxa on a larger scale, either in terms of habitat or resources provided by some plant species (Baessler & Klotz, 2006). However, with agricultural intensification comes a decline in plant diversity, often due to decreased landscape complexity and/or need to maximize crop growth and production (José-María et al., 2011). For instance, fields are often expanded to accommodate larger machinery. Some studies have found that plants at the centre of fields are influenced by local factors such as herbicides, while plant diversity at the edges of fields is more related to landscape structure (José-María et al., 2011).

The dispersal of plants also depends on agricultural landscape complexity, and often presents challenges in terms of the establishment and survival of plant species. Many plant species are now restricted to field margins, whereas in the past plants would be throughout the field, to the extent that there are differences in species diversity between core areas and edge areas. This local difference in distributions can likely be attributed to the increased use of herbicides (Baessler & Klotz, 2006). As plant diversity in arable fields has decreased, so has plant diversity in road verges (Henriksen & Langer, 2013). This in turn hinders plant dispersal in general, as it may be thought that plants have low resistance for movement in edges, but there is actually greater architectural diversity along fencerows (Fritz & Merriam, 1996). Light can penetrate these edge vegetation patches (more than forest edges), causing plants to fill the gaps in fencerow vegetative structures, which constrains plant movement overall. In an assessment in the late 1990s, fencerows were

found to be more numerous in eastern Ontario than forest edges in terms of field borders (Fritz & Merriam, 1996).

In addition to the challenges for survival of plants in farmland, their control is a major expense for farmers. However, if natural species were allowed to remain, this control would be a service provided naturally. When only crops remain in a landscape, weedy species from other regions have the ability to take over due to the lack of competition, and this cycle is perpetuated annually. Plant diversity regulates weed species at the farm and landscape scale, although applications of this type of weed suppression is still highly debated and context specific (Poggio et al., 2013). Dufлот et al. (2014a) found that heavy seeded plants remained in areas with large quantities of crops, underlining that they had survived removal and mitigation attempts by farmers. Plant diversity is aided by increased landscape heterogeneity, and in turn provides weed suppression services in areas where it is maintained.

2.3 Heterogeneity

Heterogeneity is defined as “the complexity and/or variability of a system property in space and/or time” (Li & Reynolds, 1995). Landscape heterogeneity can be considered variability in land cover types, shapes, sizes, and arrangement in an area of interest. This form of heterogeneity is also separated into compositional heterogeneity, or a measure of the number and amount of types of land cover, and configurational heterogeneity, which describes the size, shapes, and arrangement of cover types (Fahrig et al., 2011). In studies to observe the effects of landscape heterogeneity on biological indicators in agricultural areas, there are two main levels at which observations can be made. The field level assesses local heterogeneity (i.e. patterns at the center and edges of fields), while the landscape level enables an assessment of patterns, heterogeneity

and connectedness (Le Roux et al., 2008). Most studies currently use a landscape approach to implement solutions across a region, and assess for effects on multiple taxa across several scales.

To assess effects of landscape heterogeneity, it must be evaluated along a gradient (although not regionally influenced) (Holzschuh et al., 2007). In addition, while composition can be easy to evaluate (designating consistent land cover types), in agricultural areas configuration can be confounded by the amount of semi-natural and natural areas if these are not to be included in the analysis, and therefore needs to be controlled for when effects of farmland cover types are of interest (Hopfenmüller et al., 2014).

Heterogeneity of farmland areas is also not only spatial, but temporal. More crop types overall in a landscape was found by Östman et al. (2001) to be indicative of higher amounts of perennial crops (more permanent temporally). This temporal component of farmland can be beneficial for biodiversity. As an example, Holland et al. (2000) found that insect diversity was higher in areas with woody borders, which may be attributable to the presence of these areas over several years, rather than one season alone.

Landscape heterogeneity is generally beneficial in terms of species response, but there are also limits. The intermediate heterogeneity hypothesis stipulates that as more types of fields are added and broken into smaller areas, the amount of area dedicated to each type of field is gradually reduced and they are further and further apart. This indicates that there is an optimal amount of heterogeneity for species' use before there begins to be negative impacts (Redon et al., 2014).

Field enlargement is one of the most important structural alterations to heterogeneity of agricultural areas of late. Rodríguez et al. (2009) evaluated field expansion in terms of machinery efficiency, and found there to be a threshold of 1 to 2 hectares after which there was no more

increase in productivity of crops. Larger machinery and larger fields (as has been discussed) often hinders species survival and establishment, and are often linked with increased pesticide use. The study concluded by recommending in-field strips and field margins, as food is no longer the only goal of farmland areas. Biodiversity needs to be re-prioritized, and structural changes in farmland need to be revisited in terms of actual productivity increase (Rodríguez & Wiegand, 2009). Overall, it is important to note that biologically diverse areas will need to provide for diverse resource and habitat needs of many species, which can be addressed by farmland heterogeneity (Hoehn et al., 2008).

2.3.1 Landscape metrics for quantifying heterogeneity

In past studies, an evaluation of habitat quality would be used to inform on availability for species' use and habitation. These types of assessments would focus on the presence and state of habitat in given regions, and the quality of available resources and habitat areas. However, in current research, spatio-temporal effects are better evaluated in the landscape context (Dauber et al., 2003). To this end, landscape metrics are often employed. These measures can be simple, intuitive tools that are widely used in the literature, and provide quantitative information about landscape features (Tischendorf, 2001; Kupfer, 2012).

Landscape metrics are a widely used approach when quantifying the relation between land cover and ecological processes (Uuemaa et al., 2009). Metrics are calculated at the landscape level, and a landscape is defined as an area in which ecological components are affected by spatial pattern, observed at a scale relevant to both the ecological and spatial elements (Singh et al., 2010). As has been established in several studies, there are dimensions of landscape structure that can

explain a large portion of the variation in measures of biodiversity (e.g. Luoto, 2000; Riitters et al., 1995; Schindler et al., 2008).

Fragstats is software that is often used to calculate landscape metrics (Marks & McGarigal, 1994). Due to its extensive use in academic literature by ecologists and continual development, its applications and metric options are some of the most comprehensive available. Fragstats was initially designed to address landscape structure from an organism perspective, and to consider how individuals use landscapes. This single-organism approach is now only used in cases where one species is being studied, as every species responds at different scales (and possibly more than one) and uses the landscape differently (Blaschke & Petch, 1999).

Conceptually, landscape metrics based on delineated features (ie. fields in farmland) describe differing aspects of landscape heterogeneity in order to link pattern with process. There are many ways to derive values based on similar measures of features of interest, but overall, metrics derived from Fragstats describe eight main descriptors of variability or complexity of landscape heterogeneity. The example of farmland fields will be maintained for describing these categories. All categorical descriptors were derived from Marks and McGarigal (1994):

(1) Area metrics: Can be used to describe the area of fields, or the distributions of the areas of all fields in a study landscape;

(2) Patch density and variability: Descriptors of the number and variability of field types in a study landscape, as well as evenness of the presence of different field types;

(3) Edge metrics: Metrics that describe the area and intersection of edge land cover types, as well as the perimeter of fields;

(4) Shape metrics: Descriptors of the complexity of farmland field shapes. These can be based on deviations from standard shapes (such as a compact square field) or as a measure of cell distance from the centroid of each field;

(5) Core area metrics: Metrics which calculate relative area of the center of fields, derived with settings from the user. For instance, if 2 meters into a field is still considered an edge area, this can be set as a consideration for calculation of these metrics to derive values only from the areas within the 2 meter buffer section of each field;

(6) Nearest-neighbour metrics: Metrics calculated based on distance to similar fields, or the variability in the distributions of fields throughout the study landscape. These metrics are particularly pertinent when considering distances between farmland habitat areas;

(7) Diversity metrics: Metrics which measure the number of types of fields, as well as evenness between observed types. Diversity metrics can also measure a simple count of types in a study landscape, or the proportion of a type of field relative to all other types;

(8) Contagion and interspersion metrics: Descriptors of the “clumpiness” of fields (mostly derived from cell counts) for the compactness or contiguity of fields, or whether they are broken into smaller fields overall (Marks and McGarigal, 1992).

Fragstats is an attractive option for ecologists due to the variety of metrics (and scale options) that are available, which can be employed to capture the dynamic interactions of different ways in which species interact with landscape heterogeneity. Fragstats has the ability to calculate landscape characteristics at the field, class (each field type), and landscape levels (Marks & McGarigal, 1994). In terms of calculating metrics from a raster, there are many available metrics, and the program is also automated for facilitated repeatable use (Marks & McGarigal, 1994). Other

methods for calculating metrics (such as ArcGIS add-ons, PolyFrag, GRASS, QGIS, spatialEco in R, and others) are available; however Fragstats currently has the widest range of available metrics (Maclean & Congalton, 2013; Neteler et al., 2012).

Although thematic maps can be created using vector and raster data, it has been found that the outputs do not change in terms of their ability to inform for management (Wade et al., 2003). In other words, the use of either type of data will reveal spatial patterns that can then be applied to biodiversity variables, and the recommendations are often comparable. While vector-based methods can be more accurate when all features are delineated in detail, raster-based methods are typically faster in terms of processing, and have more available tools for metric calculation (Wade et al., 2003).

To calculate landscape metrics from raster data, resolution must be considered in terms of spatial, temporal, and thematic data elements. Spatial resolution is composed of grain (cell size) and extent. Extent is defined as the overall area of a study, or the area to be covered by sampling, while the grain represents “individual units of observation” (Wiens, 1989). An appropriate grain size can be selected based on the scale of ecological interactions with the landscape and the resolution that is available based on how the data were produced. Typically calculations are conducted at multiple extents to observe whether there are patterns that are would not necessarily be discernable at one standard radius (Newton et al., 2009). This also allows for the testing of landscape heterogeneity at multiple scales, since the proper scale is not immediately apparent, especially when multiple taxa are involved (Wiens, 1989). Temporal resolution is related to land use change over time, either seasonally or over several years. These temporal shifts can have an effect on species distributions, especially in terms of availability of habitat areas (Lausch & Herzog, 2002). It is of interest to study processes and pattern at the temporal intervals relevant to

the temporal dynamics of the process. This can be difficult to achieve from a data capture perspective, as not all dates can be captured (often due to expense), and not all data are unaffected by clouds, weather or other factors that contribute to errors. Finally, thematic resolution relates to the number of classes and the precision of class names as descriptors of land cover or land use, which are selected for analysis with landscape metrics. Other than binary analyses (e.g. forest and non-forested areas) the choice of how land use is classified is typically at the discretion of the analyst (Blaschke & Petch, 1999). Even small differences in the number of classes or generalizations of land use types can have substantial impacts on diversity indices, such as Shannon Diversity (Blaschke & Petch, 1999). Metrics are therefore sensitive to all types of data resolution, and selecting those which are ecologically relevant and appropriate for the landscape features of interest is integral for obtaining meaningful metric outputs (Li & Wu, 2004).

Selecting metrics is often subjective and done by the user, but there are multivariate techniques (such as principal components analysis or multiple regression analysis) that can be used to reduce dimensionality and aid in the selection of an optimal set of non-highly correlated metrics (Cunningham & Johnson, 2011). Many metrics are correlated, so parsimony is important in selecting metrics in order to capture landscape elements of interest but also choose those that are easy to apply. While many metrics are available, some are simpler to interpret with respect to ecological patterns and processes. It is beneficial to begin with the use of many metrics because not all elements of landscape structure can be described by one simple metric (Tischendorf, 2001).

Metrics are often correlated because they represent common characteristics related to patch area, length of features, and patch types (Hargis et al., 1998). In spite of these correlations, if metrics are representing distinct processes, they should be retained if they are valuable in terms of information that could be provided for management (Smith et al., 2009). Assessing all distinct

dimensions of landscape structure can aid in determining which components are most relevant to biological indicators of interest.

Metrics are only valuable insofar as they are able to be interpreted based on ecological meaning (linking pattern and process) (Li & Wu, 2004). Common issues with the use of metrics include observing pattern without considering process, and not using enough landscapes to determine whether the pattern and process relationship is consistent across a regional study area (Li & Wu, 2004). Even still, metrics can be difficult to interpret when these considerations are in place. For interpretation, there needs to be consideration of how the region of interest has changed in the past, and could reasonably change in the future (Li & Wu, 2004).

Structure patterns in land cover types and sizes are specific to particular landscapes and regions (Cushman et al., 2008). The aim of many management approaches is to determine metrics or groups of metrics that represent landscape effects on biodiversity, so that monitoring change in those metrics can aid future management action and improvements for a region (Riitters et al., 1995). In addition, the ability to use satellite data for this purpose allows for regional or even national research to accomplish this goal.

Metrics can be used for habitat assessments, land use planning, biodiversity assessments, reserve design, and observations of species of interest (Schindler et al., 2013). Often the recommendation when landscape metric analysis has been completed is the preservation of more heterogeneous landscapes, but these recommendations vary regionally, and case studies are therefore an integral component of these analyses to inform for management (Schindler et al., 2013).

2.3.2 Remote sensing data for metric calculation

Technology advances have allowed for landscape pattern to be quantified from remotely sensed data (Newton et al., 2009). The use of remotely sensed data enables studies across regions and at multiple spatial and temporal scales (Bradshaw & Fortins, 2000; Singh et al., 2010). When selecting sites across regions, attention needs to be given to the spatial independence of sites, to ensure that landscape effects are not spatially auto-correlated (Holland et al., 2004; Pasher et al., 2013). The use of imagery and metrics for agricultural areas is often appropriate because compared to other land use types, transitions are easily distinguishable, abrupt, and linear (Arnot et al., 2004). Remote sensing data can be used both to create thematic maps from which vector or raster metrics are calculated, or metrics can be calculated directly from the images based on pixel values (Duro et al., 2012).

2.3.3 Alternative metric calculation techniques

In addition to the calculation of landscape metrics, there are alternative methods for assessing landscape pattern to relate to biodiversity effects. Spatial heterogeneity can be calculated with metrics based on delineated features, spectral information, textural metrics, or surface metrics (Jacob & Weiss, 2014). While metrics based on delineated features (polygon data) are those which are most often used, with an increase in the availability and quality of image-based data, other metrics have been found to work complementarily or even better than traditional metrics.

Spectral metrics are derived from imagery and differing spectral signatures for different land cover types. One example is the Normalized Difference Vegetation Index (NDVI), which is a metric used to analyze vegetation amounts, and is expected to be positively related to plant species diversity (Singh et al., 2010). Vegetation maps are useful for locating areas for future focus,

in addition to prioritizing and planning distribution of vegetative resources (Singh et al., 2010). Duro et al. (2014) found continuous metrics derived from imagery such as NDVI to be better related to biodiversity levels than discrete metrics based on classified maps. An issue that arises with the use of continuous metrics for the purpose of management is that the findings can be difficult to apply, for instance raising NDVI levels in an area is not a directive that is easily implementable for farmland managers.

In addition to spectral metrics, texture metrics can also be derived from imagery. An example is analyzing the spatial variance of grey levels (reflectance) in given regions of the spectrum over a given area. This can inform on the variability in sites, which can be linked to vegetation or land use types, and can be summarized with the use of statistics derived from imagery (Xu & Chen, 2005; Duro et al., 2014). Similar to spectral metrics, higher levels of heterogeneity in texture are expected to be related to higher landscape heterogeneity overall, which can then be linked to ecological components.

Finally, surface metrics from digital elevation models (DEMs) and similar data sources can also contribute information which can then be used to either classify or quantify an area of interest. For instance, Millard and Richardson (2014) used DEM information to verify LiDAR accuracy for classification of land use for a bog and surrounding areas. While the use of surface metrics to add to categorical data (to aid in identification of land cover types) has been proven to be robust and is now used worldwide, this approach is not able to fully capture continuous aspects of landscape heterogeneity (McGarigal et al., 2009). Surface metrics allow for topographic derivatives to be integrated into metric calculation, with an example being angular texture, which describes the angle and magnitude of a surface. While these metrics are valuable, programs for their calculation are expensive, and the metrics are not yet as familiar as traditional metrics (McGarigal et al., 2009).

However, with continued use and application, these metrics can be integrated as valuable components of landscape heterogeneity analyses in a complementary manner to traditional methods.

For areas that have low naturalness and high human pressure (such as areas dominated by agriculture), the use of farmland fields for calculation of metrics is recommended over the use of imagery-derived metrics (such as texture metrics). This allows for features of interest to be delineated and assessed (Lausch & Herzog, 2002). In addition, as was mentioned in reference to specific approaches, metrics derived from imagery are not yet as standardized or simple to compute as discrete metrics. They also require expertise, storage space, and occasionally expensive programs for analysis. With continued study and accessible methods for calculation, image based indicators can be further developed in order to use these measures complementarily to metrics that are currently used (Lausch & Herzog, 2002).

2.4 Managing agricultural landscapes

Due to their extensive use in landscape studies, metrics have been used for the purpose of informing management action to improve biodiversity in farmland. These metrics typically only apply regionally (as farmland cover types vary by region), but the concept is that landscape structure is linked with ecological processes, so if these patterns can be identified and quantified for a region, conservation activities can have predictable effects to improve biodiversity levels (Tischendorf, 2001; Botequilha Leitao & Ahern, 2002).

While continuous metrics and other information derived from imagery may be useful for understanding trends, especially in terms of vegetation, the results of these analyses are often difficult to apply practically. This is where metrics serve as tools and proxies for improvements to

landscape structure (Botequilha Leitao & Ahern, 2002). For instance, metrics representing the number of patches or proportion of classes serve as proxies for landscape simplification or loss of heterogeneity, while proximity metrics can outline the possibility for processes to traverse the landscape (disease, predation, seed dispersal and animal movement). The use of landscape metrics also allows for transparency and ease of understanding in terms of communications with non-experts (Botequilha Leitao & Ahern, 2002).

2.4.1 Current management trends and actions

Current management practices for farmland worldwide involve linking research findings on landscape heterogeneity and feasible actions for farmers or land-use planners (Chapin et al., 2000). Current recommendations that have been realized include increasing hedgerows and beetle banks to provide carabid overwintering sites (Benjamin et al., 2008). In addition, floral and forage resources have been increased to provide resources and connect landscapes for pollinators (Klein et al., 2007). Another approach that is gaining traction is the concept of sustainable intensification, which aims for higher crop yields with reduced negative impacts. This involves innovations in the way food is produced on organic and smaller scales (such as varying multiple crop types in one field), and applying these findings to conventional farms.

Agricultural practices are not only linked to biodiversity benefits, but also have social implications (that, again, vary by region). Proponents of sustainable intensification defend the view that intrinsic fairness in the way food is produced (social, ecological, and economic) outweighs the benefits of larger amounts of food produced using conventional methodology. There is a worry that the term and the goal of “intensification” will be used as justification to continue to accelerate agricultural expansion (continued economic growth), and will only be effective insofar as the other

areas of focus (social and ecological considerations) are a valued consideration in future planning (Godfray, 2015).

In 1992, 168 countries signed an agreement to conserve biodiversity called the Convention on Biological Diversity (CBD), and Canada was the first developed country to ratify the convention (Kleijn et al., 2011). Despite biodiversity conservation commitments and overall increases in national strategies, protected areas, and extinction prevention activities, indicators from a global study by Butchart et al. (2010) found continued biodiversity decline following both the 1992 and 2002 CBD. Examples of declining trends included habitat area and quality, population trends, and an increase in extinction risk. It is clear that in spite of current efforts, and some regional successes, the overall decline in biodiversity has yet to be reversed.

Future management strategies have to consider more than simply land sharing or land sparing, and must also take into account socioeconomic concerns (Grau et al., 2013). Land sharing is preferred when it is considered that biodiversity-friendly agriculture has high yields and low production costs. It is also more resilient in the face of climate change to have multiple crop types, which has the additional benefit of local food security from variation in produced goods (Grau et al., 2013).

In addition to research in possible landscape heterogeneity improvements, studies have also been conducted to assess the receptiveness of farmers to changes in their agricultural systems. An Austrian study found that when farmers make improvements to their agricultural lands that benefit biodiversity (such as adding floral resources or reducing field sizes), these activities do not show off their skills or prowess as farmers, so there is no "cultural capital" (Burton et al., 2008). Cultural capital means the activity has to show skill, has to display results, and has to be accessible to other

members of the farming community. The study recommended that production-based schemes be promoted so that farmers are able to see the return on their actions (Burton et al., 2008). Also, the desire to have a tidy landscape is still prominent in Austria, which is contrary to many biodiversity conservation recommendations.

Another example of a study based on decision-making in farmland by Kohler et al. (2014) in France found that most of their study's farmers felt farming structure should be neat and tidy, which again is counterproductive to many conservation strategies. Farmers in this study also indicated that they were very connected to nature and the land (some of them after many generations of farming), and this caused them to be resistant to policies telling them to change their practices (Kohler et al., 2014).

A survey in England by MacDonald et al. (2000) revealed that farmers wish to protect natural areas on their properties for field sports, and required information explaining why natural areas are an end themselves. Tidiness of the land arose again as a reason for the removal of farmland field edges. The notion of a nice, clean farm was popular, and often tenant farmers were required to keep their hedges at a certain width and height as conditions of continuing to farm their respective properties. However, this study also revealed that many farmers are positive about taking advice about wildlife conservation (MacDonald & Johnson, 2000).

It is important for management solutions to be region specific based on biodiversity response to ensure that specific response to landscape heterogeneity is addressed through management action. Conservation actions should balance the needs of agriculture and biodiversity (Kumaraswamy & Kunte, 2013). In addition, managing needs a landscape perspective, given that complex landscapes are at risk with the simplification of crop types and enlargement of fields

(namely in eastern Ontario region). Some improvements can be made at the farm scale, but on the whole there are trends at the landscape scale that have far-reaching effects on taxa groups (especially because movement is not restricted to the boundaries of one farm). For instance, at the farm scale, a farmer might be increasing the size of fields, and the effect on biodiversity may appear minimal. However, as a trend at the landscape scale, all farmers increasing the size of farmland fields has a regional effect as habitat areas and resources for many species are lost (Tschardt et al., 2005). It is clear that the scale of management recommendations is pertinent when considering overall effects on biodiversity in a region.

3.0 Study Area and Data

3.1 Eastern Ontario farmland study

The study area was in eastern Ontario, and covered approximately 5000 km² of farmland (Figure 3.1) (Duro et al., 2014). Sites were located near the city of Ottawa, dispersed south and east of the city proper. The sites fell in three counties (Prescott and Russel United Counties, Leeds and Grenville United Counties, and Stormont, Dundas and Glengarry United Counties) with the exception of 5 of the 93 sites. Statistics from these counties indicate that in 2011 (first year of biodiversity data acquisition) 7.13% of farms in Ontario were located in the region, with most reporting a size under 53 hectares (approximately 130 acres) (OMAFRA, 2011). The dominant land-use is cropping, and the main crop types are corn, hay and soybean (totalling 92.8% of crop area) (OMAFRA, 2011).

Most types of natural or semi-natural land cover in eastern Canada have been decreasing in areal proportion since the 1980s as agriculture became the dominant land cover type (Bucknell & Pearson, 2006). Farms have amalgamated, and more people have moved to urban areas. With these changes, there has been a trend towards less heterogeneous distributions of fields in agricultural areas in eastern Ontario. This loss of heterogeneity is not only in terms of field enlargement, but also simplification of the overall number of crop types.

The types of crops grown in Ontario have also changed in recent decades. Many crops are now used for bioenergy, which has concentrated crop areas to a few main types (Stanley & Stout, 2013). In Ontario, between 1961 and 2001, there was a 203% increase in production of major grain crops (wheat, maize, soybean, barley, and oats) (Bucknell & Pearson, 2006). Despite the large proportion of grain crops, there is still a notable proportion of crops that require pollination and

other services provided by high levels of biodiversity. As an example, in the research area for this study, 24% of the crops at the 1 km extent are soybean fields, which require pollination for production (Klein et al., 2007). It is evident that biodiversity is required for productivity and ecosystem functioning in the region.

In order to conserve and even increase current biodiversity levels in eastern Ontario, farmland mitigation measures must be evaluated in terms of their ability to have a positive impact on multiple taxa. While land sharing and land sparing may have similar rates of biodiversity recovery, recommending one over the other is region and case specific (Barral et al., 2015). In the case of eastern Ontario, which is primarily agriculture, returning areas to natural states (with known positive effects) is not feasible nor a typical land cover conversion. As a result, it falls to studies such as this to determine alternative ways of managing existing agricultural areas that could improve biodiversity in the region.

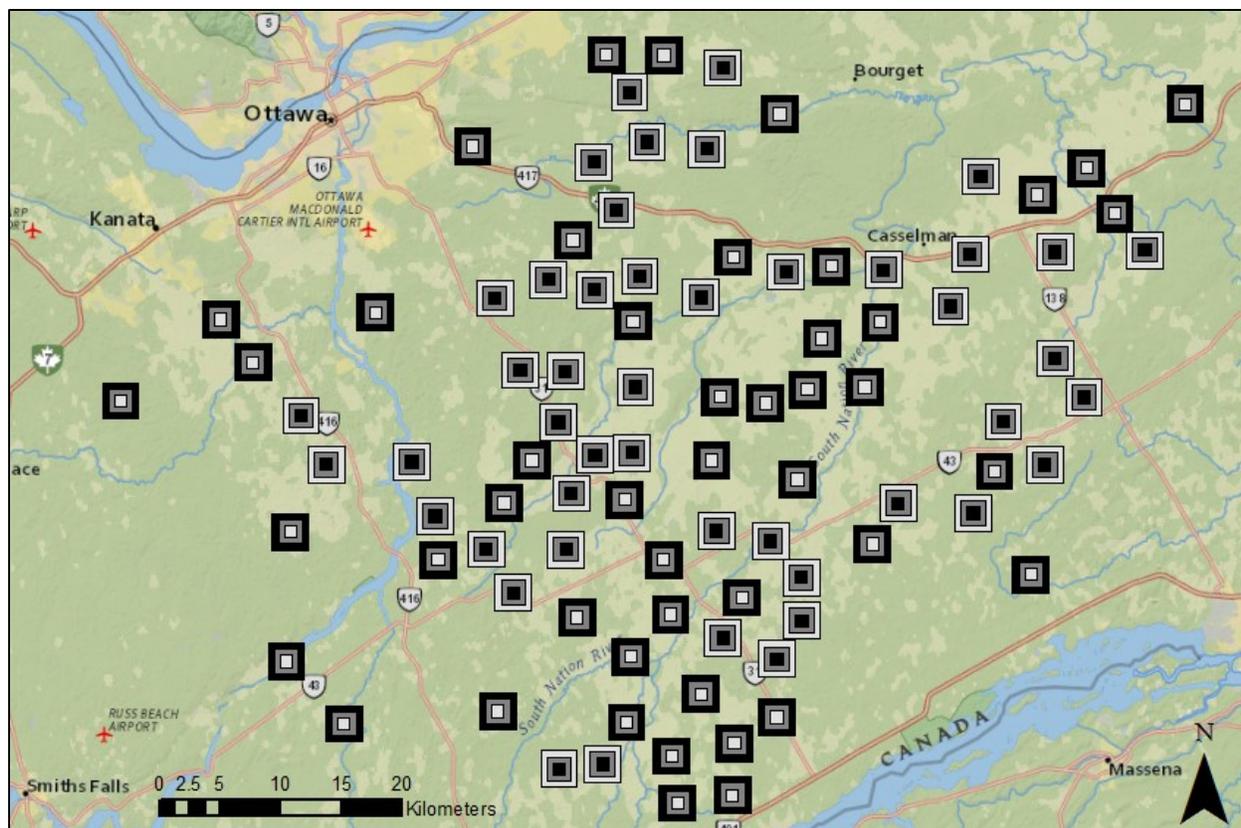


Figure 3.1: Study sites for the project. Nested squares indicate the 1x1, 2x2 and 3x3 km extent of each site. Sites surveyed in 2011 have black centres, and 2012 sites have grey centres.

3.1.1 Land cover analysis

Prior to this study, as part of the Strategic Project, 93 sites were selected based on landscape metric information derived from Landsat-5 data (30 m pixels) from 2007 (Pasher et al., 2013). Sites were selected to represent the range of compositional and configurational heterogeneity in terms of the size, arrangement, and types of farm fields present (with no geographic gradient or pattern across the study region). Full site selection details are outlined in Pasher et al. (2013). Sites were then assessed for land cover types at the 1x1, 2x2 and 3x3 km extents (hereafter referred to as the 1, 2, and 3 km extents, respectively) using 45 cm aerial photos acquired in the summers of 2011 and 2012, and verified with field observations during biodiversity surveys and from roadways in the same years.

The Shannon diversity index of field types and mean field size were used to assess levels of compositional and configurational heterogeneity at each extent. Figure 3.2 displays the plot of these two variables at all three scales assessed in the initial study. As can be seen from the graph, the relationship between the two metrics is more variable at the 1 km extent than the 2 km and 3 km extents. Therefore, a wide range of these two measures of landscape heterogeneity was captured within the 1 km extent of each site.

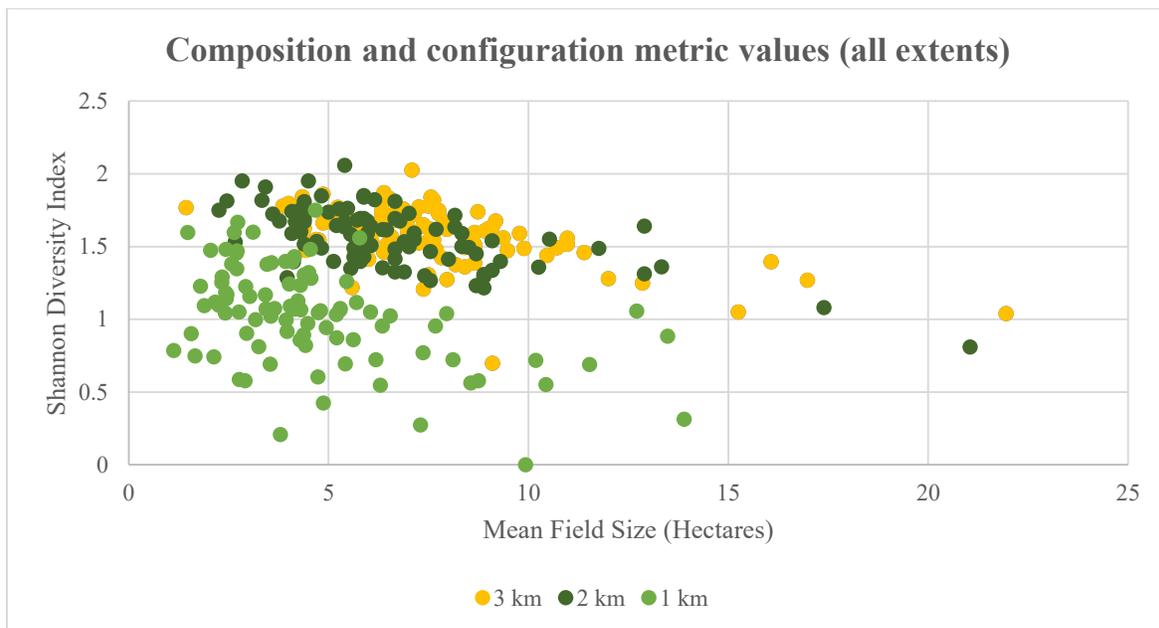


Figure 3.2: Plot of the distributions of the two heterogeneity components from Fahrig et al. (2015) study, which displays the variability of the 93 eastern Ontario sites.

3.1.2 Biodiversity surveys and data

Biodiversity data collection was completed as part of the Strategic Project; 46 sites were surveyed in 2011 and 47 sites in 2012. Seven species groups were surveyed in the 1 km extent of each study site at analysis points (within farmland field boundaries) that were at least 200 metres apart, and 50 metres from both non-crop areas and the edges of the sample landscape (Fahrig et

al., 2015). The table below presents a summary of the techniques used to sample each species group.

Table 3.1: Summary of biodiversity surveys conducted prior to this study to obtain biodiversity variables. Abridged from Fahrig et al. (2015), refer to this publication for more details.

Species group	Type of analysis conducted
Birds	10 minute point counts at four sample points
Plants	Recording species along four 50 m transects that were present within 1 m of the transect
Butterflies	Using the same transects, recorded all species within a 5 m ³ area of the transect at timed intervals
Syrphids	Same transects, using an imagined 2 m ³ area in front of the recorder, and specimens were preserved
Bees	Analyzed at 2011 sites only, tri-colour pan traps placed at three sample points and specimens were preserved and sent for identification
Carabids	Pitfall traps set at the same three sample points as bee traps in both mid-June and late July or August of both years
Spiders	Same sampling technique as carabids

Using the survey data, alpha, beta, and gamma diversity were calculated as part of the Strategic Project analysis (definitions provided in Section 2.1.1). Abundance at each site was also calculated, and was defined as the overall number of individuals found at each site (Fahrig et al., 2015). Full sampling details and lists of species that were identified are available in Fahrig et al. 2015.

3.2 Field work

Field work was conducted in May and August of 2015 to analyze the original study landscapes, and observe changes in land cover types and field sizes since the 2011 and 2012 surveys. This work was conducted to increase understanding of number of fields in the landscapes which had changed land use types (both permanent and rotational change) and field boundary changes (fields which had become bigger or combined with neighbouring fields). Elements that

were observed included in-season variability, the appearance of crop types (for identification in later imagery observations), and the spectral similarities of cover types in terms of the potential ability to discern them with classified satellite imagery. Areas between fields were assessed for loss of vegetated edge, and forest areas that had been cleared since the time of the original study. These observations were conducted in collaboration with two other graduate students (N. Alavi and T. Tanner) working on different aspects in the Strategic Project.

3.3 Data processing and parameters

In order to use the land cover data for landscape metric calculation using Fragstats, land cover data in vector shapefiles had to be converted to raster representations, and therefore a suitable spatial resolution had to be chosen. While vector metrics are also available for quantification of landscape pattern, Fragstats is comprehensive in terms of available metrics and facilitates repeat calculations (Kupfer, 2012). Using vector calculations would have required the use of multiple approaches (some calculated in R, some using ArcMap add-ons), which presents inconsistencies in how metrics are calculated and introduces uncertainty. In addition, as previously discussed in detail, Wade et al. (2003) indicated that although different values arise in the calculation of metrics for raster versus vector calculations, these values do not influence how the information is implemented in environmental management. Since this study required analysis of many metrics in terms of their applicability for management purposes and relations to biodiversity variables, the raster method was selected.

3.3.1 Land cover shapefiles raster processing

As raster conversion is an abstraction of the original land cover designations and boundaries, analysis was conducted to ensure that a relevant cell size was selected to capture landscape elements in an effective manner. Generally, a cell size should be selected that is relevant

to the variable of interest, and also half the size of the smallest feature of interest in the landscape (Wade et al., 2003). As many species groups were analyzed for this study, a relevant ecological size for all groups was not easily discernable. For this reason, land cover types were analyzed for the smallest features (fields) that would have to be captured, and the effects on metric calculation of having larger or smaller cell sizes.

This study analyzed a variety of cell sizes for metric calculation, based on the reasoning of a number of previous studies that had conducted similar tests. Other studies have analyzed the incremental differences in metric outputs when increasing cell size, but found limited impact of varying cell size at finer resolutions. Blaschke et al. (1999) tested cell sizes of 5 to 30 m at 5 m increments with Landsat imagery. They found diversity indices (such as the Shannon diversity index, which can be used to measure the proportion and evenness of land cover types) to be insensitive to cell size change, even when fields became combined as spatial resolution was coarsened (Shannon & Weaver, 1948; Blaschke & Petch, 1999). Manson et al. (2003) tested raster values of 1 m to 1000 m on areas that had transitioned from mangroves to urban development and found metrics to be relatively insensitive to different grid sizes up to 100 m, but more variable with coarser resolutions (Manson et al., 2003). These studies indicate a limit in terms of how coarse a cell size can become before metrics are affected, but relatively small effects on metric outputs when fine cell sizes are used.

Cell size impacts on metrics calculated from the data for this study were analyzed in terms of the variability of metric outputs, in addition to relevance to the dataset for capturing the landscape features (farmland fields) of eastern Ontario land cover. The data could support very high resolution representations, as sites were verified using 45 cm pixel aerial photography, in addition to ground verification from observers on foot at the sample sites, and observations made

from field vehicles. Thus, the field data were notably more detailed in terms of classification accuracy compared to most studies in the literature (e.g. Blaschke & Petch, 1999; Manson et al., 2003, which used 30 metre and digitized historical aerial photography, respectively). Finer resolutions were deemed appropriate for testing metric variability, and 2, 5 and 10 metre raster outputs were tested for the dataset.

Two lines of reasoning were considered for choosing cell size. Initially, actual farm field sizes were considered when searching for the smallest features in the landscape, and the smallest field (not cut off by a site boundary) was found to be a mixed vegetable field that measured 13 metres across. This would indicate an appropriate cell size of approximately 5 or 6 metres, in a range which has been found in other studies to be appropriate for capturing transition zones in farmland (field into semi-natural areas) – depending on the region (Arnot et al., 2004).

However, throughout the pilot metric calculation analyses, the main issue was found to be the ability to keep fields separate with differing cell sizes. Many edge areas, designated as “no data” for these analyses, became lost due to aggregation (and therefore connected previously separate but adjacent fields) at the 10 metre cell size (Figure 3.3). The smallest relevant features in our data, therefore, were found to be the distances between fields, and portions of fields on the 1, 2 and 3 km extent boundaries. While these are not features *per se*, they do have a profound effect on metric outputs, especially as fields become blended because of larger cell sizes. Based on these observations, visual inspection of the raster outputs, and pilot analyses of metric outputs, 2 metres was found to be the best cell size in terms of separating fields and capturing the smallest features of interest to this study (Figure 3.3). As can be seen from the figure, fields of the same type would become combined at 10 and even 5 metres, which stressed the importance of using a cell size able to differentiate between fields. Were fields combined, there would be significant

effect on the landscape metric outputs, especially those that measure field size, the number of fields, or perimeter and edge lengths.

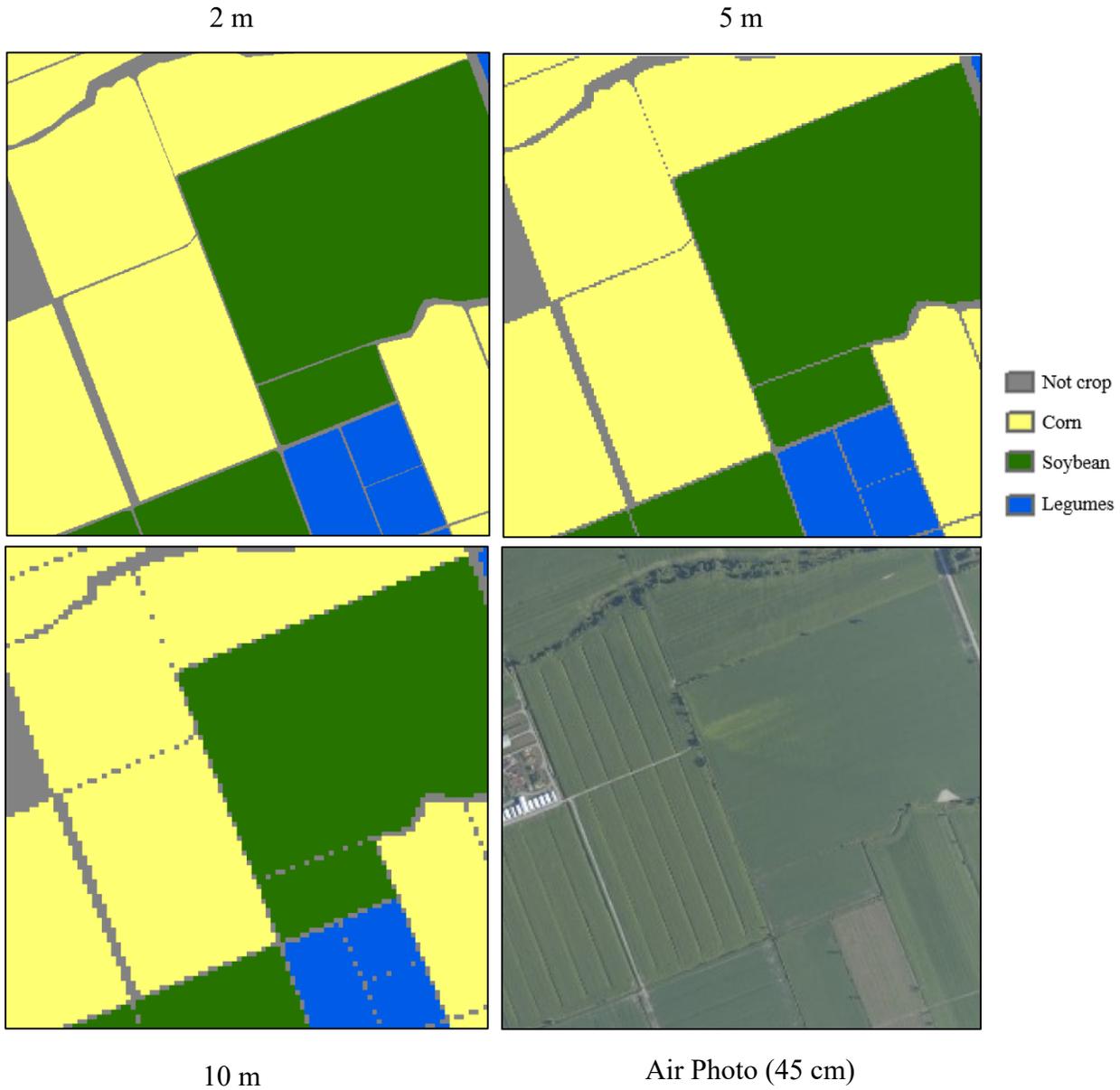


Figure 3.3: Visual representation of cell size selection for landscape metric calculation (Site HH22, 1 km extent). As cell sizes increased, fields of the same type would become amalgamated, which would have an effect on metric outputs. In this case, corn, legume, and soybean fields would all become combined when the cell size was set to 10 metres. This differentiation in cell size (to visualize the effect on metrics) is available for the 3 km extent for Site HH22 in Appendix A.

3.3.2 Fragstats parameters for metric calculation

Parameters in Fragstats were selected based on settings needed to capture landscape features specific to eastern Ontario field layouts. The 8-cell neighbourhood rule was used to capture adjacent fields while avoiding alignment effects due to row crops (Pasher et al., 2013). These alignment effects can arise due to fields in the study regions being diagonally oriented (northwest to southeast), and the 8-cell rule ensures the boundaries of these fields are captured. Metrics were calculated for whole landscapes; sub sampling was not conducted. The metrics for the 1, 2 and 3 km extent of each landscape were calculated separately. Class types were reassigned an integer value for metric calculation in Fragstats (Appendix B). Finally, for the calculation of total edge (TE) and the interspersion and juxtaposition index (IJI), edge was re-integrated into the raster study landscape files as a class in order to allow for the meeting (or intersection) of class types to calculate relevant values for these metrics.

3.4 AAFC Annual Crop Inventory data

Since highly detailed data such as the Strategic Project dataset (obtained from 45 cm aerial photography and confirmed with ground observations) are labour-intensive and expensive to obtain, an analysis was conducted to determine whether publicly available data could be used as a substitute. The aim was to determine whether the relations between landscape pattern and biodiversity found using the Strategic Project data could be replicated using coarser data, in terms of both the metrics deemed most important for each biodiversity variable and the direction of effects.

For this purpose, crop inventory data from Agriculture and Agri-food Canada were obtained for the two study years (2011 and 2012). This classification is produced annually using

multi-temporal satellite imagery and is based on discrimination of differing phenological stages of crop types (AAFC, 2014). For the study years, the final spatial resolution of the data was 30 m. The target accuracy of the product is 85% for all agricultural regions in Canada (AAFC, 2014).

The data were retrieved online, and clipped to the study landscape extents (1, 2 and 3 km). Based on visual inspection of the data, there was good alignment of the Strategic Project sites and corresponding features in the crop inventory layer. Class types used by AAFC were converted into the classes of the Strategic Project. For pasture, four Strategic Project classes were combined into one in order to match the AAFC definition of pasture (hay, alfalfa, clover, and animal pasture) (AAFC, 2014). Appendix C shows the descriptions of classes for the Strategic Project data (established previous to this study) while AAFC class descriptions are available in the Product Specifications (AAFC, 2014). An analysis was conducted to test the accuracy of the AAFC classifications using a point placed at the centroid of each field polygon identified in the Strategic Project data (Figure 3.4).

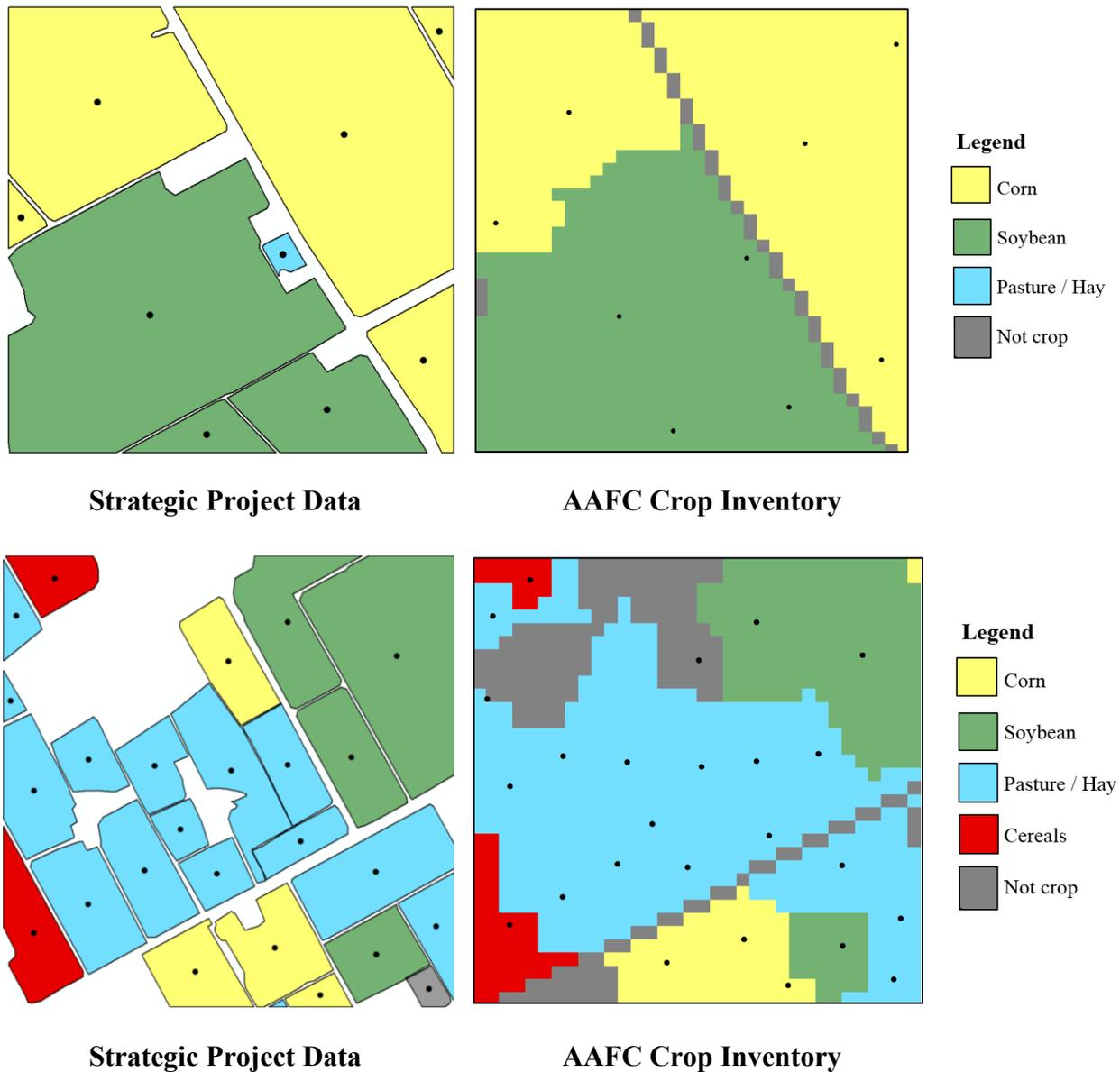


Figure 3.4: Visual representation of validation performed for comparison between Strategic Project land cover maps and Agriculture and Agri-food Canada Crop Inventory maps (sites HH9 and LL217). Points were placed at the center of each field for the Strategic Project data, and overlaid on the AAFC data.

Overall, 1689 points were produced using the identified fields for both 2011 and 2012, and these were then overlaid with the AAFC Annual Crop Inventory data. Of the 1689 points, 71.3% were classified correctly by the AAFC data (Table 3.2). This accuracy assessment was of interest to establish the ability of the coarser data to derive the same relations between landscape heterogeneity and biodiversity levels as were found by the Strategic Project data. In the table,

producer’s accuracy is indicative of the probability of a reference sample being classified correctly, and is equal to [100% - the errors of omission] (Congalton, 1991). User’s accuracy is a measure of the proportion of the samples for a given map class that are correct, and is equal to [100% - the errors of commission] (Congalton, 1991).

Table 3.2: Confusion matrix of the comparison between the Strategic Project data and the AAFC Crop Inventory. Overall, the AAFC data classified fields correctly with an accuracy value of 71.3% out of the 1609 points used for the assessment.

		Strategic Project Data (Reference data)										
		Corn	Pasture	Soybean	Fallow	Apple	Mixed vegetable	Cereal	Strawb.	Sod	Σ	User's accuracy
AAFC Crop Inventory	Not crop	35	121	25	18	5	15	5	6	0	230	N/A
	Corn	359	31	69	9	1	4	3	0	0	476	0.75
	Pasture	7	512	13	38	1	2	7	2	3	585	0.88
	Soybean	24	15	296	0	0	2	4	0	0	341	0.87
	Fallow	0	2	0	0	0	0	0	0	0	2	0
	Apple	0	0	0	0	0	0	0	0	0	0	N/A
	Mixed vegetable	0	1	1	0	0	0	0	2	0	4	0
	Cereal	0	8	1	5	0	0	36	0	0	50	0.72
	Strawberry	0	0	0	0	0	0	0	1	0	1	1
	Sod	0	0	0	0	0	0	0	0	0	0	N/A
Σ		425	690	405	70	7	23	55	11	3	1689	Total accuracy
Producer's accuracy		0.84	0.74	0.73	0	0	0	0.65	0.09	0		0.713

As can be seen from the confusion matrix, 230 points (13.6% of total sample) were classified by AAFC as “not crop”. The Strategic Project “not crop” class was not included for the purposes of this assessment, and all 230 of these points were in error, being one of the land cover types shown across the top row of the table. Despite this, the high user’s and producer’s accuracy values for the three main regional crop types (corn, soybean, and pasture/hay) indicate a strong ability for this dataset to capture most of these land cover types in the classification.

Some class types with few fields (such as strawberry or mixed vegetable) are less common regionally, which makes this accuracy assessment unreliable for those classes. In some cases, crop types were a part of the categories available in the AAFC classification, but these fields were not correctly classified by the data (sod fields and apple orchards). N/A was therefore assigned to the User's accuracy for these classes; it was deemed inappropriate to assign an accuracy of 0% when no actual samples of these classes were present. Overall, given the moderate accuracy of the AAFC classification for the main crop types, this dataset was hypothesized to be appropriate for use to replicate the landscape heterogeneity-biodiversity analysis and to allow comparison with models created using metrics derived from the high resolution reference maps for each study landscape.

4.0 Methods

4.1 Analyzing biodiversity levels

Alpha, beta, and gamma diversity and abundance were calculated for all seven taxonomic groups prior to this study (except plant abundance). These measures of diversity were used for this assessment in order to assess the number of species, rather than simply the number of individuals (Noss, 1990). While abundance is not a measure of diversity, these variables will be referred to collectively as “biodiversity variables” for consistency. Therefore, there were 27 biodiversity variables overall (alpha, beta, gamma and abundance for six taxa, and plants did not have an abundance value). The seven taxa were bees, birds, butterflies, syrphids, spiders, plants and carabids. While multivariate distance-based versions of beta diversity are available, the classical approach (using gamma and alpha diversity values) was used for this study for consistency and comparability with the technique used in Fahrig et al. (2015). Thus, the three metrics were calculated according to the following formula using additive rather than multiplicative components:

$$\text{Beta diversity } (\beta) = \text{Gamma diversity } (\gamma) - \text{Alpha diversity } (\alpha)$$

These variables were calculated as one value per study landscape, since taxa were sampled within the 1 km extent of each landscape. In other words, gamma diversity represented the total number of species per study landscape (93 in total) regardless of the extent at which these values were compared to landscape metrics.

The proportion of agriculture in each landscape was also regressed against each biodiversity variable, as increased agriculture has a known negative effect on biodiversity in crop

fields (e.g. Duro et al., 2012; Flohre et al., 2011; José-María, et al., 2011). This study was designed to assess biodiversity in agricultural fields (to suggest solutions without taking land out of production), thus this assessment was conducted to determine the magnitude of this known overall negative effect on the biodiversity variables (Fahrig et al., 2015).

4.2 Calculation of landscape metrics

Landscape metrics were used to quantify landscape structure at the 93 study sites in eastern Ontario (outlined in Section 3). The highly detailed spatial resolution (45 cm cell size) and clear transitions between field cover types made the use of landscape metrics a viable choice for quantification of landscape effects on biodiversity.

4.2.1 Selection of metrics

The initial component of this study involved selection and calculation of relevant metrics for the seven taxa that were assessed in 2011 and 2012. To begin, the entire set of available metrics in Fragstats was considered. Metrics were categorized as either representing compositional or configurational heterogeneity, or both. Each metric was analyzed for its definition in terms of heterogeneity, and the list was reduced in pre-analysis due to either inapplicability to this study, or due to statistically significant ($p < 0.05$) correlation with other metrics that represented similar (or inverse) measures of landscape structure. In pairings that were correlated, metrics were retained that were easier to interpret. Inapplicability arose with metrics such as core area, which depend on a subjective definition of edge width and would be correlated with field size. Metrics that require a subjective value definition (such as a standard edge width for all landscapes) require a thorough understanding of the system and its effects on biodiversity (Marks & McGarigal, 1994). As many

taxa were considered, these subjective decisions would have likely introduced uncertainty in the ability to capture values that addressed all ecological processes.

Metrics that were most often highly correlated with each other included the range, standard deviation, and coefficient of variation of many metrics. In addition, many of the compositional landscape metrics were highly correlated. The linearity of the relationships between pairs of landscape metrics was also tested. Some landscape metrics appeared to be linearly related to other landscape metrics, while other pairs of metrics had high scatter and no discernable relationship. None appeared to be associated in a non-linear fashion, with the exception of the percentage of like adjacencies and the number of patches, and cohesion and the area metrics (retained in both cases as they measure different components of landscape structure) (Appendix D (a)). Biodiversity metrics were analyzed, and were found to be highly correlated within each taxon, but not across taxa (Appendix E).

Given the above results, correlation was used as a means to reduce the numbers of landscape metrics. One metric of a pair was often eliminated when the following condition was met: $r > 0.75$ and $p \leq 0.05$ (Appendix F). The metric that was easier to interpret was retained as the goal of this study was to identify metrics which would be useful for farmland management implications. In addition, metrics that were highly correlated with many other metrics (which were less easy to interpret) were retained, allowing for the others to be eliminated, thereby providing significant variable reduction. Despite these rules, several landscape composition metrics were retained that had significant and high correlations with others because the number of composition metrics was much lower than the number of configuration metrics. Most that were eliminated were the coefficient of variation or standard deviation derivatives of metrics which were retained (Appendix G). In this way, deciding on which metrics to retain was both a qualitative and

quantitative process, based both on ease of interpretability for management, but with some metrics retained based on individual aspects of landscape heterogeneity which they described. Table 4.1 outlines the 30 retained landscape metrics for this study.

Table 4.1: Retained landscape metrics for random forest regression. Table includes definitions from the Fragstats Manual for brevity, and full definitions and formulas are provided in the manual (McGarigal, 2014). In the descriptions, “field” and “patch” are used as interchangeable terms based on descriptions from the Fragstats Manual. Each metric was classified as either composition (COMP), configuration (CONF), or both, a justification for the classification is provided, and each metric’s values were interpreted in terms of landscape heterogeneity. AM = Area weighted mean, CV = Coefficient of variation, SD = Standard deviation, RA = Range.

	Metric and Fragstats code	Notes	Type	Justification for Type (Composition or configuration)	Relation to Farmland Heterogeneity
1	Largest Patch Index (LPI)	Percentage of the landscape that is the largest patch. This is a simple measure of dominance.	CONF	Indicates the percent, but not the type of the largest patch.	The larger the largest patch, the less heterogeneity. Maximum value is when the site is all one patch, so smaller values are better.
2	Total Edge (TE)	Sum of edge segments in the landscape. When comparing landscapes of identical size, TE and Edge Density are completely redundant.	CONF	Different sized patches would result in different amounts of edge, regardless of patch types.	More edges in the landscape means more heterogeneity. An edge is measured at the intersection of two differing land cover types. Therefore more fields (smaller) and more types would result in a higher TE value.
3-5	Patch Area Distribution (AREA_MN, _AM, _CV)	Mean of the areas of the patches of all types in the landscape. The area weighted mean is calculated based on the overall area within all patches, and the relative area of individual patches.	CONF	Based on the sizes of patches in the landscape, regardless of their type.	The higher the mean field size, the less heterogeneity there would be (because a lower value would mean more patches overall). For range and standard deviation, higher values could mean more variety in patch areas, which could be indicative of increased heterogeneity.

6-8	Radius of Gyration Distribution (GYRATE_MN, _AM, _RA)	Distance between each cell in the patch and the patch centroid. It is a measure of shape that is affected by the extent and compaction of the patch (mean of these values, etc.).	CONF	Has to do with the shape of each patch in the landscape regardless of the types.	Increased complexity would be reflected in higher values of all of these metrics, which could also be indicative of higher heterogeneity rather than compact shapes. Difficult to discern because many small patches of different types would return a low gyrate value.
9-11	Shape Index Distribution (SHAPE_MN, _RA, _SD)	This metric measures the complexity of each patch shape compared to a standard shape (square) which alleviates the issue with PARA. It is a measure of the complexity of the shape of a field, and is calculated based on the perimeter of fields compared with a square field.	CONF	Looking at complexity of the shape, regardless of the type.	Similar to above, higher values could indicate higher complexity (potentially higher heterogeneity), but could be confounded.
12-15	Related Circumscribing Circle Distribution (CIRCLE_MN, _AM, _RA, _SD)	If you were to put a circle around the patch, this would give you the size of the circle. Long but narrow shapes will have a big circle, while smaller or more compact ones would fit into a more compact circle. This is a measure of extensiveness, as well as size of fields.	CONF	Looking at shape compactness and elongation, regardless of the type.	Lower values mean smaller fields which means higher heterogeneity. However this could be confounded by very long but thin fields (as the circle would have to be large to surround it).
16-19	Contiguity Index Distribution (CONTIG_MN, _MD, _RA, _SD)	Calculated with the use of a 3x3 cell template that evaluates cells of the same type (same field classes). Looks at contiguity of cells in a patch (how many are in a line, either vertical, horizontal, or diagonal).	BOTH	Also has to do with the complexity of shapes, or whether they are not spotty and simply all one cover type throughout.	Lower values indicate increased complexity or small fields, which is indicative of increased heterogeneity.
20	Contagion (CONTAG)	A measure of how clumpy patches in the landscape are (or whether there are fine scale differences in "texture" or "graininess" of the map). Approaches 0 as patch types are disaggregated (ie. each pixel is a different patch type), and 100 as they are maximally aggregated.	BOTH	Dependent on the arrangement of patches and their type.	Lower values indicate that patches are more broken up, and therefore more heterogeneity overall in the landscape.

21	Interspersion & Juxtaposition Index (IJI)	Indicates the evenness or unevenness of patch adjacencies (not cell adjacencies like contagion). If all patch types are equally adjacent to other patch types, IJI is 100, and it approaches 0 as the distribution of adjacencies becomes increasingly uneven.	BOTH	The value of this metric indicates complexity in the types of patches and in their arrangement.	A higher value indicates a higher variety of types, and therefore more heterogeneity.
22	Percentage of Like Adjacencies (PLADJ)	PLADJ measures the degree of aggregation of patch types based on cell adjacencies. Thus, a landscape containing larger patches with simple shapes will contain a higher percentage of like adjacencies than a landscape with smaller patches and more complex shapes.	BOTH	Can be affected both by the arrangement of patches (few types evenly dispersed) and the number of types in a landscape.	A lower value is a landscape with smaller patches and more complex shapes, which is indicative of higher heterogeneity.
23	Patch Cohesion Index (COHESION)	Percentage which represents the level of connectedness of class types in the landscape, but at the landscape level the behaviour of the metric has not been evaluated.	BOTH	Dependent on connectedness of patches in the landscape and whether they are the same cover type.	A higher value means more connectedness, so lower heterogeneity overall.
24	Number of Patches (NP)	The number of patches in a landscape. If landscape area is held constant, it can be useful for interpretation.	CONF	Indicates the number of patches, regardless of their type.	Higher number of patches means higher heterogeneity.
25	Landscape Division Index (DIVISION)	Division can be interpreted as the probability that two pixels chosen in the landscape can be found in the same patch. It is calculated based on the patch areas relative to the total area in a study landscape. Value is 0 when the landscape consists of a single patch, and achieves the maximum value when every pixel is a separate patch.	CONF	Dependent on how the patches are divided, regardless of types.	A higher value indicates a higher level of breakup and higher heterogeneity

26	Patch Richness (PR)	Measures the number of patch types present, and is not affected by the spatial arrangement of patches.	COMP	Dependent on the number of types, regardless of how they are arranged.	A higher value means more patch types and more heterogeneity.
27	Shannon's Diversity Index (SHDI)	Looks at how many types of fields there are in a landscape, and how equal all the types are. The more unequal the abundances of the types, the smaller the value. If a landscape is all one type, the value approaches 0.	COMP	Dependent on the types and equality in abundances of cover types, regardless of their arrangement in the landscape.	Higher value means more types and higher heterogeneity
28	Modified Simpson's Diversity Index (MSIDI)	Minus the log of the sum, across all patch types, of the proportional abundance of each patch type squared. Removes the simplistic interpretability of Simpson's, but places it into a general class of evenness indices to which Shannon's belongs.	COMP	Same reasoning as Shannon's.	Same as above
29	Shannon's Evenness Index (SHEI)	This metric is calculated based on the proportion of area dedicated to field types, based on how many field types there are in total. An even distribution among patch types results in maximum evenness.	COMP	Dependent on how even patch types are in a landscape, regardless of how they are arranged.	Higher value means more evenness, which is indicative of higher heterogeneity
30	Modified Simpson's Evenness Index (MSIEI)	Similar to modified Simpson's, but with regards to how even the types are given the number of patches. This metric is calculated based on the observed diversity divided by maximum diversity for the number of patch types in the landscape.	COMP	Same reasoning as Simpson's diversity.	Higher value means more evenness, which is indicative of higher heterogeneity

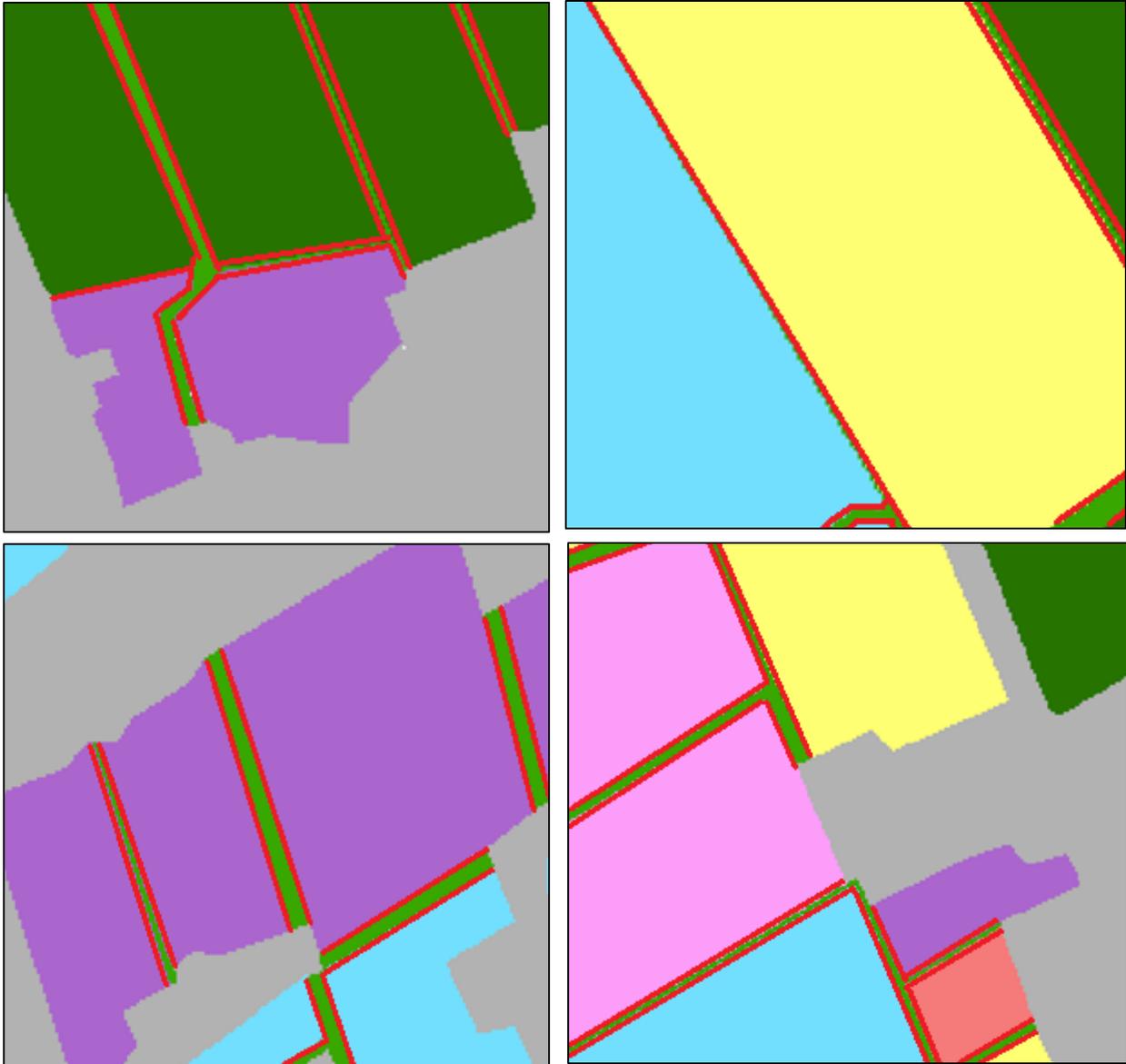
Thirty metrics were selected based on the above method and used in random forest regression (RFR) with the biodiversity variables (Section 4.3) to select the landscape metric of

most importance to each biodiversity variable. Including such a large set of metrics introduced some redundancy between metrics, especially as there weren't many compositional metrics to select from the initial list compared to configurational metrics. However, retaining these composition metrics enabled the RFR to capture subtle differences in their output values in order to retain the best metrics overall (Cushman et al., 2008). Also, random forest regression is not affected by large numbers of input variables (Breiman, 2011), so it was deemed to be better to include more metrics than to try to further reduce their numbers at the risk of information loss.

Statistical selection of metrics was found in a comparative study by Schindler et al. (2015) to be superior to random selection of metrics, and both of these methods slightly outperformed expert choice. For this reason, this non-parametric statistical approach (random forest regression) was selected in order to obtain the most pertinent metrics for each taxa and biodiversity variable. Random forest regression adds an additional layer of randomness to bagging, which is a decision tree approach that does not depend on earlier trees for construction of subsequent trees. Random forest regression enables the output of variable importance measures, which can then be used to pare down on variables of most importance to the response variables, while considering the effects of all predictors tried at each node. This information can then be used for prediction (if high values of variance explanation are found) by withholding a portion of study landscapes, predicting biodiversity variable values from landscape metric values, and comparing predicted and actual values (Liaw and Wiener, 2002). All random forest regression calculations were performed in R using the rfUtilities and randomForest packages (Wiener & Liaw, 2002; Evans & Murphy, 2014, respectively), modified from a script created for random forest classification by K. Millard.

4.2.2 Calculation of metrics

The landscape metrics were calculated at the 1, 2 and 3 km extent surrounding each study landscape in order to determine whether effects of landscape heterogeneity varied with extent for each taxon. The assessment was conducted at the landscape scale (whole landscapes) in order to capture heterogeneity patterns in each extent (Cushman et al., 2008). Total edge for this analysis was considered as the field boundary of two cover types, as the analysis only considered agricultural fields. This means that landscapes with smaller fields would have greater values for total edge. Total edge and mean field size have an r value of -0.44 ($p < 0.001$). Also, with more land cover types, even if not separated by natural or semi-natural edge vegetation, there would be more edge (total edge and the Shannon diversity index have an r value of 0.20 , $p = 0.05$). Therefore, this is a metric of configurational heterogeneity (potentially affected by composition due to the edges between two differing field cover types in this case). Figure 4.1 presents a diagram illustrating this metric as it was calculated for this study.



- Legend**
- Edge
 - Corn
 - Hay
 - Pasture
 - Soybean
 - Legumes
 - Fallow
 - Not crop

Figure 4.1: Illustration of total edge (TE) as defined in Fragstats and as a metric of configurational heterogeneity in this study (zoomed view of sites HL53, HH18, LL100 and LH88). Red highlighted areas are those that would have been summed by Fragstats to provide a value for this metric. As can be seen from the visual, where edges have a width, they would be double counted in Fragstats and therefore weighted more than two crops with no edge area in between.

4.3 Selecting of best landscape metrics using random forest regression against biodiversity variables

A non-parametric multi-variate approach was employed to determine the most important landscape variable associations with each biodiversity variable, as implementing many bivariate correlation analyses can lower the strength of findings and increase the probability of finding significant correlations (Moran, 2003). Non-parametric approaches also do not assume normality of the distributions of variables, and as a result, more complex data are better analysed in this manner. As many metrics were evaluated, an ensemble decision tree approach was selected to regress the biodiversity variables many times against all possible metrics using random forest regression (Breiman, 2011). Other approaches were considered but not selected based on applicability to the dataset and study goals. To provide an example, the use of the Akaike Information Criterion (AIC) was considered, although this would have required a selection of a smaller set of metrics in advance of testing the relative model qualities. The Median Test was also considered, which relates the medians of independent groups, although this approach would have produced several results (one for each possible pairing) and would have led to difficulty in interpretation (Harris & Jarvis, 2011). Additional approaches to considering multidimensional relationships such as redundancy analysis and canonical correlation analysis would also likely be appropriate for this type of analysis (Harris & Jarvis, 2011). Random forest regression was selected based on variable importance measures that were able to be derived, the non-parametric abilities of the tool, and the ability to evaluate important predictors for each biodiversity variable.

Random forest regression was run for each biodiversity variable with 100 iterations. Each iteration produced 1000 trees, and 10 of the 30 variables were randomly selected at each split. Many iterations were selected to ensure that the full range of possible outcomes was produced,

and 1000 trees has been found to be sufficient when using random forest classification (i.e. more trees do not produce better results overall) (Breiman, 2011; Millard & Richardson, 2015). Outputs from the random forest regression (RFR) included the list of landscape metrics and their percent Increase in Mean Squared Error (%IncMSE). A higher value of %IncMSE is indicative of a variable that is more important to the random forest regression model, and would cause significant shifts in the data when removed from the model (Moisen et al., 2006). This value can either be positive or negative and is deemed higher as it becomes larger in either direction. Therefore, outputs from the 100 iterations were ranked and sorted, and the top metric in each case was considered to be the most important predictor of the given biodiversity variable. In most cases, the top metric was ranked first in over 50% of the 100 iterations. In rarer cases where metrics were ranked similarly, and contended for a close second place, multiple metrics were retained as a group, and this group often appeared across biodiversity variables in one taxon. A table that displays a summary of the ranking information for all metrics is available in Appendix H.

Random forest regression and classification includes a procedure where a portion of the data are set aside during the construction of each tree and this “out-of-bag” sample is used to calculate the resulting tree’s prediction error. Alternatively, reference data may be withheld entirely from the complete RFR procedure and used in independent validation of the model’s predictive capabilities. In this research, the goal was not to use models for prediction and mapping, so all available data were used in the RFR procedure (c.f. Millard & Richardson, 2015). The out-of-bag sample was set as 1/3 of the total sample data; in RFR it is used to produce the measures of percent variance explained and the mean of squared residuals. For each tree, the percent variance explained by the model represents the proportion of the variance explained in the one third sample. The mean of squared residuals is also calculated for this extracted group, and is indicative of the

residual values, or the difference between the observed and predicted values (Breiman, 2011). These error values were retained and averaged across diversity values, and more generally across taxa.

Six main metrics that were common to all biodiversity variables in terms of having been selected by random forest regression (at least once, although not necessarily found to be the most important) were found following initial analyses. Four of these were consistent in terms of the overall direction of response from biodiversity variables. These four metrics were then used to conduct an additional random forest regression analysis, in order to determine whether one or two of them were deemed important in the majority of cases, or whether all four metrics represented differing dimensions of landscape heterogeneity and could be used complementarily to inform management strategies. The random forest regression method was maintained for this portion of the analysis both for consistency with the approach used with all metrics, and also to evaluate variable importance. This method allowed for metrics to either be identified as important as individual metrics, or as clusters which explained the variance in the biodiversity variables. The same parameters described above (100 iterations of 1000 trees) were retained for consistency with the previous analysis.

4.4 Describing the relation between landscape and biodiversity variables

In Fahrig et al. (2015), Akaike Information Criterion (AIC) model coefficients were used to determine the direction and relative magnitude of effects between models, although in that case, only three landscape metrics were being considered in all possible combinations. For this study, with a larger number of metrics and models being compared, and the ability for each biodiversity variable to respond to landscape effects differently, correlation analysis following the metric

selection with RFR was used to analyze the relationships between the best landscape metrics selected using RFR and the biodiversity variables. This technique was selected as a straightforward method of determining the strength and direction of effects of each selected landscape variable on each individual biodiversity variable, and the results were presented in boxplots (Belfrage et al., 2014). Each pair of predictor and response variables was plotted, and the direction, magnitude and significance (r value, p value) of each relationship were determined in order to analyze the consistency of responses between biodiversity variables and in order to create boxplots to visualize the effects.

4.5 Analyzing bird species groups

It was hypothesized early in the study that there may be groupings in a given taxon that may respond differently to field heterogeneity than the whole group. For instance, do functional groups respond differently to compositional and configurational farmland heterogeneity? Functional groups, indicative of life traits, can often provide insight into a taxon that responds in smaller subsets of species based on how resources or land cover types are used (Barbaro & van Halder, 2009; Turner, 1989). Upon completing the initial analysis, it was evident that birds may have actually been responding in smaller groups of species. In the Fahrig et al. 2015 paper, although mean field size was found to have a negative effect on birds, percent agriculture had an even stronger negative effect. This indicated that other measures of landscape heterogeneity in agricultural areas may be affecting bird groups in a different way.

Birds were divided into functional groups based on their interactions with agricultural land cover types, and the response of diversity in these subgroups to landscape metrics was examined at all three extents. The groups were farmland specialists, farmland generalists, and other bird

species. Farmland specialists are defined as those that use specific areas of farmland, such as specific crops. Farmland generalists are those that use multiple farmland cover types as habitat. Other species are those that are only incidentally found in farmland, and are more typically seen in forest or other habitats (Kreuzberg, 2011). This classification was derived from Kreuzberg's system, which employed the use of the European Bird Census Council (EBCC) guidelines and expert opinion (Kreuzberg, 2011). For 18 of the 52 species in our data that were not already classified by Kreuzberg (2011), the Birds of North America manual was used given the previously established criteria, and the additional classifications were confirmed with expert knowledge (Vuilleumier, 2009). Classifications are available in Appendix I.

Alpha, beta, gamma and abundance of farmland bird specialists, farmland bird generalists, and other bird species were calculated for the species found at sampling sites for this study. While Kreuzberg (2011) stipulated that the concept of farmland birds is not yet well established in North America, findings that demonstrate differing responses in groups should support the need for observing landscape effects in species groupings when appropriate.

4.6 Comparing findings with coarser landscape data

In order to determine whether coarser resolution, publicly available land cover data could produce the same landscape effect trends on biodiversity variables, the Agriculture and Agri-Food Canada Annual Crop Inventory map for the study years was used. Initially, random forest regression was run with the 30 retained metrics from RFR as described above for the Strategic Project data, and an analysis was conducted to see whether the same metrics were selected as most important. When no similarity in the two sets of metric outputs was found, two of the metrics that were most consistently selected across taxa using the high resolution data (two of the final six

metrics – mean field size and Shannon Diversity) were also calculated using the AAFC crop inventory map. These two metrics were the metrics of interest in Fahrig et al. (2015) as representatives of compositional and configurational heterogeneity, and were therefore used in this graphical analysis between the two data types. The trends of these two metrics from both sources of data were plotted to determine if the coarser data would result in similar landscape patterns overall.

5.0 Results

5.1 Biodiversity variables

Biodiversity variables and the proportion of land in agriculture of each site were regressed in order to determine the direction and magnitude of effects. This revealed a stronger (and negative) relationship for plant diversity than for any of the other six taxa. The largest r value was for plant alpha diversity (-0.59) at the 1 km extent (Figure 5.1).

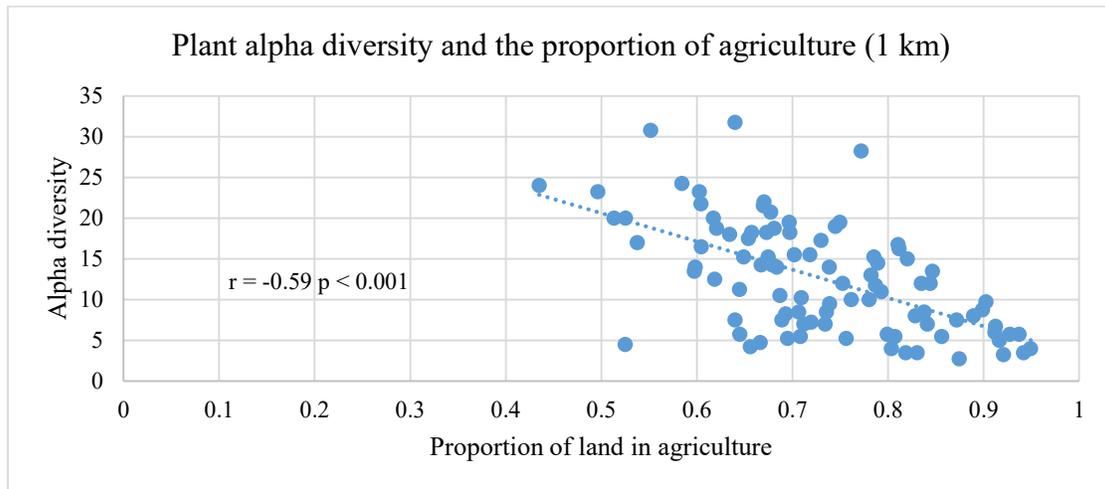


Figure 5.1: Plot of the strongest effect of the proportion of agriculture in the study landscapes at the focal extent of 1 km. Percent agriculture was assessed to control for the known negative effect on many groups.

Percent agriculture had a weaker and generally negative effect on the remainder of the biodiversity variables across all extents. Table 5.1 lists the strength and direction of these relationships. Statistically significant negative responses were found for plants, spiders and carabids (all diversity variables and abundance at all extents), and for some bird and syrphid variables (Table 5.1). As was previously determined in Fahrig et al. (2015), percent agriculture had a more variable effect across taxa groups than mean field size, and is therefore less pertinent in terms of management when the aim is to consider metrics with consistent effects across taxa.

Also, the percent of agriculture is not considered a manageable aspect of landscape structure, as reducing agricultural areas is not feasible in many cases for eastern Ontario farm owners.

Table 5.1: Correlation coefficient for correlations between the proportion of agriculture in each site at each extent, and each biodiversity variable for the taxa. Darker shading is indicative of a stronger effect. Significance codes: * = $p \leq 0.05$, ** = $p \leq 0.01$, *** = $p \leq 0.001$.

		1 km	2 km	3 km
Butterflies	Alpha	-0.06	-0.08	-0.10
	Beta	0.08	-0.01	-0.02
	Gamma	0.01	-0.04	-0.06
	Abundance	-0.07	0.01	-0.02
Plants	Alpha	-0.59***	-0.52***	-0.51***
	Beta	-0.48***	-0.43***	-0.42***
	Gamma	-0.54***	-0.48***	-0.48***
Birds	Alpha	-0.20*	-0.13	-0.13
	Beta	-0.19	-0.05	-0.005
	Gamma	-0.21*	-0.08	-0.05
	Abundance	-0.21*	-0.18	-0.20*
Spiders	Alpha	-0.40***	-0.37***	-0.44***
	Beta	-0.34***	-0.39***	-0.44***
	Gamma	-0.39***	-0.40***	-0.46***
	Abundance	-0.35***	-0.21*	-0.26*
Syrphids	Alpha	-0.007	-0.09	-0.06
	Beta	-0.01	-0.12	-0.11
	Gamma	-0.01	-0.11	-0.09
	Abundance	-0.10	-0.22*	-0.20
Carabids	Alpha	-0.22*	-0.25*	-0.25*
	Beta	-0.46***	-0.49***	-0.51***
	Gamma	-0.39***	-0.42***	-0.43***
	Abundance	0.17	0.11	0.07
Bees	Alpha	0.15	0.24	0.12
	Beta	-0.08	0.07	0.10
	Gamma	0.04	0.20	-0.43
	Abundance	0.18	0.15	0.16

	0 to +/- 0.20
	+/- 0.20 to +/- 0.40
	+/- 0.40 to +/- 0.60

5.2 Metric elimination

Overall, from the set of 117 initial landscape metrics, 30 were retained for use in the random forest regression. The list of metrics, their definitions, and their categorization as either composition or configuration metrics were outlined in Table 4.1.

5.3 Patterns in taxa

The out-of-bag error equivalent for random forest regressions is comprised of the percent variance explained and the mean of squared residuals for one third of the samples of each RFR run. Table 5.2 shows the outputs of these error measures by taxon, and a division of error values for each biodiversity variable is presented in Appendix J. As can be seen from the table, percent variance (average of the squared differences from the mean) explained by the sample third of the data was often low (or negative), which aligns with the low proportion of variance explained by the landscape metrics overall when bivariate regressions were conducted with the biodiversity variables in order to create boxplots (Section 5.4). A negative percent variance is indicative of a poor model, as this means that the percent variance for the 1/3 sample of the dataset retained for error analysis was larger than the total variance, or the variance of the remaining 2/3 of the data (Liaw & Wiener, 2002). This negative value is typical of smaller sample sizes, and is often rectified with linear modeling of the variables (conducted with biodiversity variable and landscape metric pairings for this dataset) (Millard, 2016, personal communication). The mean of squared residuals (measure of discrepancy from the estimation model) was highest for carabids, which is attributable to carabid abundance, and is likely related to the most prominent (introduced) species in the dataset (to be discussed in Section 6.2.1).

Table 5.2: Error measures from the random forest regressions summarized by taxon. The percent variance (% Var) and mean of squared residuals (MSR) are calculated on one third of the samples in each tree created in the RFR runs.

	Bees		Birds		Butterflies		Carabids	
	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>
Mean	-15.7	0.03	-11.1	15.4	7.8	86.2	-4.0	15611.3
Min	-18.9	0.03	-21.4	1.0	-0.9	1.8	-18.5	3.9
Max	-11.9	0.03	-1.2	51.9	12.3	342.2	6.6	63774.2
Std. Dev.	1.1	0.0003	5.8	20.6	3.5	142.5	7.7	27063.0
	Plants		Spiders		Syrphids			
	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>		
Mean	27.2	85.7	7.4	315.8	-6.1	299.2		
Min	16.6	28.5	-6.5	4.0	-12.4	2.5		
Max	36.3	168.2	14.0	1272.4	2.6	1210.0		
Std. Dev.	6.6	57.3	6.5	533.2	4.0	510.4		

Following the model runs, it was immediately clear that there were metrics that were important for certain species groups, but not overall. For instance, the modified Simpson’s evenness index was found to be the most important metric across all four bee biodiversity variables at the 1 km extent (alpha, beta, gamma, and abundance) but it was not the most important for other taxa. The metrics deemed most important for each taxon are given in Table 5.3, with a percent value to indicate the proportion of the four biodiversity variables for which the given metric was selected as the most important predictor. This measure is similar to the concept of “universality”, as outlined by Cushman et al. (2008) and is used in this case to present a potential metric of importance for each group.

Table 5.3: Metric deemed most important across the four biodiversity variables by RFR is highlighted (shaded) for each taxon. Percent value indicates the proportion of the four biodiversity variables for which the best metric was selected as most important. Metrics were retained as a cluster when they were within 5 occurrences of each other, but often one metric dominated in over half of the 100 RFR iterations. As can be seen from the table, the most consistent responses for each taxon (a single metric was most important for 50-100% of the four biodiversity variables) were found at the 1 km extent. Metric definitions can be found in Section 5.2, and are explained in detail in Section 6.2.1.

1 km	ABUNDANCE	ALPHA	BETA	GAMMA	% of four biodiversity variables with metric of most importance
Birds	CONTIG_RA	GYRATE_RA	CIRCLE_RA / CONTIG_RA	LPI	50%
Syrphids	CIRCLE_MN	TE / IJI	MSIDI	CIRCLE_AM	50%
Carabids	PLADJ	PLADJ	SHDI	PLADJ	75%
Butterflies	TE	GYRATE_AM	TE	TE	75%
Plants	N/A	DIVISION / AREA_AM	DIVISION / AREA_AM / GYRATE_AM	DIVISION / AREA_AM / GYRATE_AM	100%
Spiders	COHESION	IJI	AREA_MN / IJI	IJI	75%
Bees	MSIEI	MSIEI	MSIEI	MSIEI	100%

2 km	ABUNDANCE	ALPHA	BETA	GAMMA	
Birds	LPI	CONTAG	AREA_CV	IJI	0%
Syrphids	PR / IJI	SHAPE_SD	LPI	GYRATE_AM	0%
Carabids	AREA_AM / SHAPE_SD	SHDI	LPI / AREA_CV	AREA_CV	50%
Butterflies	MSIDI	IJI	CIRCLE_AM / CONTIG_MN	CIRCLE_AM	50%
Plants	N/A	LPI / AREA_CV	LPI / AREA_CV	LPI / AREA_CV	100%
Spiders	AREA_CV	AREA_CV	LPI	LPI	50% / 50%
Bees	CIRCLE_RA / CIRCLE_SD	CONTIG_MN	PLADJ	CONTIG_MN	50%

3 km	ABUNDANCE	ALPHA	BETA	GAMMA	
Birds	LPI	LPI	AREA_MN	NP / AREA_MN	50%
Syrphids	DIVISION	AREA_AM / COHESION	DIVISION	COHESION	50%
Carabids	SHAPE_MN	SHDI	AREA_AM	SHDI	50%
Butterflies	LPI	LPI	AREA_CV	AREA_CV	50% / 50%
Plants	N/A	LPI	LPI / AREA_AM / COHESION	LPI	100%
Spiders	AREA_CV / COHESION	LPI	LPI	LPI	75%
Bees	GYRATE_AM	CONTIG_MD	PLADJ	CIRCLE_MN	25%

Patterns in metric importance were found in groups at the 1 km extent; however, with the exception of plants, the metrics deemed most important at the 2 and 3 km extents did not have the same levels of universality as the 1 km extent (typically 75% or higher). Thus the remaining analysis was conducted using the 1 km land cover data.

5.4 Strength and direction of effects

To determine whether there were metrics of compositional and configurational heterogeneity that have consistent effects across groups (other than those used in Fahrig et al. (2015)), the metrics that had been identified as the most important at least once in the 100 RFR iterations for each biodiversity variable were analyzed for presence in metric importance lists across taxa. The results showed that six metrics had occurred as the most important across all biodiversity variables, even if they did not represent the majority of important metrics after the 100 iterations (Table 5.4). These six metrics were mean field size and total edge (configuration metrics), Shannon diversity index and the modified Simpson's evenness index (composition metrics), and the percentage of like adjacencies and the interspersion and juxtaposition index (both composition and configuration).

Table 5.4: Metrics identified as most important at least once in the results of the random forest regression for all taxa. The fraction indicates the proportion of the seven species groups that had the metric listed in their ranked list of variables deemed important by RFR, followed by their response (positive/negative) and the percent of biodiversity variables where the overall response was true.

Metric Type	Proportion of taxa where the given metric was found to be most important in RFR biodiversity modelling		Biodiversity response: Overall positive / negative?	Percent of 27 biodiversity variables with overall response
Composition	(1) Shannon Diversity Index	5/7	Positive	77%
	(2) Modified Simpson's Evenness Index	6/7	Positive	85.2%
Configuration	(3) Mean Field Size	7/7	Negative	96.2%
	(4) Total Edge	6/7	Both	48.2% Positive 51.8% Negative
Both	(5) Percentage of Like Adjacencies	7/7	Negative	88.9%
	(6) Interspersion and Juxtaposition Index	4/7	Both	44.4% Positive 55.6% Negative

Table 5.4 shows that the response direction was very consistent for the 27 biodiversity variables (four for each taxon with the exception of plants) for modified Simpson's evenness index and percentage of like adjacencies. It was also very consistent for mean field size with the exception of carabid abundance. This reverse response of carabid abundance was previously addressed in Fahrig et al. (2015), where it was attributed to dominance by the most abundant carabid species (*Pterostichus melanarius*), an introduced species to eastern Ontario farmland (Fahrig et al., 2015). This consistently negative response of the biodiversity variables to mean field size reinforces its importance as a representative landscape metric as found using general additive modeling for these taxa in Fahrig et al. (2015). Shannon diversity index and modified Simpson's

evenness index were positively associated with biodiversity for 77% and 85.2% of the models across the 7 taxa, respectively, indicating that more heterogeneity in field land cover types contributes to higher diversity values. As a metric which represented both composition and configuration, the percentage of like adjacencies was found to be negative for 88.9% of the 27 biodiversity variables, which is not quite as consistent a response as mean field size, but it shows that overall biodiversity declines as adjacent field cover types become the same and less variably distributed across the landscape. Correlations of these four landscape metrics are shown in Table 5.5. As can be seen from the table, mean field size and the percentage of like adjacencies have a statistically significant positive relationship ($r = 0.85$, $p < 0.001$). This indicates that larger fields tend to also have cover types that are the same within this dataset. While the effect of percentage of like adjacencies on biodiversity was generally negative, the effect of mean field size was more consistent across the 27 biodiversity variables.

Table 5.5: Correlations between the four landscape metrics found to have the most consistent responses overall in terms of direction of response from biodiversity variables. Graphical representations of these correlations are available in Appendix D (b).

	Mean field size	Percentage of like adjacencies	Modified Simpson's evenness index
Percentage of like adjacencies	0.85***		
Modified Simpson's evenness index	-0.14	-0.10	
Shannon Diversity Index	-0.46***	-0.39***	0.61***

Responses to total edge and the interspersion and juxtaposition index were not as clear in terms of overall biodiversity response. In fact, almost half of the biodiversity variables responded oppositely in both cases (Table 5.4). For total edge, this may be partially attributable to the fact

that this metric may have been influenced by composition in some cases (when two fields of the same type were less than 2 metres apart).

Shannon diversity and mean field size were selected in Fahrig et al. (2015) to represent compositional and configurational heterogeneity, and to have sites that represented many levels of both of these types of landscape heterogeneity. In this study, the modified Simpson's evenness index had more consistent biodiversity responses across groups than Shannon diversity, but mean field size remained the most consistent overall, and the most important configuration metric across biodiversity variables. As mean field size was deemed important across taxa from iterations of the random forest regression, these findings support the Fahrig et al. (2015) conclusion that smaller fields contribute to increased biodiversity in eastern Ontario farmland.

Following assessment of the consistency of responses across taxa, the direction and magnitude of biodiversity response was assessed for each taxon. As can be seen from Figure 5.2, while the response of percentage of like adjacencies was not entirely negative (positive for syrphid alpha and carabid abundance; no effect for bee abundance, bee alpha, syrphid gamma, and syrphid abundance), where it was negative, it was consistently found to have a stronger negative effect than mean field size (21 of 21 comparisons). This finding supports the assertion that the percentage of like adjacencies is a relevant landscape metric in deriving the effects of landscape heterogeneity on the seven studied taxa.

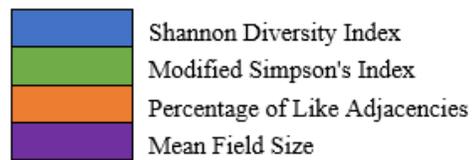
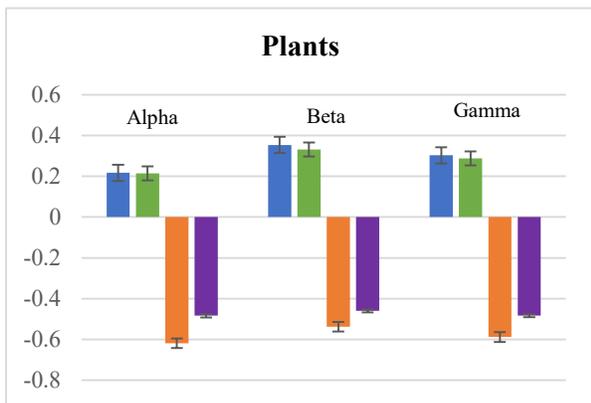
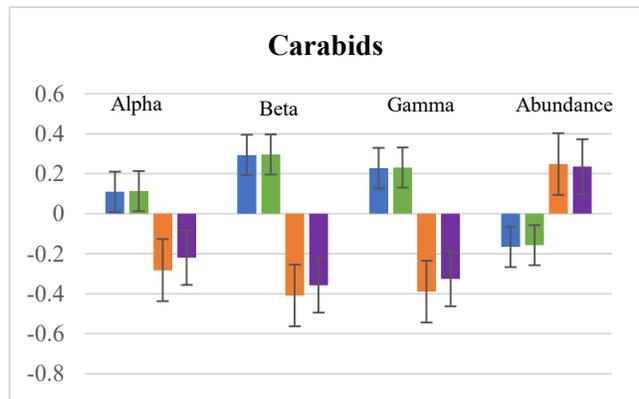
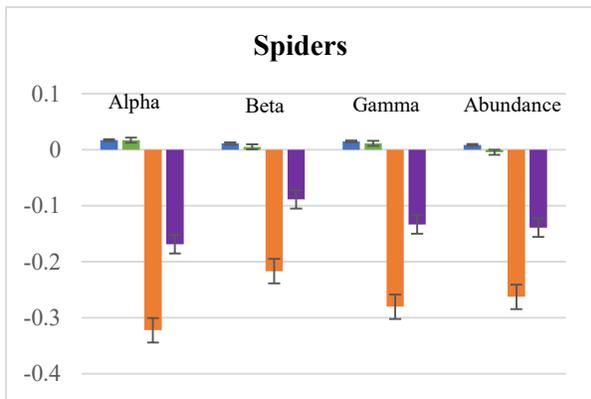
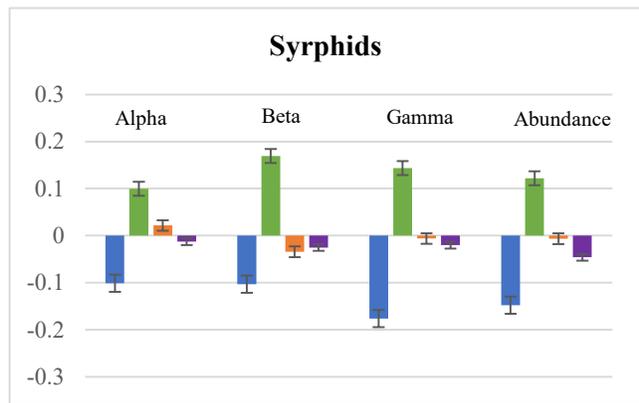
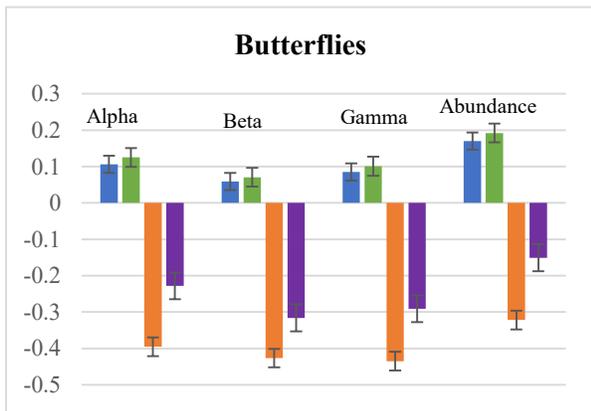
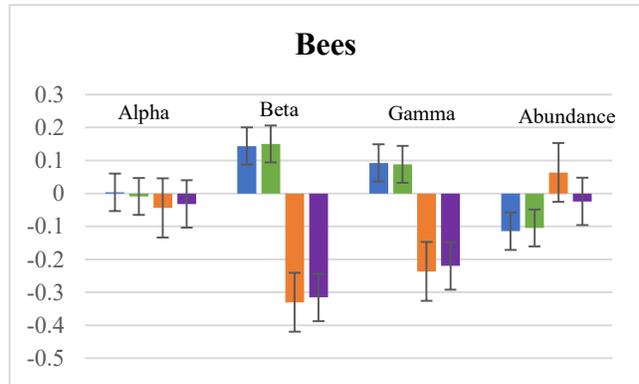
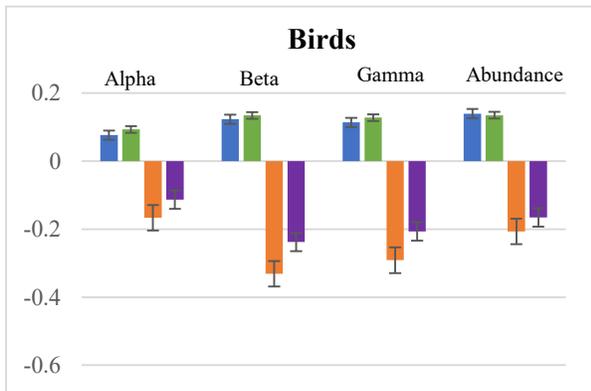


Figure 5.2: Boxplots representing the direction and magnitude (r value) of effects for the four most consistent landscape metrics (in terms of direction of biodiversity response) retained following RFR analysis. Error bars represent standard error for each r value.

The four metrics which were found to have the most consistent response across biodiversity variables (mean field size, the percentage of like adjacencies, Shannon diversity index, and the modified Simpson’s evenness index) were used for an additional random forest regression analysis. The results of this analysis are presented in Table 5.6.

Table 5.6: Ranking information for the four metrics used for the secondary random forest regression analysis. Out of the 100 iterations of random forest, the values below each biodiversity variable indicate the number of times the landscape metric was deemed the most important based on variable importance values (%IncMSE – described below). PLADJ: Percentage of like adjacencies, AREA_MN: Mean field size, SHDI: Shannon diversity index, MSIEI: Modified Simpson’s evenness.

	Bees				Birds			
	Abundance	Alpha	Beta	Gamma	Abundance	Alpha	Beta	Gamma
PLADJ	100	98	100	100	100	1	0	54
AREA_MN	0	0	0	0	0	99	0	46
SHDI	0	2	0	0	0	0	100	0
MSIEI	0	0	0	0	0	0	0	0
	Butterflies				Carabids			
	Abundance	Alpha	Beta	Gamma	Abundance	Alpha	Beta	Gamma
PLADJ	92	100	97	100	100	98	6	100
AREA_MN	5	0	3	0	0	2	21	0
SHDI	0	0	0	0	0	0	73	0
MSIEI	3	0	0	0	0	0	0	0
	Spiders				Syrphids			
	Abundance	Alpha	Beta	Gamma	Abundance	Alpha	Beta	Gamma
PLADJ	0	26	5	13	100	100	86	100
AREA_MN	100	74	92	83	0	0	0	0
SHDI	0	0	3	4	0	0	14	0
MSIEI	0	0	0	0	0	0	0	0
	Plants							
	Alpha	Beta	Gamma					
PLADJ	100	99	100					
AREA_MN	0	1	0					
SHDI	0	0	0					
MSIEI	0	0	0					

As can be seen from the table, for the majority of taxa (with the exception of spiders) nearly all biodiversity variables deemed the percentage of like adjacencies to be the most important based on rankings performed using the variable importance metric, percent increase in mean squared

error (%IncMSE – described in Section 4.3). The error information for this random forest regression can be found in Appendix K.

5.5 Bird species groups

Bird data had the least consistent response for all biodiversity variables at the taxon level (1 km extent), therefore this group was also analyzed in divisions of farmland specialists, generalists, and other bird species and at all three extents (1, 2 and 3 km) to see if scaling was a factor in the varying responses. Overall, it was found that the three groups responded to two components of landscape structure at two different extents (Table 5.7). Most consistently, farmland specialists and other bird species responded negatively to the radius of gyration at the 1 km extent for all eight biodiversity variables. Hypothesized biological reasoning for this consistent negative response is outlined in Section 6.2.2.

Table 5.7: Bird group results. Metrics were found to be consistent across groups (statistically significant but weak responses), with varying scales of effect. The percent of variables which reflected the metric is indicative of the proportion of the alpha, beta, gamma, and abundance models that selected this metric as most important over the 100 iterations of RFR. Significance codes: * = $p \leq 0.05$, ** = $p \leq 0.01$, *** = $p \leq 0.001$

Bird group	Landscape metric deemed most important by RFR	% of biodiversity variables that reflected this metric (/4)	p-value range & r value range	Landscape Extent
Farmland specialists	Radius of gyration	100%	0.0005*** – 0.06 -0.03 to -0.13	1 km
Farmland generalists	Contiguity	75%	0.008** – 0.02* -0.25 to -0.27	2 km
Other	Radius of gyration	100%	0.006** – 0.03* -0.23 to -0.27	1 km

Similar to the overall taxa analysis of the proportion of agriculture to analyze this known effect, r values were obtained in order to observe the strength and direction of effects on each bird functional group. Overall, bird specialists and other bird species were the most negatively affected by the amount of agriculture in each site, with the strongest effect explaining 34% of the variation in bird specialist abundance. Table 5.8 lists all r values for bird group variables.

Table 5.8: Correlation coefficients for analysis of the bird functional groups and the percent of each site which was agriculture at all three extents. Significance codes: * = $p \leq 0.05$, ** = $p \leq 0.01$, *** = $p \leq 0.001$.

		1 km	2 km	3 km
Bird Generalists	Alpha	-0.06	-0.07	-0.01
	Beta	0.05	-0.006	0.06
	Gamma	-0.02	-0.07	0.03
	Abundance	-0.06	-0.07	-0.01
Other Bird Species	Alpha	-0.25*	-0.24*	-0.14
	Beta	-0.29***	-0.28**	0.17
	Gamma	-0.29***	-0.27**	-0.17
	Abundance	-0.24*	-0.23*	-0.13
Bird Specialists	Alpha	-0.19	-0.30**	-0.34***
	Beta	-0.12	0.05	0.09
	Gamma	-0.27**	-0.20	-0.20*
	Abundance	-0.19	-0.30**	-0.34***

	0 to +/- 0.20
	+/- 0.20 to +/- 0.40

5.6 Biodiversity modelling comparison using landscape metrics derived from coarser resolution AAFC land cover classifications

To assess whether coarser, publicly available data could be used to assess effects of landscape structure on biodiversity, the RFR modelling methods described previously were applied using the same 30 landscape metrics but calculated from the Agriculture and Agri-food Crop Inventory map (AAFC, 2014). Results showed that very few metric rankings matched those

that had been found using the Strategic Project data, and there were no patterns in taxa for metric importance across multiple biodiversity variables.

As outlined in previous sections, the AAFC inventory maps had an overall accuracy of 71.3%. While the main classes (soy, hay, and corn) were well classified, generalization of patch sizes due to the coarser (30 m) resolution may have had significant effects on metric outputs. When two fields of the same type were next to each other, in the AAFC maps they were often joined, while smaller fields were often not classified at all. This would have a significant effect on metric outputs related to size, number of patches, arrangement, shape, and even the diversity of types.

As the RFR analysis did not find the same metrics for each group (and effects were weaker overall), an assessment was then conducted to see whether the two heterogeneity variables of interest from Fahrig et al. (2015) (mean field size and Shannon diversity) calculated from the AAFC data produced similar trends to the highly detailed data (direction and magnitude of effect). This was done in order to see whether the metrics trended together in spite of the differences in derived variables of importance from the random forest regression, and also to observe the correlation between the metric outputs. As an example, Figure 5.3 shows the trends and correlation plots for the two metrics at the 2 km extent, and some similarities in the peaks of these values at certain sites. All three extents (1, 2, and 3 km) were used to graphically analyze the AAFC and Strategic Project data trends for these two landscape metrics, and the graphs for all extents can be found in Appendix L.

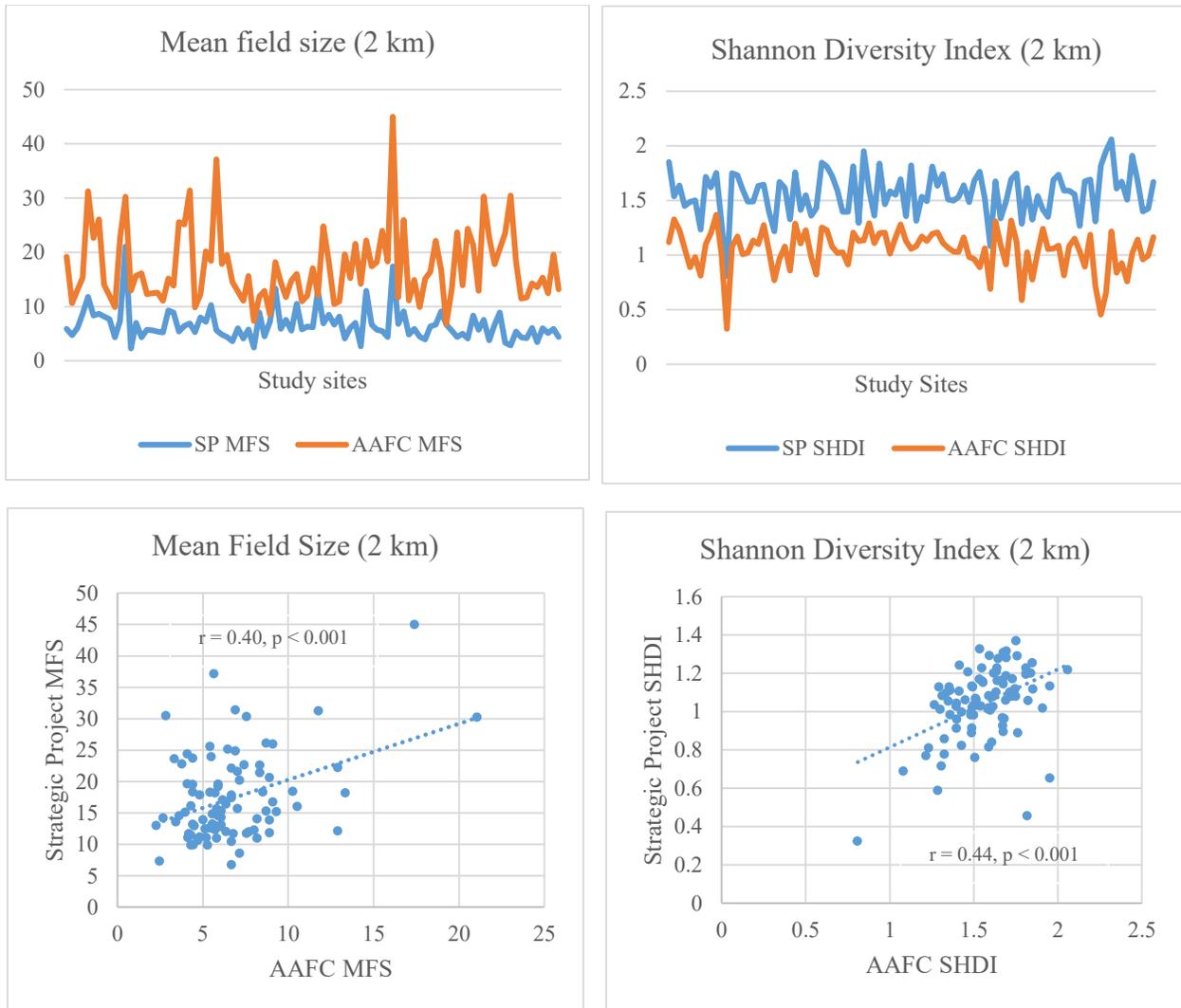


Figure 5.3: Trends of mean field size and Shannon diversity from the Strategic Project data and the AAFC Annual Crop Inventory across all 93 study sites at the 2 km extent. The sites along the x-axis of the line graphs are matched for the SP and AAFC data, and are arbitrarily ordered only to aid visualization of the correspondence between the two datasets. The correlations are weak for SHDI and MFS derived from the two data sets.

Although visual patterns can be seen in the graphs, the potential to derive the same landscape metrics from both is not strong enough to substitute the AAFC Crop Inventory map for the higher resolution data for the purposes of this analysis. This is further evidenced by low (but significant) correlation values as seen in Figure 5.3.

6.0 Discussion

6.1 Major findings

The overall finding from this analysis was that mean field size is a representative metric across the seven taxa. All species groups, with the exception of carabid abundance (as discussed in Section 5.4) responded negatively to mean field size, which reinforces the assertion by Fahrig et al. (2015) that field sizes should be made smaller if biodiversity conservation is a goal of eastern Ontario farmland management. While this finding is consistent with the previous study, it is important to note two additional main findings:

(1) In specific taxa, other metrics were more prominent than mean field size in the RFR variable selection analysis, and it is important to consider the biological reasons behind these indicator metrics when applying these findings to management considerations.

(2) For both compositional and configurational landscape metrics, the second place metric only had an opposite response for 2 or 3 biodiversity variables, so these metrics are evidently also important when considering landscape effects on biodiversity in eastern Ontario farmland. This includes the percentage of like adjacencies, which generally had a stronger negative association than mean field size.

Hypothesized biological reasons for point (1) will be discussed in Section 6.2.1. Point (2) presents an additional finding from this research which could be integrated into best management practices for eastern Ontario farmland. Fahrig et al. (2015) established the importance of mean field size for biodiversity and other previous studies have found that configurational heterogeneity is important for biodiversity, especially as habitat areas are reduced (e.g. Singh et al., 2010; Flick

et al., 2012). Compositional heterogeneity has also been previously established as an important component of landscape structure in terms of effects on biodiversity (e.g. Bennett et al., 2006; Miyashita et al., 2012).

In this study, the percentage of like adjacencies was found to often have a stronger negative effect than mean field size, although it was not consistently negative across species groups (positive in two cases, no effect in four cases as presented in Section 5.4). This finding is aligned with a study by Burel et al. (1998), which also used the percentage of like adjacencies as an indicator of land cover and effects on biodiversity. The percentage of like adjacencies (PLADJ) is a measure of field cover types and their proximity to each other, and reaches a value of 100 when all field cover types are maximally aggregated (all the same cover type). Smaller values of this metric are indicative of more discontinuity of cover types. This metric is representative of both compositional and configurational heterogeneity. For configuration, two sites can have the same number of field cover types, and can have very different PLADJ values based on the size, arrangement, and adjacency of class types. For composition, the distribution and evenness of field cover types affects how often fields of the same type will be adjacent (measured by cell adjacencies in this case). The negative response of many species groups from this study indicates that biodiversity levels are higher in study landscapes that have smaller PLADJ values, or more variety in the distribution of field cover types. Mean field size was maintained as the most consistent metric overall in terms of direction of effects, and had a significant positive correlation with PLADJ ($r=0.85$, $p<0.001$), though this metric often displayed a stronger negative effect. Also, an r value of 0.85 is only an r^2 value of 0.72, so there is 28% variance not common to both. This variance could be due to composition effects which are captured by PLADJ, making it more representative overall, and a better single variable than field size in terms of the response of many

of the biodiversity variables. Both metrics, therefore, have strong attributes. Mean field size had greater consistency of a negative effect across taxa and biodiversity variables, and the percentage of like adjacencies had a stronger negative effect in 21 of the 27 biodiversity variables. Based on these findings, one important assertion of this study is that not only should fields be made smaller in order to conserve biodiversity, but the field cover types should also be variably distributed wherever possible.

It is important to note that many of the landscape metrics retained in this study were highly correlated, and that elimination decisions were made early in the study based on these high correlations and because they described similar aspects of landscape heterogeneity. Metrics were often retained if they were easier to interpret, so while the percentage of like adjacencies was found to have a stronger negative response in all real effects when compared to mean field size, it is likely that metrics that PLADJ was correlated with (for example, the aggregation index, $r = 0.98$) would also have been able to describe the aspects of landscape heterogeneity captured by the hybrid metric PLADJ. Thus, an important caveat of this study is that due to the decision technique used, the concept of the interaction between smaller fields that are more variably distributed is suspected to be explaining the variability in the response variables. This interaction between both aspects of heterogeneity is captured by PLADJ, however, there are other metrics which would also adequately capture the same dynamic interaction between compositional and configurational landscape heterogeneity.

The four metrics which were found to have the most consistent response across biodiversity variables were re-assessed using random forest regression. It is interesting to note that in the majority of cases (20 of 27 biodiversity variables) the percentage of like adjacencies was found to have been more important to the model than any of the remaining three metrics. This revealed that

although mean field size and the percentage of like adjacencies are correlated, it is possible that the percentage of like adjacencies is a metric which captures the relation between aspects of landscape compositional and configurational heterogeneity and biodiversity better than mean field size. As stated above, this interpretation is made with the caveat that many metrics were highly correlated, and it is the concept of this interaction between both types of heterogeneity that is of interest to findings for practical implementation. This finding is central to the study goal of identifying potential better metrics to inform management and land cover planning in eastern Ontario farmland.

6.2 Effects on species groups

6.2.1 Overall effects on taxa

The metrics which discussed in section 6.1 had consistent or mostly consistent responses across all seven taxa (e.g. mean field size and percentage of like adjacencies). The metrics to be discussed in this section are specific to individual taxon response, and the adapted measure of universality, or the percent of consistent responses from the biodiversity variables (Cushman et al., 2008). These landscape metrics were deemed important in the majority of the 100 iterations of random forest regression with the four biodiversity variables (alpha, beta, and gamma diversity and abundance), and will be discussed with reference to potential biological explanations for their importance for each taxon. All landscape metric definitions and interpretations of value meanings in this section are from the Fragstats manual (McGarigal, 2014).

6.2.1.1 Bees

Based on the random forest regression (RFR) analysis, bee biodiversity variables deemed the modified Simpson's evenness index the most important landscape metric for 100% of the

variables at the 1 km extent (alpha, beta, and gamma diversity and abundance). Modified Simpson's evenness is defined as "minus the log of the sum, across all patch types, of the proportional abundance of each patch type squared" (McGarigal, 2014). The modified version of this metric makes output values comparable to Shannon diversity metric values, which is why it was selected over the original metric format for this study. As an interpretation of this metric, a higher value means more patch diversity in each landscape.

The effect of the modified Simpson's evenness index was positive, indicating that more field cover types with increased evenness means more species of bees. This result aligns well with findings from Colla et al. (2012), who assert that bee distributions are limited by floral preferences, the availability of hosts (when applicable, for cleptoparasites) and habitat accessibility (Colla et al., 2012). In addition, a diversity of flower types has been found to have a positive effect on bee diversity (Holzschuh et al., 2007). These findings demonstrate a need for distribution of resources and multiple field cover types, and that they must be evenly distributed in order to be accessible for all aspects of bee survival.

In addition to the availability of multiple land cover types, habitat, foraging, and nesting areas must be in an accessible range for use by bee species. Isaacs et al. (2010) indicated that larger fields reduce suitability for bee habitat and nesting resources, particularly in the case of wild bees (Isaacs & Kirk, 2010). This 2010 study found that managed bees were providing the majority of the pollination services. In eastern Ontario, bees are also managed as a part of agricultural productivity (S. Cardinal, 2015, personal communication), and so having more field cover types in an accessible distance would possibly increase population distributions and diversity of wild bees (and thus pollination contribution from this group).

While some bee species are well studied in North America, there are many species that require additional research to understand habitat and resource requirements. For this reason, designing species-specific conservation programs is problematic (Colla & Packer, 2008). From these findings and previous findings about the effects of landscape structure on bees, it is clear that an evenly distributed diversity of field cover types (wherever possible) would benefit multiple bee species for their various uses of different types of land cover. Crop yields decrease when bees are lost, so it is clear that it is of interest to farming management to consider this taxa when planning the layout of farming regions (Colla & Packer, 2008).

6.2.1.2 Butterflies

Based on the RFR analysis with butterfly data variables, total edge (TE) was important in 75% of the four biodiversity variables. In the case of this study, total edge was calculated at the boundary of two differing field cover types (including edge polygons) and is therefore a measure of configurational heterogeneity, potentially affected by composition due to the study area characteristics (Section 4.2). More edges would occur with more field cover types, and more edges would occur when fields are smaller.

The effect was positive, indicating that more patch types and more boundaries between field cover types (smaller fields) has a positive effect on butterfly diversity. The implication of this finding is that when fields are expanded and distances between resources are increased, not all butterfly species would be able to travel these longer distances. For butterflies and carabids, the ability to fly further is considered to be an adaptation to change and helps populations to remain robust (Barbaro & van Halder, 2009). Flick et al. (2012) found that butterflies respond to agricultural land use effects at the scale of their daily movements. Similar to the findings of this study, this means that butterfly abundance is higher in landscapes with many small fields. This

also means that in some cases, positive effects for butterflies can be had at the individual farm scale (through arrangement of field cover types in a pattern with smaller sizes overall) (Flick et al., 2012).

Natural areas in agricultural landscapes have also been found to have an effect on butterfly diversity in past studies. Barbaro et al. (2009) found that butterflies have a significant positive association with shrubland cover, edge density and Shannon diversity, and a negative association with mean patch area and mature pine cover. While natural areas were not considered for this study, the findings of a positive relation with edge density and a negative relation to mean field size are notably similar to the definition of total edge, and the positive association elicited by three of the four biodiversity variables for butterflies. It is evident that smaller fields and additional edge areas would benefit butterfly diversity in the region.

6.2.1.3 Syrphids

Syrphid (hoverfly) random forest regression results indicated that the related circumscribing circle was the most important landscape metric for 50% of the biodiversity variables. This metric is based on imagined circles around each patch, and the derived values based on patch size and shape. In general, as values of this metric decrease, field sizes gradually become smaller. In the case of this study, configurational heterogeneity increases as field sizes become smaller overall.

The effect of the related circumscribing circle was positive, demonstrating that larger or elongated fields have a positive effect on syrphid diversity, however this was only found to be the case for syrphid abundance and gamma diversity. For syrphid alpha diversity, total edge and the interspersed and juxtaposition index were found to be most important from the 100 RFR

iterations, and the modified Simpson's index was found to be most important for syrphid beta diversity. This finding of only half of the biodiversity variables responding consistently to a metric was the least consistent response of all taxa, with the exception of birds (which were further analyzed in species groups for this reason). Identification of a consistent metric of most importance did not improve at the 2 km or 3 km extent. Given the inconsistent response of differing measures of syrphid diversity, it is difficult to speculate as to a potential management recommendation or potential biological explanation based on these findings.

It is possible that an analysis with subsets of syrphid species would be valuable for further insight into interactions with landscape structure. Jauker et al. (2009) found that syrphid abundance did not decline with distance between habitat areas (larger fields), which indicates not only that this taxon must be considered separately from others, but also that some syrphids species may interact with landscape in counterintuitive ways (i.e. respond positively to less heterogeneity in some cases). While landscape effects in this taxon are unclear for the eastern Ontario dataset, it is possible that groups of syrphid species are responding to landscape structure in different ways. For instance, it is possible that syrphid specialists (saprophagus – feed on decomposing matter, phytophagus – feed on plant tissues) and generalists (aphidophagus – feed on aphids or lice) are responding to landscape structure in different ways (Haenke et al., 2009). This analysis of groupings based on resource use will be further discussed as an area of future study in Section 6.4.2.

6.2.1.4 Spiders

For spider biodiversity variables it was found that the interspersed and juxtaposition index was important (through iterations of the RFR) in 75% of the four variables. This index analyzes the evenness or unevenness of patch adjacencies. In this case, a higher value indicates that the

types are distributed more evenly, or there is more compositional heterogeneity overall. This also depends on the arrangement of patches in the landscape.

The effect of the interspersion and juxtaposition index was negative, meaning that higher evenness of patch types contributed to less spider diversity. It is unclear why an evenness in patch types would contribute to less spider diversity. One possible explanation is based on the findings of Sunderland et al. (2000), who found that spiders would not walk into a field from an edge unless it was similar (in terms of appearance and vegetation) to where they just came from. Given that the three main types of field in eastern Ontario are hay, corn, and soybean, the only field type which may be similar to a vegetated edge strip would be hay (not a row crop). Field edges have been found to be beneficial for spider populations in many agricultural studies (Sunderland & Samu, 2000; Clough et al., 2005; Schmidt et al., 2005). This may be a group for which it would be beneficial to look at the differences between edge sample site diversity as compared to diversity at the centre of fields, which will be discussed in more detail as an alternative study approach in Section 6.4.2.

6.2.1.5 Plants

For plants, a landscape metric cluster consisting of mean field size, the landscape division index, and the radius of gyration were all deemed important in 100% of the 100 iterations of the random forest regression. The landscape division index indicates the probability that two pixels will be in the same patch, with higher values indicating that there are more patch types distributed across the landscape. The radius of gyration is a measure of the distance between each field centre and all other cells in the patch, increasing with larger and more complex shapes.

The effect of the landscape division index was positive, meaning that more field cover types contributes to higher plant diversity. The effects of mean field size and the radius of gyration were negative, implying that larger fields are associated with lower plant diversity. All of these findings correspond well to previous studies that have indicated that higher heterogeneity contributes to higher plant diversity overall. Dispersal ability has been found to be pertinent when considering landscape effects on plants. Smaller and more variable field cover types enables wind-dispersing plants to travel and become established elsewhere and makes it easier for non-wind dispersed plants to do the same (José-María et al., 2011). Other studies have also found higher plant diversity in field edges (likely from edge vegetation) (e.g. Poggio et al., 2013). It is evident from these findings, and from those established in other studies, that plant diversity benefits from close proximity to other field cover types, and would benefit greatly from the overall management recommendation that mean field size should be decreased in farmland in eastern Ontario.

6.2.1.6 Birds

For birds, contiguity was found to be the metric ranked highest for 50% of the biodiversity variables. Contiguity describes the geometric arrangement of like cells in patches, where lower values would be indicative of increased shape complexity or smaller fields.

The effect on the groups was negative, indicating that bird diversity decreased with increased contiguity of field cover types (decreasing shape complexity) or larger fields. This finding aligns with associations identified by Barbaro et al. (2009), which found the strongest positive association to be with edge density and deciduous wood cover, and the strongest negative association with mean patch area (both indicative of a positive effect of increased complexity). While this is an intuitive finding, and is supported by previous research, contiguity was only deemed the most important metric for bird abundance and beta diversity. Bird alpha diversity

indicated the radius of gyration to be the most important metric ($r = -0.27$, $p = 0.006$), while bird gamma diversity designated the largest patch index to be the most important ($r = -0.22$, $p = 0.03$) following 100 iterations of RFR. The radius of gyration is similar to contiguity in that it is a measure of shape complexity, however the negative effect is counterintuitive as higher values of this metric are indicative of higher distances between each cell and the patch centroid (higher shape complexity). The negative effect of the largest patch index is the expected finding due to the fact that as the largest patch dominates more and more, it is expected that configurational heterogeneity decreases. While contiguity and the radius of gyration appear to be describing shape complexity in some form, their correlation with each other was very low ($r = 0.001$, $p = 0.98$). However, the largest patch index and the radius of gyration were significantly correlated ($r = 0.71$, $p = 2.069e-15$). These inconsistencies in relations between landscape pattern and biodiversity variables appeared to indicate that birds may be responding as different groups, or at different scales. This assumption was tested, and the results of this analysis are discussed in Section 6.2.2.

6.2.1.7 Carabids

The percentage of like adjacencies (PLADJ) was found to be most important for 75% of the carabid biodiversity variables. The effect was positive for carabid abundance, and negative for carabid alpha and gamma diversity, indicating that larger fields with simple shapes increase carabid abundance, but decrease diversity. Larger fields would also cause PLADJ values to increase in terms of compositional heterogeneity, as it is calculated on a cell basis, and larger fields overall means less types in a landscape. This agrees with the findings of Fahrig et al. (2015), which found a positive effect of mean field size for carabid abundance.

A European study found that larger beetles are often observed in rural areas, while smaller ones are found in more urbanized areas (Alaruiikka et al., 2003). It is possible that this is also the

case in our study area. Classification of the species as brachypterous (small winged), macropterous (large winged), or dimorphic (both long and short wings in the same species) has been used as a proxy for dispersal ability (Fischer et al., 2013). As the study landscapes are located in rural areas, it is expected that the species found would be mostly larger. This was found to be true in a pilot analysis using the carabid dataset; 72% of species were macropterous, and another 12.5% were dimorphic. Thus, most of the species in this study can fly longer distances, which explains the positive effect of large field sizes (and simplified distribution of field cover types) on carabid abundance.

Fahrig et al. (2015) also found the positive response of mean field size to be due to the most abundant species (*Pterostichus melinarius*), which is non-native species that uses agricultural lands as habitat. This species is also macropterous, which again explains the positive effect of carabid abundance for mean field size, and could also possibly be an explanation for the positive effect of the percentage of like adjacencies. The added information from these findings reinforces the overall finding for all taxa, distributing field cover types variably (in addition to them being smaller in size) could contribute to increased carabid diversity.

6.2.2 Bird groups effects

As aforementioned in Section 6.2.1.6, it was hypothesized that bird species were responding to landscape heterogeneity in sub-groups based on the inconsistent responses found at the taxon level. Farmland bird specialist diversity was most associated with the radius of gyration in the RFR biodiversity analysis at the 1 km extent. The radius of gyration (conceptually) is a measure of the distance an organism could travel before reaching the field boundary. Field size may not be as important as field shape for some species, which is reflected in this metric. Higher

values of this metric are indicative of higher complexity, which in the case of birds in farmland would mean that the distance to other cover types would decrease with higher complexity (as opposed to a compact square field of the same size). However, as fields become larger overall, the radius of gyration value would also increase as the distance between each cell and the patch centroid increases. In this way, this metric is a measure not only of size, but also of shape and vastness (for longer fields) of farmland fields (McGarigal, 2014).

The response of farmland bird specialists to the radius of gyration was negative for all four diversity measures. This seems to be indicative of a negative response to larger patches and square or compact field geometry, however there are other metrics which also look at the size of patches which were not deemed as important as the radius of gyration. This begs the question, why was this landscape metric selected over others which also provide measures of field size? Farmland specialists are defined as species which use one type of land cover in farmland (Kreuzberg, 2011). It is possible that this response is linked to the distance that a farmland specialist would have to disperse or search in order to access the crop type they use as habitat. More extensive (and larger) fields as described by the radius of gyration inhibit ease of access between habitat areas for specialists, which is one possible explanation for this negative response. Increased complexity of fields would ease access to appropriate field cover types, and would also ease access when certain field cover types are only used for obtaining food or as nesting sites (increased access and ability to return to habitat of specialization). This is especially true when it is considered that many of the specialist species analyzed in this study were further categorized as pasture specialists, which is not a dominant land cover type in eastern Ontario.

It is expected that this component of habitat access (inhibition by larger and more extensive fields) also contributed to the negative response of the radius of gyration for other bird species.

Similar to farmland specialist species, the response of other species was found to be consistently negative across all four biodiversity variables at the 1 km extent. Other bird species are defined as those which are only incidentally in farmland, and use these areas only since they are adjacent to their native habitat areas (forests or other habitats) (Kreuzberg, 2011). Similar to accessibility to pasture lands for specialist species, access to semi-natural or natural areas such as forests would also be inhibited by extensive fields as quantified by the radius of gyration. In addition, the measure of total edge for this study is not the traditional definition of edge areas, otherwise this may have been found to be more important for other bird species. In this case, total edge was defined as the interface or border between two land cover types (including fields and edge areas), but was not a true descriptor of the amount of edge available for habitat. This is due to the fact that the boundary of fields does not necessarily imply vegetation or habitat area (as two fields intersecting without a vegetated edge was also counted towards the total edge value in this case).

Finally, contiguity was found to be the metric of most importance for farmland bird generalists for alpha and gamma diversity, and abundance at the 2 km extent. This finding is intuitive in terms of farmland generalists' use of many different land cover types in farmland areas; smaller fields with more complex shapes would ease access to these multiple cover types (Kreuzberg, 2011). It is expected that this metric was selected over mean field size as it is not only a descriptor of size, but also complexity of fields. Increased complexity in this case contributes to more field boundaries and edge areas, which again is not fully captured by the total edge metric in this study. This is also expected to be the case given that total edge was deemed the most important metric for farmland bird generalist beta diversity. Due to the fact that neither total edge nor contiguity fully capture the amount of edge for use by bird generalist species (who, by definition, use many of these areas as habitat), it is expected that an analysis which discerned the types and

amounts of edge for a landscape structure analysis would provide additional insight into these findings. This area for additional study will be discussed further in Section 6.4.2. It is also interesting to note that farmland generalist species responded to complexity of field shapes and distributions at the 2 km extent, which was larger than the response at the 1 km extent for specialists and other species. This may be attributable to the various land cover types which are able to be used by generalist species, thus allowing them to use resources and habitat areas in a larger overall area in eastern Ontario farmland. This finding addresses the research sub-question as to whether some species groups may be responding to landscape structure at different scales.

Jobin et al. (1996) conducted a study in southern Quebec agricultural areas and found that bird species richness and abundance were higher in places with heterogeneous landscapes rather than those dominated by cash crops. They asserted that the change to cash crops in recent decades is directly linked to the decline of some species (especially those associated with dairy farming), while some (like the ring billed gull and rock dove) are benefiting from the change (Jobin et al., 1996). In addition, there is a temporal aspect to the success of certain species in habitat areas, as perennial crops provide good habitat and are already present in the spring when migratory birds are returning while cash crops are very short in height at that point. This study therefore concluded that heterogeneity is important, that cash crops should be avoided, and that the destruction of hedgerows and edges inhibits spring breeding (as these are often the only remaining habitat areas). This link is particularly relevant in eastern Ontario, which has a large proportion of crops in soybean and corn. It is clear from the findings of the random forest regression analysis (and from links to previous research) that farmland specialists, generalists and other species require a variety of land cover types for habitat. While some generalist species may thrive in current conditions, diversity is crucial to avoid continued decline in farmland bird populations.

6.3 Use of alternative data sources

For highly detailed land cover datasets, field verification of the types and arrangements of fields is required in order to increase the quality and accuracy of classifications from imagery, but this is not always feasible or cost-effective. This study analysed the ability of the AAFC Annual Crop Inventory to be used as a substitute for the Strategic Project data (delineated with 45 cm imagery and verified from roadways and field surveys).

As the AAFC data showed moderate to high correspondence with the high resolution field and air photo classifications (Section 3.4), RFR was applied to metrics derived from the AAFC data for comparison. The metrics selected as most important with respect to the biodiversity variables did not reveal the same overall aspects of landscape structure, and were not consistent with the findings using metrics derived from the high resolution land cover maps.

The sensitivity of landscape metrics to both spatial and thematic resolution is established in the literature (Riitters et al., 1995; Hargis et al., 1998; Manson et al., 2003; Mas et al., 2010). Given this sensitivity, metrics from the AAFC data would have had very different output values than those calculated from the Strategic Project data. Visual inspection of the AAFC data revealed that due to the 30 m cell size, many adjacent fields the same type were combined and many smaller fields were lost. This would have an impact on metrics that calculate values based on the types of fields, and any that have values based on the size, shape, or number of fields. If there was a more variable distribution of cover types in the study landscapes, there would be less probability of like cover types being adjacent and merged, which would contribute to more accurate landscape metric outputs (both composition and configuration metrics). In addition to these sensitivities to the spatial resolution, thematic alterations also had to be made to compare the two datasets. As was

previously discussed, hay, legumes, clover, and pasture were combined based the definition of the AAFC product specifications, while researchers were able to separate these field cover types for the Strategic Project data (AAFC, 2014). This generalization of field cover types would have had an impact on landscape metric outputs related to the number of field cover types, as these four types would now only be considered one (pasture).

The ability to link metric findings to actual ecological processes depends on the ability to accurately capture landscape heterogeneity for quantification and relation to biological variables. In areas like eastern Ontario where agricultural cover tends to be dominated by large areas of similar crops (many of which are the same type as neighbouring fields) the ability to use the AAFC Annual Crop Inventory as a substitute for this analysis is currently not feasible. If the analysis related biodiversity levels to the amount of land in each type of dominating crop, the AAFC data would likely provide insight into potential effects. However, for the purposes of this analysis, which requires identification of individual fields in order to draw conclusions in terms of specific ecological relationships, the data is not a viable substitute at this time.

6.4 Research limitations and recommendations

6.4.1 Research limitations

This research was limited by low correlation values, and occasionally non-significant findings in terms of the relation between biodiversity variables and landscape metrics. This study aimed to find consistent response across groups, and this goal was achieved. However, the effects of percent agriculture (which was also analyzed) are often stronger and more negative than the effects described by landscape metrics. This result aligns with findings of Cunningham and

Johnson (2011), who found that percent tree cover was a useful overall metric for evaluating the effects of landscape heterogeneity on biodiversity. The study by Cunningham and Johnson only evaluated this metric for use for bird management strategies, and this study incorporated six additional taxa for consideration. While percent tree cover was not analyzed in this study, this metric is similar to percent agriculture as it describes a component of the inverse of the percent of area affected by agricultural landscape structure.

However, the goal of this study was to analyze metrics which could inform on improvements for biodiversity in agricultural areas. Percent agriculture (as a metric) does not provide insight into these relations, and would only produce a recommendation to decrease agricultural areas, which is not easy to implement without compensating incentives. Percent agriculture was analyzed in this study, and while the effects described by the selected landscape metrics are secondary in terms of the magnitude of effects, they describe these effects in greater detail and are expected to be components of the overall negative effect of increased agriculture.

An additional limitation of the study was the inability to relate landscape effects to species groups. As described in the background section, analyzing effects on groups that use similar resources or contribute similar services to an ecosystem can provide additional insight on the relation between pattern and process. While this was conducted for bird species groups in terms of their land cover type specializations, there is often a lack in studies for all species of all taxa in terms of resource use, habitat preference, and behavioural traits (Colla & Packer, 2008). This limitation is discussed further in Section 6.4.2.

In terms of limitations for metric calculation, there are many additional ways to calculate landscape metrics that were not used in this study. The background section detailed additional

methods of calculating metric values from texture, vector data, and other components of landscape data (Lausch & Herzog, 2002). For this study, Fragstats and commonly used raster metrics were selected in order to analyze a variety of metrics which may be able to inform for management. The use of additional metrics for this dataset could provide complementary additional information to the findings of this study, which could then be used to strengthen or adjust recommendations for farmland management.

6.4.2 Additional areas for research

While there may be patterns and landscape structure elements of interest for different taxa, there is a dynamic element to the effects of landscape structure on biodiversity, and the decline of species does not have a linear relationship with loss of heterogeneity in agricultural areas (Burel et al., 1998). In other words, different species groupings respond to heterogeneity in different ways (Katayama et al., 2014). For this reason, it is important to consider the multitude of landscape heterogeneity components that may be affecting declines in certain groups. This was done for bird species groups for this study, but could be extended to other taxa.

The relative effects of landscape heterogeneity depend on which group is being observed, and often sub-groups in taxa will respond as a group based on resource use or behavioural components (Hopfenmüller et al., 2014). In general, with the expansion of fields and homogenization of land cover types in agricultural areas, specialist species are in decline while generalists are becoming dominant (Barbaro & van Halder, 2009). This decline outlines the possible importance of researching functional groups, or groups which contribute to the same processes or functions of an ecosystem (Blondel, 2003). Categorization and analysis of these groups can provide insight into the heightened sensitivity of some groups over others. Functional

homogenization in ecosystems is to be avoided, as a variety of species with many varied traits contributes to increased resilience to disturbance and invasive pests. If only a few resilient generalists remain, these species could foreseeably be eliminated by disease or disturbance, and are also not able to contribute all of the ecosystem services of a diverse group (Perović et al., 2015). Potential categories for the seven taxa analyzed in this study (and links to heterogeneity variables) are presented in Table 6.1.

Table 6.1: Possible species groupings which could provide insight when analyzed in terms of the effects of landscape heterogeneity in farmland. These possible categorizations are not exhaustive, but could provide additional information to multi-taxa studies.

Taxon	Species groupings and definitions	Links to landscape heterogeneity
Birds	<p>Farmland specialists: Use specific farmland cover types</p> <p>Farmland generalists: Use multiple farmland cover types</p> <p>Other species: Species only incidentally in farmland</p>	Use of different land cover types in farmland (Kreuzberg, 2011)
Bees	Floral resources are often used, but bees can also be assessed in terms of nesting habits: cavities and stems, ground, hives, wood or parasite	Nesting habits are linked to available resources for nesting (or availability of other species for parasites) (Potts et al., 2005)
Butterflies	Mobility classes based on wing size, can split regional species into four classes: Mobile – very mobile, Moderately mobile, Sedentary, Very sedentary	Similar to above, can be used as a proxy for dispersal distance, and access to resources (compositional heterogeneity) (Sekar, 2012)
Syrphids	<p>Aphidophagus (generalists): Feeds on aphids or lice, considered generalists as they can use a variety of habitats.</p> <p>Saprohagus and phytophagus (specialists): Feed on decomposing matter and plant tissues, respectively. Considered specialists as they are usually found in non-crop habitat.</p>	Connected to land cover types in farmland, and availability of resources (Haenke et al., 2009)
Spiders	<p>Generalists: Species which use multiple habitat types</p> <p>Specialists: Species which prefer specific habitats</p>	Links to the importance of multiple available habitat types (Mallis & Hurd, 2005)
Carabids	<p>Macropterous: Large or long wings</p> <p>Brachypterous: Very reduced wings</p> <p>Dimorphic: Both long and short wings in the same species</p>	Proxy for flight ability and dispersal distance, which can be linked to accessible habitats in farmland (Fischer et al., 2013)
Plants	Native and non-native species, also the diversity of species groups	Would be of interest to farmers (more heterogeneity would be hypothesized to have less invasive species, and more diversity overall) (Honnay et al., 2003)

While researching effects on species groups is an attractive option for obtaining additional detail for the effects of landscape heterogeneity, life traits or behavioural components of species are not always easy to discern (Katayama et al., 2014). As an example, pollinators are often a group of interest in agricultural studies. The case for the use of functional traits for bees is strengthened by studies such as Frund et al. (2013), which found far more explanatory power when

using functional groupings rather than overall bee diversity. However, pollinator behavioural ecology is understudied (Colla & Packer, 2008). There are gaps in bee trait information that make these separations difficult. These gaps are related to research on bee resource use, finding bees and their hosts (when applicable) and species that are vastly understudied compared to others (Colla & Packer, 2008; Hoehn et al., 2008). In addition, floral resources are well studied, but nesting resources information is less prominent in research, and nesting habits are directly linked to landscape structure (Potts et al., 2005).

This difficulty in divisions based on functional traits is not only true of bee analyses. For butterflies, wingspan can be a problematic proxy for dispersal ability, but it is often the only trait information that is available for many species, and can only be used with cautious interpretation of results (Sekar, 2012). Improvements for these understudied traits would require significant expertise and resources.

Functional groups can also be used to link species in terms of their ecosystem function. For instance, plants can be distinguished in terms of their value to pollinators, which could inform on which groups of plants would be beneficial for bees at the landscape scale (Henriksen & Langer, 2013). Plants have previously been analysed in terms of their dispersal ability, as this trait has been found to be the most pertinent characteristic when looking at landscape effects and the ability for species to establish themselves in spite of landscape simplification (José-María et al., 2011). Combining functional trait use for analyses of function between species groups and for interactions with landscape heterogeneity would provide key details for how management of these landscapes could be improved.

Another area for future analysis for this dataset could possibly integrate edge data. Edge polygons were not included in this analysis, but could be integrated in terms of edge type and size. While this is not productive land, there are undoubtedly interactions with edge areas for many farmland species, and the management of these areas falls to the same decision-makers who implement crop types or adjust the size of fields (MacDonald & Johnson, 2000). A related area of study would be an analysis of differences in species distributions at edge and field-centre sampling sites. While sampling sites were placed in these areas, this study did not analyze differences in edge and field sites in terms of species diversity. Gabriel et al. (2011) found there to be more diversity near the edges of fields, which may be the case for our study area as well, and this may also be dependent on the types of fields which were sampled. These additional approaches for analysis would also provide further insight into landscape heterogeneity effects on species diversity in farmland in eastern Ontario.

6.4.3 Farmland management strategies

Policy and management strategies have the ability to positively influence biodiversity in agricultural areas. This is often inhibited by the perception that agricultural areas are standalone places with neutral or necessary negative impacts on biodiversity, and this needs to be rectified in order to make meaningful change (Scherr & McNeely, 2008). As an example of successful policy alterations, the monitoring of British breeding birds has resulted in significant policy and management change. These improvements are due to the breadth of the study, the repeated evidence that bird populations were declining in farmlands, and the regional consistency of findings (Greenwood, 2003). These consistent and repeated findings enabled science to be linked to policy in order to attempt to reverse the decline of farmland bird populations.

In spite of examples of policy successes, some aspects of landscape structure continue to be altered in contradiction of findings which outline the negative effects on biodiversity. The trend towards expansion of field sizes in agricultural areas in North America and Europe, for example, has continued in recent decades. Regardless of increasingly unanimous research in Europe outlining that organic farming practices and a variety of field cover types are two ways to enhance biodiversity, there is still a trend towards enlargement of fields and reduction of crop diversity (Belfrage et al., 2014). In this case, farm size is also suspected to be linked to farm practices (larger farms typically use more chemicals or large machinery for management), so if smaller field sizes are recommended and implemented, this will likely have an effect on regional farming practices. No matter the practices implemented by individual farmers, the number of species experiencing negative effects of field cover type simplification and expansion far outweighs those experiencing positive effects (Singh et al., 2010). Perović et al. (2015) outlined that not having enough types of fields will have a negative effect on species diversity, but not having smaller fields will have the much more serious consequence of eradicating entire groups that are not well adapted to agricultural areas. Despite these repeated findings, configurational heterogeneity is often neglected in plans, and the focus is typically at the scale of improvements that can be made for one farm (Perović et al., 2015).

The effectiveness (or ineffectiveness) of policy or management recommendations may be a reflection of the context in which benefits are presented, or the scale at which action is recommended. As an example, homogenous agricultural areas have not only been found to be detrimental for many species, but these areas are also more susceptible to the spread of fire (Vega-García & Chuvieco, 2006). In addition, many policies regulate at the field scale, but not at the landscape scale, which can make regional efforts ineffective overall (Burel et al., 1998).

Collaborative efforts between landscape ecologists and remote sensing specialists are required to rectify these management strategy shortcomings, which involves using biologically relevant indicators and reporting on thematic error when making maps for looking at landscape effects (Newton et al., 2009). Transparency and clarity in the presentation of findings can aid in an ease of translation into implementable management action.

It is recommended that regional examples of scientific evidence be presented to encourage and facilitate improvements in eastern Ontario farmland. Solutions must be replicable, and the benefits to biodiversity must be clear (Kumaraswamy & Kunte, 2013). Studies such as this one aid in identifying areas of focus, and support previous findings on the main components of landscape heterogeneity that should be addressed if biodiversity conservation is a priority for farmland management. In addition, few studies present the benefits of ecosystem services in agricultural settings that might encourage conservation action and tangible incentives to alter current landscape layouts (Bommarco et al., 2012). Regional examples of success and assessed benefits of biodiversity would aid in implementing evidence-based solutions in eastern Ontario farmland.

7.0 Conclusion

This study assessed landscape heterogeneity in eastern Ontario related to birds, bees, butterflies, syrphids, spiders, carabids, and plants previously surveyed in 2011 and 2012 at 93 study landscapes (1, 2 and 3 km extents). Landscape metrics were evaluated based on representing aspects of compositional and configurational heterogeneity (or elements of both). Random forest regression was used to identify landscape metrics of importance for each taxon and overall metrics which responded consistently across all groups. For the taxa level analysis, it was found that metrics were of most importance at the 1 km extent, and varied across groups. This variation in metrics of most importance is expected to be due to differing interactions with agricultural landscape heterogeneity, and these metrics and findings were aligned with similar previous findings in the literature. Across taxa, mean field size was found to have the most consistent response, which was negative with the exception of carabid abundance. However, although the percentage of like adjacencies was found to have a less consistent direction of effects and a significant positive correlation with mean field size, the mostly negative response to this metric was often stronger than that of mean field size. Also, when random forest regression was performed using only the four main variables, the percentage of like adjacencies was found to be the most important metric for 20 of the 27 biodiversity variables. This finding asserts the importance of a variable distribution of field cover types, even in landscapes where only a few field cover types dominate. In other words, mean field size and the percentage of like adjacencies show that configurational and compositional heterogeneity matter for biodiversity in eastern Ontario farmland.

Bird groups were also assessed using random forest regression with landscape metrics since their response at the taxon level was not as consistent across biodiversity variables as other

taxa. Birds were split into farmland specialists, generalists, and other bird species. The response of farmland bird specialists and other bird species to selected metrics implied that access to habitat types was important, given that the radius of gyration (a measure of patch complexity and extensiveness) affected both of these groups negatively at the 1 km extent. Farmland generalist species responded to landscape complexity through the relation with contiguity at the 2 km extent, which may be attributable to their use of multiple land cover types at larger scales. An analysis of habitat preferences in these groups would be beneficial for improved information on interpretations of why these metrics were selected as most important for these groups. However, the assumption these groups may be responding as categorical groups, and at differing scales was confirmed through the distinct pattern in response across biodiversity variables.

Finally, the comparison of results obtained with field data versus the AAFC Annual Crop Inventory revealed that the generalization (and often combination) of fields of the same type had significant effects on landscape metric outputs. While overall patterns were distinguishable in graphed trends, the value differences were too large to substitute this dataset for the original high resolution land cover maps in order to replicate results at smaller time intervals. The use of alternative data sources for re-analysis of the sites will require a dataset with truer delineations of field boundaries, or a repeated assessment of sites with the original methodology.

Studies that inform on biodiversity response to landscape heterogeneity can reveal regional patterns that can then be addressed in management strategies. This study found that if biodiversity conservation is important to farmland planning and management in eastern Ontario, field sizes should not only be smaller, but field cover types should also be variably distributed wherever possible.

8.0 References

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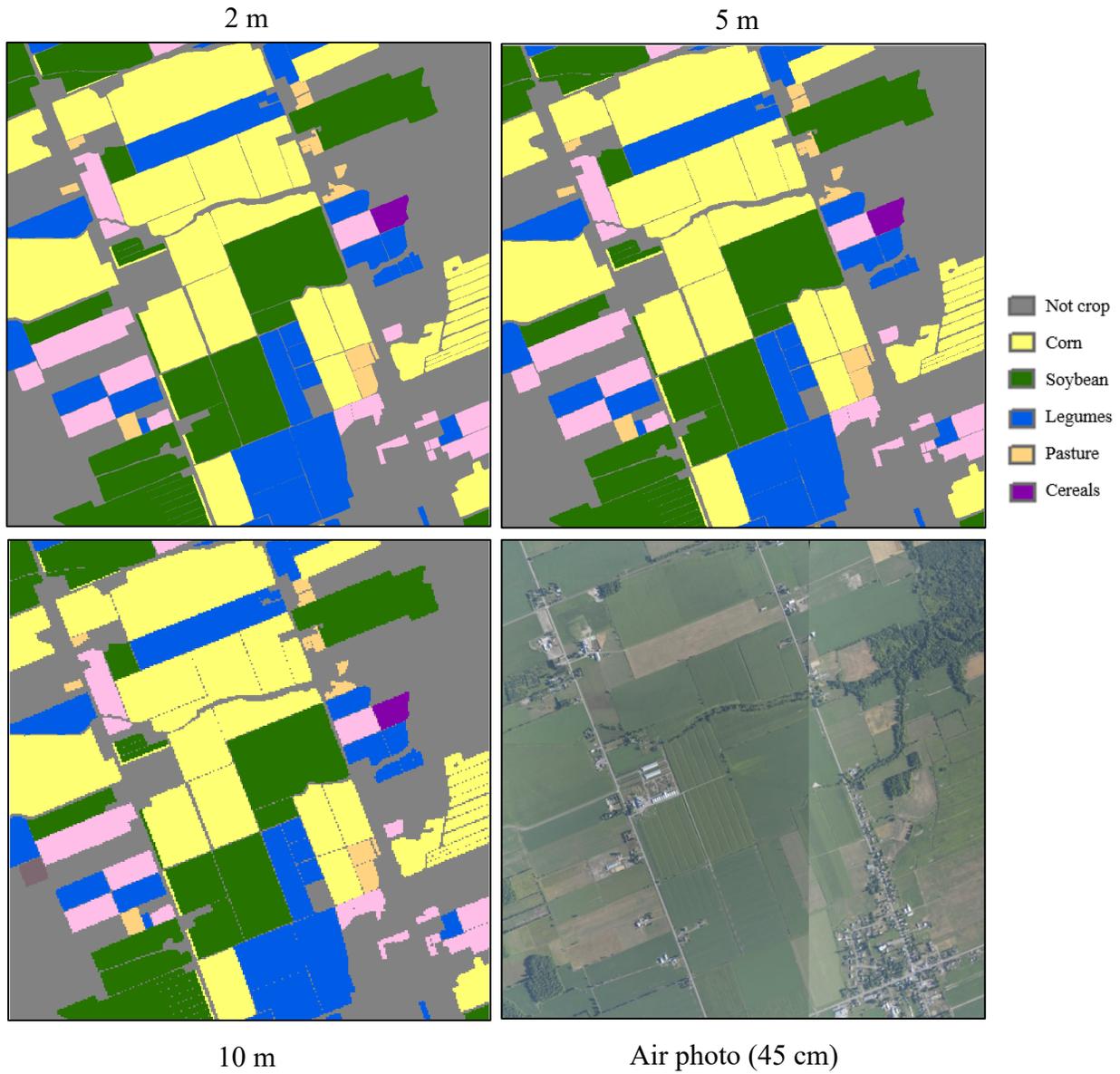
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9.0 Appendix

Appendix A: Visual representation of different cell sizes which were tested. Larger cell sizes were found to combine fields and have an effect on landscape metric output values. This figure shows the 3 km extent of site HH22.



Appendix B: Class types were re-assigned integer values for Fragstats metric calculations.

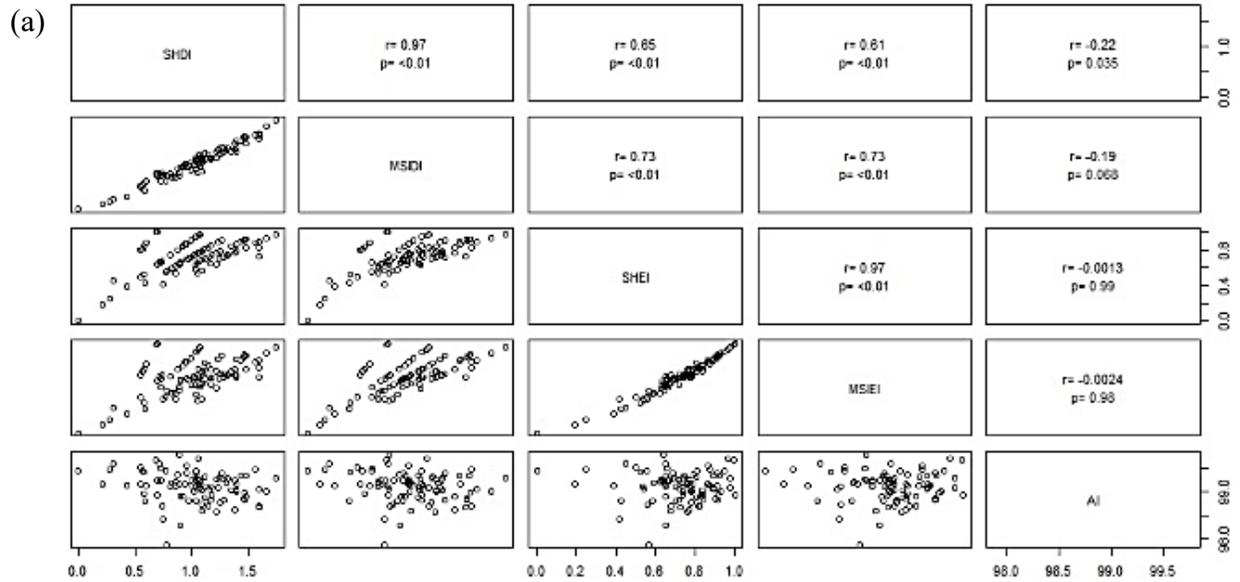
Class name	Integer value	Class name	Integer value
notcrop / unknown	0	mixed vegetable	8
corn	1	cereal	9
hay / hay unknown	2	strawberry	10
pasture	3	sod	11
soybean	4	sunflower	12
legumes	5	canola	13
fallow	6	peas	14
apple	7		

Appendix C: Land use descriptions established prior to this study for the Strategic Project data (Kirby, 2015). Those identified as a “field” in the land use column are those which were used for this analysis. For the AAFC comparison, pasture, legumes, and hay were combined in order to match the description in the AAFC Product Specifications.

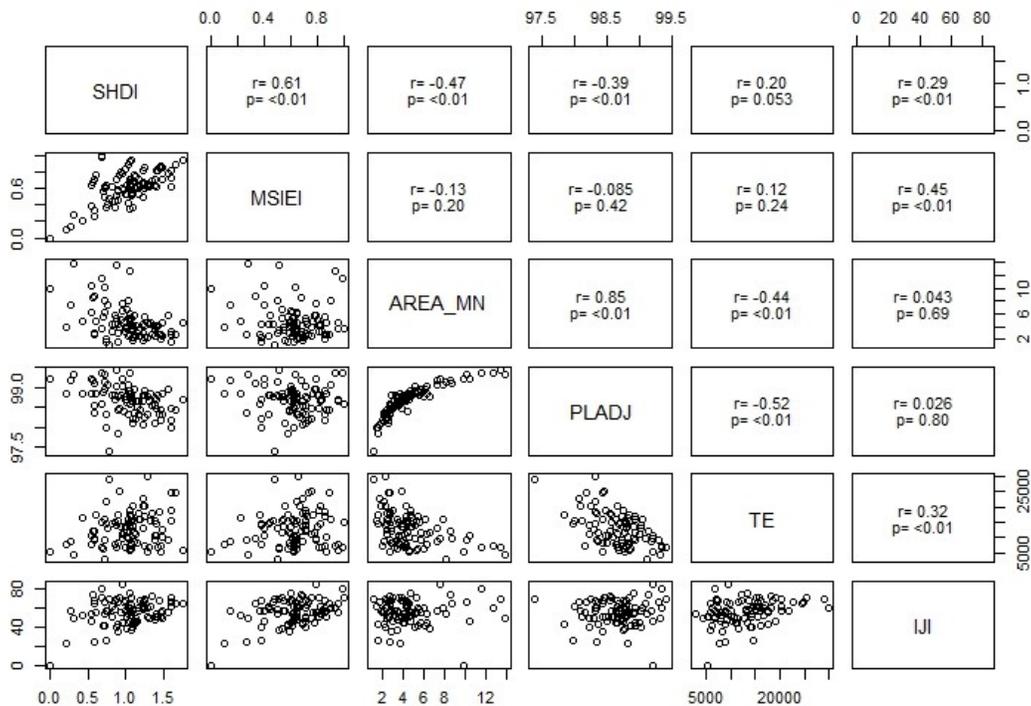
Land use	Crop type	Description
abandoned	abandoned	Abandoned agriculture that is at least partially overgrown with woody vegetation
clearcut	clearcut	A clear cut area that was previously forested
development	development	Land cleared for residential development, or residential construction in progress
driveway	driveway	Driveway leading to residence or business
edge	edge	Edge between adjoining fields. Includes hedgerows, ditches, fence lines and areas of unplanted land between adjacent crops
farmhouse	farmhouse	Residence with at least one outbuilding. Includes associated lawns and vegetation.
field	apple	Apple orchard
field	canola	Agricultural field planted with canola
field	cereal	Agricultural field planted with cereal. Primarily spring wheat, also barley, oats, etc.
field	corn	Agricultural field planted with corn
field	fallow	Agricultural field not planted with crop in previous year
field	hay	Agricultural field planted with approximately >75% grass hay
field	legumes	Agricultural field planted with alfalfa and or clover with <75% grass hay
field	mixed vegetable	Agricultural field planted with vegetables
field	pasture	Pasture land - animals seen grazing or evidence of animals (manure or active electrical fences) present
field	peas	Agricultural field planted with peas
field	sod	Sod crop
field	soybean	Agricultural field planted with soybean
field	strawberry	Agricultural field planted with strawberries
field	sunflower	Agricultural field planted with sunflower
field	unknown	Agricultural field planted with unknown crop
forest	forest	Forested area, also includes forested swamps
golf course	golf course	Includes all land and vegetation associated with golf course
horsetrack	horsetrack	Non-vegetated circuit used for horses
house	house	Residence with no outbuildings. Includes associated lawns and vegetation

industrial	industrial	Primarily paved or cleared and used for industry/commerce
institution	institution	Includes schools and similar institutional buildings
other	other	Other land uses not mentioned elsewhere (e.g. rough grass, powerlines, cemeteries) and unknown land uses
quarry	quarry	N/A
railway	railway	N/A
riparian/wetland	riparian/wetland	Wetlands and vegetation alongside streams/rivers/ponds
road	road	N/A
trail	trail	Walking trail
verge	verge	Strips of roadside vegetation between crop fields and roads
water	water	Includes streams, rivers, ponds etc. Only digitized when at least 10 metres wide

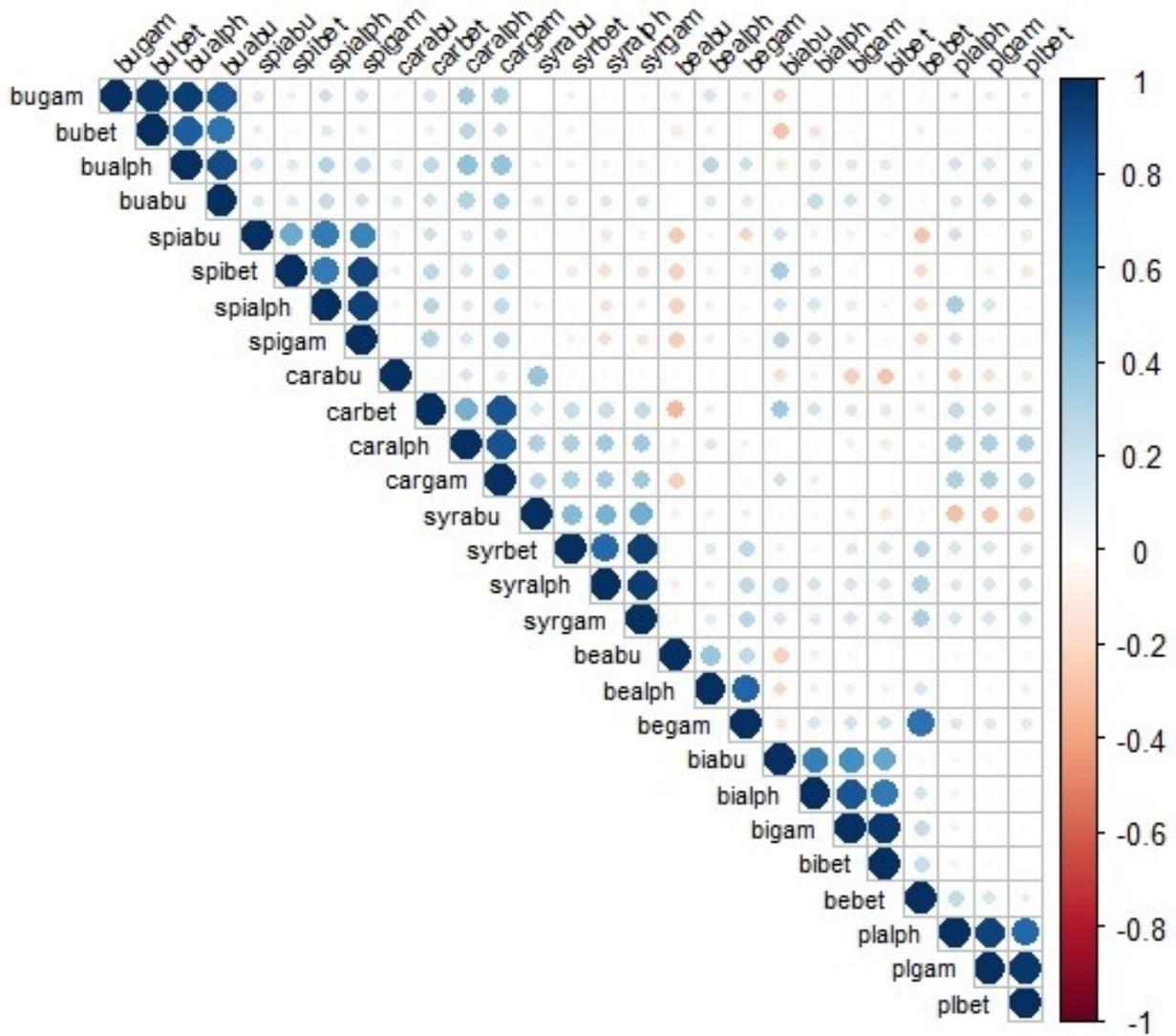
Appendix D: A subset of the scatterplot matrices used to observe the correlations between metrics in order to eliminate those which represented similar (or exact) elements of landscape structure for a parsimonious list of landscape metrics (SHDI= Shannon Diversity Index, MSIDI = Modified Simpson’s Diversity Index, SHEI= Shannon Evenness Index, MSIEI = Modified Simpson’s Evenness Index, AI = Aggregation Index).



(b) Additional subset of correlation plots for the six main landscape metrics found to be consistently identified as important across biodiversity variables in the initial RFR analysis (AREA_MN = Mean field size, PLADJ = Percentage of like adjacencies, TE = Total Edge, IJI = Interspersion and juxtaposition index).



Appendix E: Correlation information for all biodiversity variables. Larger circles represent higher correlation coefficients, as well as blue or red for positive and negative correlations, respectively. Biodiversity variable syntax is as follows: first three letters of taxon (butterflies, spiders, carabids, syrphids, bees, birds, and plants) followed by first 3-4 letters of diversity measure (gamma, beta, alpha and abundance).



Appendix F: Correlation tables for all 30 retained metrics for this study. R values above or below +/- 0.75(used as an indicator value for metric elimination) are represented in dark grey shading.

Metric	GYRATE_MN	GYRATE_AM	GYRATE_MD	GYRATE_RA	GYRATE_SD	GYRATE_CV	SHAPE_MN
NP	-0.85	-0.73	-0.66	-0.32	-0.64	0.03	-0.05
LPI	0.60	0.88	0.24	0.72	0.75	0.42	-0.04
TE	-0.01	0.06	-0.19	0.10	0.12	0.17	0.25
LSI	-0.01	0.06	-0.19	0.10	0.12	0.17	0.25
AREA_MN	0.92	0.83	0.64	0.39	0.70	0.02	-0.12
AREA_AM	0.69	0.93	0.29	0.65	0.83	0.40	-0.06
AREA_MD	0.76	0.33	0.87	-0.05	0.14	-0.48	-0.20
AREA_RA	0.58	0.88	0.21	0.74	0.76	0.45	-0.03
AREA_SD	0.72	0.93	0.32	0.64	0.85	0.37	-0.04
AREA_CV	-0.19	0.41	-0.48	0.61	0.39	0.80	0.07
GYRATE_MN	1.00	0.78	0.82	0.37	0.65	-0.13	0.13
GYRATE_AM	0.78	1.00	0.37	0.77	0.94	0.47	0.12
GYRATE_MD	0.82	0.37	1.00	0.00	0.22	-0.49	0.13
GYRATE_RA	0.37	0.77	0.00	1.00	0.82	0.73	0.18
GYRATE_SD	0.65	0.94	0.22	0.82	1.00	0.63	0.20
GYRATE_CV	-0.13	0.47	-0.49	0.73	0.63	1.00	0.08
SHAPE_MN	0.13	0.12	0.13	0.18	0.20	0.08	1.00
SHAPE_AM	0.01	0.09	-0.06	0.25	0.19	0.23	0.83
SHAPE_MD	0.17	0.16	0.20	0.19	0.23	0.08	0.86
SHAPE_RA	-0.18	-0.13	-0.24	0.06	-0.02	0.17	0.60
SHAPE_SD	0.04	0.07	-0.06	0.18	0.17	0.18	0.74
SHAPE_CV	0.00	0.04	-0.11	0.16	0.14	0.19	0.65
CIRCLE_MN	0.40	0.36	0.37	0.29	0.39	0.08	0.70
CIRCLE_AM	0.12	0.11	0.09	0.31	0.22	0.20	0.61
CIRCLE_MD	0.35	0.34	0.31	0.35	0.38	0.11	0.64
CIRCLE_RA	-0.43	-0.39	-0.32	-0.13	-0.27	0.07	0.02
CIRCLE_SD	-0.22	-0.17	-0.17	0.04	-0.07	0.15	-0.02
CIRCLE_CV	-0.30	-0.25	-0.26	-0.05	-0.17	0.11	-0.22
CONTIG_MN	0.44	0.27	0.38	-0.07	0.09	-0.37	-0.04
CONTIG_AM	0.79	0.84	0.52	0.52	0.76	0.24	-0.19
CONTIG_MD	0.64	0.24	0.73	-0.02	0.15	-0.50	-0.28
CONTIG_RA	-0.39	-0.35	-0.27	-0.01	-0.20	0.13	-0.02
CONTIG_SD	-0.33	-0.27	-0.24	0.06	-0.11	0.20	-0.03
CONTIG_CV	-0.33	-0.26	-0.24	0.06	-0.10	0.21	-0.03
CONTAG	-0.13	-0.12	-0.05	-0.07	-0.16	-0.03	-0.06
PLADJ	0.80	0.83	0.54	0.51	0.74	0.21	-0.20
COHESION	0.84	0.89	0.55	0.59	0.82	0.28	0.04
DIVISION	-0.69	-0.90	-0.31	-0.64	-0.80	-0.36	0.11
PR	-0.50	-0.44	-0.39	-0.17	-0.42	-0.01	0.03
SHDI	-0.36	-0.43	-0.19	-0.23	-0.41	-0.15	0.01
MSIDI	-0.31	-0.41	-0.13	-0.24	-0.38	-0.18	-0.01
SHEI	-0.03	-0.22	0.12	-0.17	-0.21	-0.21	-0.09
MSIEI	-0.02	-0.20	0.13	-0.17	-0.19	-0.21	-0.10
AI	0.76	0.79	0.51	0.46	0.69	0.19	-0.22

Metric	SHAPE _AM	SHAPE _MD	SHAPE _RA	SHAPE _SD	SHAPE _CV	CIRCLE _MN	CIRCLE _AM
NP	0.05	-0.11	0.26	0.03	0.05	-0.31	0.01
LPI	-0.07	0.02	-0.21	-0.05	-0.08	0.11	-0.18
TE	0.15	0.02	0.62	0.64	0.64	0.01	0.11
LSI	0.15	0.02	0.62	0.64	0.64	0.01	0.11
AREA_MN	-0.20	-0.04	-0.29	-0.12	-0.13	0.16	-0.16
AREA_AM	-0.10	0.01	-0.23	-0.07	-0.09	0.13	-0.20
AREA_MD	-0.29	-0.15	-0.31	-0.20	-0.20	0.07	-0.10
AREA_RA	-0.05	0.04	-0.20	-0.05	-0.07	0.11	-0.18
AREA_SD	-0.09	0.04	-0.23	-0.06	-0.08	0.15	-0.19
AREA_CV	0.17	0.06	0.06	0.09	0.07	0.02	-0.02
GYRATE_MN	0.01	0.17	-0.18	0.04	0.00	0.40	0.12
GYRATE_AM	0.09	0.16	-0.13	0.07	0.04	0.36	0.11
GYRATE_MD	-0.06	0.20	-0.24	-0.06	-0.11	0.37	0.09
GYRATE_RA	0.25	0.19	0.06	0.18	0.16	0.29	0.31
GYRATE_SD	0.19	0.23	-0.02	0.17	0.14	0.39	0.22
GYRATE_CV	0.23	0.08	0.17	0.18	0.19	0.08	0.20
SHAPE_MN	0.83	0.86	0.60	0.74	0.65	0.70	0.61
SHAPE_AM	1.00	0.68	0.51	0.62	0.56	0.49	0.62
SHAPE_MD	0.68	1.00	0.33	0.44	0.35	0.67	0.53
SHAPE_RA	0.51	0.33	1.00	0.93	0.94	0.19	0.37
SHAPE_SD	0.62	0.44	0.93	1.00	0.99	0.38	0.45
SHAPE_CV	0.56	0.35	0.94	0.99	1.00	0.30	0.41
CIRCLE_MN	0.49	0.67	0.19	0.38	0.30	1.00	0.69
CIRCLE_AM	0.62	0.53	0.37	0.45	0.41	0.69	1.00
CIRCLE_MD	0.47	0.70	0.23	0.36	0.31	0.88	0.67
CIRCLE_RA	0.07	0.06	0.42	0.25	0.30	-0.26	0.07
CIRCLE_SD	0.03	0.04	0.28	0.21	0.25	-0.25	0.02
CIRCLE_CV	-0.11	-0.15	0.19	0.07	0.13	-0.52	-0.18
CONTIG_MN	-0.15	-0.11	-0.29	-0.17	-0.21	0.11	-0.13
CONTIG_AM	-0.25	-0.09	-0.36	-0.18	-0.18	0.14	-0.14
CONTIG_MD	-0.31	-0.16	-0.47	-0.36	-0.36	0.01	-0.16
CONTIG_RA	0.08	0.06	0.30	0.12	0.17	-0.20	0.08
CONTIG_SD	0.09	0.07	0.25	0.12	0.17	-0.17	0.11
CONTIG_CV	0.09	0.07	0.25	0.13	0.17	-0.17	0.11
CONTAG	-0.07	-0.03	0.02	-0.02	-0.03	-0.29	-0.27
PLADJ	-0.26	-0.10	-0.37	-0.18	-0.18	0.16	-0.13
COHESION	0.01	0.10	-0.23	-0.01	-0.03	0.31	0.04
DIVISION	0.15	0.03	0.24	0.09	0.10	-0.10	0.22
PR	0.06	-0.01	0.24	0.09	0.10	-0.21	0.02
SHDI	0.02	0.00	0.16	0.06	0.08	-0.09	0.16
MSIDI	-0.01	-0.02	0.12	0.03	0.05	-0.07	0.16
SHEI	-0.10	-0.07	-0.01	-0.03	0.00	0.05	0.20
MSIEI	-0.12	-0.09	-0.03	-0.04	-0.02	0.05	0.18
AI	-0.29	-0.12	-0.37	-0.19	-0.19	0.14	-0.14

Metric	CIRCLE_MD	CIRCLE_RA	CIRCLE_SD	CIRCLE_CV	CONTIG_MN	CONTIG_AM	CONTIG_MD	CONTIG_RA	CONTIG_SD
NP	-0.23	0.51	0.29	0.34	-0.42	-0.86	-0.62	0.45	0.35
LPI	0.12	-0.38	-0.17	-0.18	0.32	0.74	0.19	-0.36	-0.31
TE	0.03	0.10	0.03	0.02	0.02	-0.02	-0.27	-0.04	-0.03
LSI	0.03	0.10	0.03	0.02	0.02	-0.02	-0.27	-0.04	-0.03
AREA_MN	0.14	-0.42	-0.20	-0.22	0.40	0.85	0.56	-0.38	-0.31
AREA_AM	0.14	-0.39	-0.18	-0.19	0.31	0.80	0.24	-0.36	-0.30
AREA_MD	0.04	-0.33	-0.18	-0.19	0.39	0.55	0.77	-0.27	-0.24
AREA_RA	0.13	-0.37	-0.16	-0.17	0.30	0.73	0.17	-0.35	-0.30
AREA_SD	0.16	-0.39	-0.17	-0.19	0.31	0.82	0.28	-0.36	-0.29
AREA_CV	0.01	-0.09	-0.04	-0.04	-0.10	0.15	-0.55	-0.09	-0.06
GYRATE_MN	0.35	-0.43	-0.22	-0.30	0.44	0.79	0.64	-0.39	-0.33
GYRATE_AM	0.34	-0.39	-0.17	-0.25	0.27	0.84	0.24	-0.35	-0.27
GYRATE_MD	0.31	-0.32	-0.17	-0.26	0.38	0.52	0.73	-0.27	-0.24
GYRATE_RA	0.35	-0.13	0.04	-0.05	-0.07	0.52	-0.02	-0.01	0.06
GYRATE_SD	0.38	-0.27	-0.07	-0.17	0.09	0.76	0.15	-0.20	-0.11
GYRATE_CV	0.11	0.07	0.15	0.11	-0.37	0.24	-0.50	0.13	0.20
SHAPE_MN	0.64	0.02	-0.02	-0.22	-0.04	-0.19	-0.28	-0.02	-0.03
SHAPE_AM	0.47	0.07	0.03	-0.11	-0.15	-0.25	-0.31	0.08	0.09
SHAPE_MD	0.70	0.06	0.04	-0.15	-0.11	-0.09	-0.16	0.06	0.07
SHAPE_RA	0.23	0.42	0.28	0.19	-0.29	-0.36	-0.47	0.30	0.25
SHAPE_SD	0.36	0.25	0.21	0.07	-0.17	-0.18	-0.36	0.12	0.12
SHAPE_CV	0.31	0.30	0.25	0.13	-0.21	-0.18	-0.36	0.17	0.17
CIRCLE_MN	0.88	-0.26	-0.25	-0.52	0.11	0.14	0.01	-0.20	-0.17
CIRCLE_AM	0.67	0.07	0.02	-0.18	-0.13	-0.14	-0.16	0.08	0.11
CIRCLE_MD	1.00	-0.05	-0.04	-0.29	-0.08	0.12	0.00	0.03	0.07
CIRCLE_RA	-0.05	1.00	0.84	0.82	-0.69	-0.46	-0.36	0.76	0.73
CIRCLE_SD	-0.04	0.84	1.00	0.95	-0.64	-0.23	-0.24	0.61	0.64
CIRCLE_CV	-0.29	0.82	0.95	1.00	-0.60	-0.24	-0.22	0.60	0.62
CONTIG_MN	-0.08	-0.69	-0.64	-0.60	1.00	0.31	0.45	-0.88	-0.94
CONTIG_AM	0.12	-0.46	-0.23	-0.24	0.31	1.00	0.55	-0.37	-0.26
CONTIG_MD	0.00	-0.36	-0.24	-0.22	0.45	0.55	1.00	-0.27	-0.25
CONTIG_RA	0.03	0.76	0.61	0.60	-0.88	-0.37	-0.27	1.00	0.97
CONTIG_SD	0.07	0.73	0.64	0.62	-0.94	-0.26	-0.25	0.97	1.00
CONTIG_CV	0.07	0.74	0.66	0.64	-0.95	-0.25	-0.26	0.96	1.00
CONTAG	-0.29	0.05	0.00	0.08	0.05	-0.06	-0.01	0.02	-0.02
PLADJ	0.13	-0.47	-0.23	-0.25	0.33	1.00	0.57	-0.38	-0.27
COHESION	0.27	-0.46	-0.22	-0.28	0.30	0.96	0.49	-0.38	-0.26
DIVISION	-0.12	0.35	0.13	0.14	-0.30	-0.80	-0.29	0.32	0.27
PR	-0.16	0.28	0.11	0.15	-0.14	-0.48	-0.35	0.24	0.15
SHDI	-0.03	0.24	0.17	0.16	-0.09	-0.40	-0.16	0.16	0.11
MSIDI	-0.01	0.24	0.20	0.17	-0.10	-0.36	-0.09	0.15	0.12
SHEI	0.07	0.08	0.13	0.08	0.02	-0.11	0.15	0.00	0.01
MSIEI	0.08	0.09	0.16	0.10	-0.01	-0.10	0.16	0.01	0.03
AI	0.10	-0.47	-0.23	-0.25	0.35	0.97	0.55	-0.39	-0.29

Metric	CONTIG _CV	CONTAG	PLADJ	COHSN	DIVISION	PR	SHDI	MSIDI	SHEI	MSIEI	AI
NP	0.35	0.10	-0.87	-0.91	0.61	0.55	0.41	0.36	0.08	0.07	-0.86
LPI	-0.31	0.07	0.73	0.75	-0.93	-0.31	-0.39	-0.39	-0.26	-0.26	0.70
TE	-0.03	0.09	-0.03	0.02	0.01	0.11	0.01	-0.02	-0.09	-0.10	-0.02
LSI	-0.03	0.09	-0.03	0.02	0.01	0.11	0.01	-0.02	-0.09	-0.10	-0.02
AREA_MN	-0.31	-0.08	0.85	0.84	-0.86	-0.53	-0.47	-0.41	-0.16	-0.13	0.81
AREA_AM	-0.30	-0.02	0.79	0.80	-0.98	-0.41	-0.47	-0.45	-0.29	-0.26	0.75
AREA_MD	-0.24	0.00	0.56	0.51	-0.35	-0.38	-0.22	-0.16	0.10	0.10	0.54
AREA_RA	-0.29	0.07	0.72	0.74	-0.93	-0.30	-0.38	-0.39	-0.27	-0.27	0.69
AREA_SD	-0.29	-0.04	0.81	0.82	-0.98	-0.44	-0.48	-0.46	-0.28	-0.25	0.76
AREA_CV	-0.06	0.14	0.13	0.19	-0.37	0.13	-0.09	-0.17	-0.26	-0.29	0.13
GYRATE_MN	-0.33	-0.13	0.80	0.84	-0.69	-0.50	-0.36	-0.31	-0.03	-0.02	0.76
GYRATE_AM	-0.26	-0.12	0.83	0.89	-0.90	-0.44	-0.43	-0.41	-0.22	-0.20	0.79
GYRATE_MD	-0.24	-0.05	0.54	0.55	-0.31	-0.39	-0.19	-0.13	0.12	0.13	0.51
GYRATE_RA	0.06	-0.07	0.51	0.59	-0.64	-0.17	-0.23	-0.24	-0.17	-0.17	0.46
GYRATE_SD	-0.10	-0.16	0.74	0.82	-0.80	-0.42	-0.41	-0.38	-0.21	-0.19	0.69
GYRATE_CV	0.21	-0.03	0.21	0.28	-0.36	-0.01	-0.15	-0.18	-0.21	-0.21	0.19
SHAPE_MN	-0.03	-0.06	-0.20	0.04	0.11	0.03	0.01	-0.01	-0.09	-0.10	-0.22
SHAPE_AM	0.09	-0.07	-0.26	0.01	0.15	0.06	0.02	-0.01	-0.10	-0.12	-0.29
SHAPE_MD	0.07	-0.03	-0.10	0.10	0.03	-0.01	0.00	-0.02	-0.07	-0.09	-0.12
SHAPE_RA	0.25	0.02	-0.37	-0.23	0.24	0.24	0.16	0.12	-0.01	-0.03	-0.37
SHAPE_SD	0.13	-0.02	-0.18	-0.01	0.09	0.09	0.06	0.03	-0.03	-0.04	-0.19
SHAPE_CV	0.17	-0.03	-0.18	-0.03	0.10	0.10	0.08	0.05	0.00	-0.02	-0.19
CIRCLE_MN	-0.17	-0.29	0.16	0.31	-0.10	-0.21	-0.09	-0.07	0.05	0.05	0.14
CIRCLE_AM	0.11	-0.27	-0.13	0.04	0.22	0.02	0.16	0.16	0.20	0.18	-0.14
CIRCLE_MD	0.07	-0.29	0.13	0.27	-0.12	-0.16	-0.03	-0.01	0.07	0.08	0.10
CIRCLE_RA	0.74	0.05	-0.47	-0.46	0.35	0.28	0.24	0.24	0.08	0.09	-0.47
CIRCLE_SD	0.66	0.00	-0.23	-0.22	0.13	0.11	0.17	0.20	0.13	0.16	-0.23
CIRCLE_CV	0.64	0.08	-0.25	-0.28	0.14	0.15	0.16	0.17	0.08	0.10	-0.25
CONTIG_MN	-0.95	0.05	0.33	0.30	-0.30	-0.14	-0.09	-0.10	0.02	-0.01	0.35
CONTIG_AM	-0.25	-0.06	1.00	0.96	-0.80	-0.48	-0.40	-0.36	-0.11	-0.10	0.97
CONTIG_MD	-0.26	-0.01	0.57	0.49	-0.29	-0.35	-0.16	-0.09	0.15	0.16	0.55
CONTIG_RA	0.96	0.02	-0.38	-0.38	0.32	0.24	0.16	0.15	0.00	0.01	-0.39
CONTIG_SD	1.00	-0.02	-0.27	-0.26	0.27	0.15	0.11	0.12	0.01	0.03	-0.29
CONTIG_CV	1.00	-0.03	-0.27	-0.26	0.26	0.14	0.11	0.11	0.01	0.04	-0.28
CONTAG	-0.03	1.00	-0.08	-0.09	0.00	0.16	-0.23	-0.33	-0.40	-0.48	-0.12
PLADJ	-0.27	-0.08	1.00	0.96	-0.79	-0.49	-0.39	-0.35	-0.10	-0.09	0.98
COHESION	-0.26	-0.09	0.96	1.00	-0.77	-0.50	-0.41	-0.38	-0.13	-0.12	0.93
DIVISION	0.26	0.00	-0.79	-0.77	1.00	0.39	0.42	0.40	0.22	0.20	-0.74
PR	0.14	0.16	-0.49	-0.50	0.39	1.00	0.77	0.66	0.10	0.05	-0.34
SHDI	0.11	-0.23	-0.39	-0.41	0.42	0.77	1.00	0.97	0.65	0.61	-0.22
MSIDI	0.11	-0.33	-0.35	-0.38	0.40	0.66	0.97	1.00	0.73	0.73	-0.19
SHEI	0.01	-0.40	-0.10	-0.13	0.22	0.10	0.65	0.73	1.00	0.97	0.00
MSIEI	0.04	-0.48	-0.09	-0.12	0.20	0.05	0.61	0.73	0.97	1.00	0.00
AI	-0.28	-0.12	0.98	0.93	-0.74	-0.34	-0.22	-0.19	0.00	0.00	1.00

Appendix G: Metrics which were eliminated from this study, either in pre-analysis (typically due to subjective values needed), and correlation analysis (statistically significant correlation of 0.75 or more with a metric which described a similar component of landscape structure)(McGarigal, 2014).

Eliminated metric	Stage Eliminated	Reason for Eliminating
Total Area (TA)	Pre-analysis	Useful for preliminary analyses, but total area will be the same in all cases.
Edge Density (ED)	Pre-analysis	Since the landscape sizes will all be the same (and comparable) this will be the same as total edge for my purposes, and will be redundant.
Perimeter-Area Fractal Dimension (PAFRAC)	Pre-analysis	Radius of gyration calculates a similar value (based on shape complexity) and this metric has the caveat that there should be many patches in the landscape for it to work well.
Perimeter-Area Ratio Distribution (PARA_MN, _AM, _MD, _RA, _SD, _CV)	Pre-analysis	The issues with this metric are resolved by SHAPE, so SHAPE has been selected over this one.
Fractal Index Distribution (FRAC_MN, _AM, _MD, _RA, _SD, _CV)	Pre-analysis	Complexity of shapes is covered by other metrics in a format easier to interpret.
Total Core Area (TCA)	Pre-analysis	Would be the correlated with total area if edge is held constant.
Number of Disjunct Core Areas (NDCA)	Pre-analysis	Core area is subjective - dependent on user settings and different patch types.
Disjunct Core Area Density (DCAD)	Pre-analysis	Same as NDCA.
Core Area Distribution (CORE_MN, _AM, _MD, _RA, _SD, _CV)	Pre-analysis	Same as NDCA.
Disjunct Core Area Distribution (DCORE_MN, _AM, _MD, _RA, _SD, _CV)	Pre-analysis	Same as NDCA.
Core Area Index Distribution (CAI_MN, _AM, _MD, _RA, _SD, _CV)	Pre-analysis	Same as NDCA.
Contrast-Weighted Edge Density (CWED)	Pre-analysis	Removed as this is both composition and configuration. Also weighted by patch types (subjective).

Total Edge Contrast Index (TECI)	Pre-analysis	Removed as this is both composition and configuration. Also has to do with the contrast of patch types.
Edge Contrast Index Distribution (ECON_MN, _AM, _MD, _RA, _SD, _CV)	Pre-analysis	Removed as this is both composition and configuration. Also has to do with the contrast of patch types.
Patch Density (PD)	Pre-analysis	Not relevant for my study since all of the extents will be comparable (held constant) for the three study extents. Will be the same idea as number of patches.
Splitting Index (SPLIT)	Pre-analysis	Difficult to interpret - addressed by other metrics.
Effective Mesh Size (MESH)	Pre-analysis	This is already addressed by Division.
Euclidean Nearest Neighbor Distance Distribution (ENN_MN, _AM, _MD, _RA, _SD, _CV)	Pre-analysis	Removed as this is both composition and configuration. Useful for distance between habitat patches.
Proximity Index Distribution (PROX_MN, _AM, _MD, _RA, _SD, _CV)	Pre-analysis	Removed as this is both composition and configuration. Useful for distance between habitat patches.
Similarity Index Distribution (SIMI_MN, _AM, _MD, _RA, _SD, _CV)	Pre-analysis	Removed as this is both composition and configuration. Also considers similarity of patch types, which is subjective.
Connectance (CONNECT)	Pre-analysis	Removed as this is both composition and configuration. Looks at connections in a user defined distance - which is subjective.
Patch Richness Density (PRD)	Pre-analysis	Not relevant for my study since all of the extents will be comparable (held constant) for the three study extents. Will be the same idea as patch richness.
Relative Patch Richness (RPR)	Pre-analysis	Only has interpretive value, and is redundant.

Simpson's Diversity Index (SIDI)	Pre-analysis	Decision made to only keep modified Simpson's (instead of both) since it makes the results comparable with the general class of evenness indices (as outlined by Modified Simpson's notes).
Simpson's Evenness Index (SIEI)	Pre-analysis	Same reasoning as Simpson's – retaining only the modified version (even though simple interpretation is lost).
Patch Area Median (AREA_MD)	Correlation	High significant correlation with another metric which values' are easier to interpret.
Patch Area Range (AREA_RA)	Correlation	High significant correlation with another metric which values' are easier to interpret.
Patch Area Standard Deviation (AREA_SD)	Correlation	High significant correlation with another metric which values' are easier to interpret.
Radius of Gyration Standard Deviation (GYRATE_SD)	Correlation	High significant correlation with another metric which values' are easier to interpret.
Shape Index Median (SHAPE_MD)	Correlation	High significant correlation with another metric which values' are easier to interpret.
Shape Index Area Weighted Mean (SHAPE_AM)	Correlation	High significant correlation with another metric which values' are easier to interpret.
Shape Index Coefficient of Variation (SHAPE_CV)	Correlation	High significant correlation with another metric which values' are easier to interpret.
Related Circumscribing Circle Coefficient of Variation (CIRCLE_CV)	Correlation	High significant correlation with another metric which values' are easier to interpret.
Contiguity Index Coefficient of Variation (CONTIG_CV)	Correlation	High significant correlation with another metric which values' are easier to interpret.
Aggregation Index (AI)	Correlation	High significant correlation with another metric which values' are easier to interpret.
Contiguity Index Area Weighted Mean (CONTIG_AM)	Correlation	High significant correlation with another metric which values' are easier to interpret.

Radius of Gyration Median (GYRATE_MD)	Correlation	High significant correlation with another metric which values' are easier to interpret.
Radius of Gyration Coefficient of Variation (GYRATE_CV)	Correlation	High significant correlation with another metric which values' are easier to interpret.
Related Circumscribing Circle Median (CIRCLE_MD)	Correlation	High significant correlation with another metric which values' are easier to interpret.
Landscape Shape Index (LSI)	Correlation	High significant correlation with another metric which values' are easier to interpret.

Appendix H: This table outlines a score which was created to represent the importance of each landscape metric. The metric was counted when it was in one of the top three spots following each of the 100 random forest regression iterations for each biodiversity variable (four total: alpha, beta, gamma diversity and abundance). The top three metrics were retained in order to consider metrics which had very similar % increase in mean squared error values, or may have appeared in an importance cluster. Each scoring column is out of 1200 for this reason (100 iterations x four variables x top three places). Each landscape metric has the potential to have a maximum score of 400, which would indicate that the metric was deemed important in every iteration of RFR for every biodiversity variable (except for plants, which without abundance, would be out of 300).

Birds		Bees		Butterflies		Carabids	
Landscape Metric	Score (/400)						
GYRATE_RA	242	MSIEI	285	TE	299	PLADJ	284
LPI	195	CONTIG_MN	139	GYRATE_AM	276	COHESION	243
CONTIG_RA	153	NP	131	NP	146	DIVISION	141
AREA_AM	116	GYRATE_AM	131	CONTIG_RA	134	AREA_AM	113
DIVISION	106	SHDI	115	PLADJ	80	SHDI	100
CONTIG_SD	88	MSIDI	86	AREA_AM	77	LPI	60
CIRCLE_AM	62	AREA_AM	67	COHESION	72	NP	47
CIRCLE_RA	60	SHEI	54	AREA_MN	43	AREA_MN	46
CONTAG	36	PLADJ	38	IJI	35	GYRATE_AM	36
TE	25	PR	38	DIVISION	16	CONTIG_MD	26
CIRCLE_MN	19	CONTIG_SD	29	GYRATE_RA	8	MSIDI	26
AREA_CV	18	DIVISION	23	SHEI	5	CIRCLE_RA	24
GYRATE_AM	17	TE	19	AREA_CV	3	CONTIG_MN	21
MSIDI	17	CONTAG	12	CIRCLE_SD	3	TE	9
AREA_MN	9	AREA_MN	9	LPI	1	CONTIG_RA	8
SHAPE_RA	9	CONTIG_MD	7	CONTIG_SD	1	GYRATE_MN	5
PLADJ	9	COHESION	7	MSIDI	1	SHAPE_RA	5
SHEI	5	AREA_CV	2	GYRATE_MN	0	SHAPE_SD	3
COHESION	4	GYRATE_MN	2	SHAPE_MN	0	GYRATE_RA	2
SHDI	4	GYRATE_RA	2	SHAPE_RA	0	AREA_CV	1
GYRATE_MN	3	CONTIG_RA	2	SHAPE_SD	0	SHAPE_MN	0
SHAPE_MN	2	CIRCLE_SD	1	CIRCLE_MN	0	CIRCLE_MN	0
CONTIG_MN	1	IJI	1	CIRCLE_AM	0	CIRCLE_AM	0
NP	0	LPI	0	CIRCLE_RA	0	CIRCLE_SD	0
SHAPE_SD	0	SHAPE_MN	0	CONTIG_MN	0	CONTIG_SD	0
CIRCLE_SD	0	SHAPE_RA	0	CONTIG_MD	0	CONTAG	0
CONTIG_MD	0	SHAPE_SD	0	CONTAG	0	PR	0
PR	0	CIRCLE_MN	0	PR	0	SHEI	0
MSIEI	0	CIRCLE_AM	0	SHDI	0	MSIEI	0
IJI	0	CIRCLE_RA	0	MSIEI	0	IJI	0

Plants		Spiders		Syrphids	
Landscape Metric	Score (/300)	Landscape Metric	Score (/400)	Landscape Metric	Score (/400)
DIVISION	300	IJI	315	IJI	222
AREA_AM	293	AREA_MN	244	TE	212
GYRATE_AM	270	COHESION	182	PLADJ	173
COHESION	35	TE	123	CIRCLE_AM	167
PLADJ	2	GYRATE_MN	65	GYRATE_AM	113
NP	0	CONTIG_MD	57	CIRCLE_MN	97
LPI	0	NP	49	MSIDI	95
AREA_MN	0	CONTIG_SD	41	AREA_AM	57
AREA_CV	0	SHAPE_SD	28	COHESION	49
GYRATE_MN	0	SHAPE_RA	23	LPI	8
GYRATE_RA	0	GYRATE_RA	22	DIVISION	3
SHAPE_MN	0	CIRCLE_RA	8	GYRATE_RA	1
SHAPE_RA	0	CONTIG_MN	8	SHAPE_MN	1
SHAPE_SD	0	LPI	6	CONTIG_MD	1
CIRCLE_MN	0	CONTIG_RA	6	PR	1
CIRCLE_AM	0	SHDI	5	NP	0
CIRCLE_RA	0	AREA_AM	4	AREA_MN	0
CIRCLE_SD	0	SHAPE_MN	4	AREA_CV	0
CONTIG_MN	0	PLADJ	4	GYRATE_MN	0
CONTIG_MD	0	MSIDI	4	SHAPE_RA	0
CONTIG_RA	0	GYRATE_AM	1	SHAPE_SD	0
CONTIG_SD	0	CIRCLE_AM	1	CIRCLE_RA	0
CONTAG	0	AREA_CV	0	CIRCLE_SD	0
PR	0	CIRCLE_MN	0	CONTIG_MN	0
SHDI	0	CIRCLE_SD	0	CONTIG_RA	0
MSIDI	0	CONTAG	0	CONTIG_SD	0
SHEI	0	DIVISION	0	CONTAG	0
MSIEI	0	PR	0	SHDI	0
TE	0	SHEI	0	SHEI	0
IJI	0	MSIEI	0	MSIEI	0

Appendix I: Strategic Project bird species and their classifications as farmland specialists, generalists, or other species based on literature review and expert opinion. (*) indicates species which were classified as a part of this study (in addition to the original classification).

FARMLAND GENERALISTS

American Crow (*Corvus brachyrhynchos*)
 American Goldfinch (*Carduelis tristis*)
 American Robin (*Turdus migratorius*)
 Baltimore Oriole (*Icterus galbula*)
 Blue Jay (*Cyanocitta cristata*)
 Brown Thrasher (*Toxostoma rufum*)
 Cedar Waxwing (*Bombycilla cedrorum*)
 Chipping Sparrow (*Spizella passerina*)
 Common Raven (*Corvus corax*)*
 Common Yellowthroat (*Geothlypis trichas*)
 Eastern Kingbird (*Tyrannus tyrannus*)
 Eastern Phoebe (*Sayornis phoebe*)
 Great Crested Flycatcher (*Myiarchus crinitus*)
 Indigo Bunting (*Passerina cyanea*)
 Northern Flicker (*Colaptes auratus*)
 Red-winged blackbird (*Agelaius phoeniceus*)
 Ring-billed Gull (*Larus delawarensis*)
 Song Sparrow (*Melospiza melodia*)

FARMLAND SPECIALISTS

Barn Swallow (*Hirundo rustica*)
 Bobolink (*Dolichonyx oryzivorus*)
 Brown-headed Cowbird (*Molothrus ater*)
 Common Grackle (*Quiscalus quiscula*)
 Eastern Meadowlark (*Sturnella magna*)
 European Starling (*Sturnus vulgaris*)
 Grasshopper Sparrow (*Ammodramus savannarum*)
 Gray Partridge (*Perdix perdix*)

Horned Lark (*Eremophila alpestris*)
 Killdeer (*Charadrius vociferus*)
 Mourning Dove (*Zenaidura macroura*)
 Rock Pigeon (*Columba livia*)
 Savannah Sparrow (*Passerculus sandwichensis*)
 Short-eared Owl (*Asio flammeus*)
 Tree Swallow (*Tachycineta bicolor*)
 Upland Sandpiper (*Bartramia longicauda*)
 Vesper Sparrow (*Pooecetes gramineus*)

OTHER SPECIES

Alder Flycatcher (*Empidonax alnorum*)*
 Bank Swallow (*Riparia riparia*)
 Black-capped Chickadee (*Poecile atricapillus*)*
 Cooper's Hawk (*Accipiter cooperii*)*
 Eastern Wood-Pewee (*Contopus virens*)*
 Gray Catbird (*Dumetella carolinensis*)*
 Hairy Woodpecker (*Leuconotopicus villosus*)*
 Northern Cardinal (*Cardinalis cardinalis*)*
 Pine Siskin (*Carduelis pinus*)*
 Purple Finch (*Haemorhous purpureus*)*
 Red-eyed Vireo (*Vireo olivaceus*)*
 Rose-breasted Grosbeak (*Pheucticus ludovicianus*)*
 Spotted Sandpiper (*Actitis macularius*)*
 Swamp Sparrow (*Melospiza georgiana*)*
 Warbling Vireo (*Vireo gilvus*)*
 White-breasted Nuthatch (*Sitta carolinensis*)*
 Wilson's Snipe (*Gallinago delicata*)*
 Yellow Warbler (*Setophaga petechia*)*

Appendix J: Error summary for the random forest regression runs. Error components are comprised of the mean squared residuals and % variation.

	Bees							
	Abundance		Alpha		Beta		Gamma	
	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>
Mean	-15.7	0.03	-15.9	0.0	-15.7	0.0	-15.7	0.03
Min	-18.1	0.03	-18.8	0.0	-18.9	0.0	-18.0	0.03
Max	-13.3	0.03	-13.5	0.0	-11.9	0.0	-13.8	0.03
Std. Dev.	1.1	0.0003	1.1	0.0	1.1	0.0	1.0	0.0003
	Birds							
	Abundance		Alpha		Beta		Gamma	
	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>
Mean	-19.0	50.9	-13.3	1.0	-8.2	3.0	-3.7	6.5
Min	-21.4	49.3	-16.9	1.0	-11.5	2.9	-6.3	6.3
Max	-15.2	51.9	-10.2	1.1	-4.1	3.1	-1.2	6.7
Std. Dev.	1.3	0.6	1.1	0.0	1.3	0.04	0.9	0.1
	Butterflies							
	Abundance		Alpha		Beta		Gamma	
	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>
Mean	2.0	332.6	10.1	1.8	9.2	2.5	9.8	7.7
Min	-0.9	325.0	7.7	1.8	6.5	2.5	8.1	7.5
Max	4.2	342.2	12.3	1.9	11.4	2.6	12.2	7.9
Std. Dev.	1.0	3.4	0.9	0.02	1.0	0.03	0.9	0.1
	Carabids							
	Abundance		Alpha		Beta		Gamma	
	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>
Mean	-16.0	62424.7	-4.6	4.1	4.6	3.9	0.1	12.7
Min	-18.5	60799.7	-6.8	4.0	1.8	3.9	-2.3	12.4
Max	-13.0	63774.2	-1.6	4.2	6.6	4.0	2.1	13.0
Std. Dev.	1.0	561.9	1.0	0.04	0.8	0.03	0.8	0.1
	Spiders							
	Abundance		Alpha		Beta		Gamma	
	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>
Mean	-3.6	1238.2	11.0	4.1	9.8	4.9	12.4	16.1
Min	-6.5	1210.2	8.6	4.0	7.3	4.8	10.2	15.8
Max	-1.3	1272.4	13.1	4.3	12.1	5.1	14.0	16.5
Std. Dev.	1.1	13.5	1.1	0.1	1.0	0.1	0.9	0.2

	Syrphids							
	Abundance		Alpha		Beta		Gamma	
	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>
Mean	0.2	1182.1	-10.2	2.9	-7.5	2.6	-6.9	9.4
Min	-2.2	1153.3	-12.4	2.8	-10.1	2.5	-10.3	9.1
Max	2.6	1210.0	-7.8	2.9	-5.2	2.7	-3.9	9.7
Std. Dev.	1.0	12.4	1.1	0.03	1.0	0.03	1.1	0.1
	Plants							
	Abundance		Alpha		Beta			
	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>		
Mean	34.6	29.2	18.7	63.7	28.2	164.1		
Min	33.2	28.5	16.6	62.1	26.4	160.3		
Max	36.3	29.9	20.7	65.3	29.8	168.2		
Std. Dev.	0.6	0.3	0.8	0.6	0.6	1.4		

Appendix K: Error summary for the second random forest regression analysis, conducted with mean field size, the percentage of like adjacencies, Shannon diversity, and the modified Simpson’s evenness index. Similar to the error summary for the initial analysis, carabids have the highest range and values for % variance, which again is potentially due to the introduced species which dominates the data for the taxa.

	Bees		Birds		Butterflies		Carabids	
	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>
Mean	603.2	-12.59	15.6	-14.8	91.4	1.2	14591.5	-4.4
Min	4.9	-19.12	1.0	-22.2	1.8	-6.3	4.1	-10.6
Max	2437.6	-5.34	52.2	-5.4	360.7	10.8	59527.2	1.6
Std. Dev.	1033.4	3.0936	20.7	4.8	151.0	5.2	25294.2	3.5
	Plants		Spiders		Syrphids			
	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>	<i>% Var</i>	<i>MSR</i>		
Mean	94.30	19.49	332.25	-6.06	340.52	-15.02		
Min	33.27	11.84	4.78	-11.03	2.86	-23.21		
Max	186.46	25.60	1326.49	-2.72	1369.09	-9.12		
Std. Dev.	63.84	4.05	558.93	1.81	581.41	3.83		

Appendix L: Trend graphs and scatter plots of mean field size and Shannon diversity values obtained for the 93 study sites using both the Strategic Project data and the AAFC data. While trends can be seen in the patterning of the two heterogeneity variables, the low r-values indicate the inability to use this AAFC data in place of the higher resolution data for these purposes.

