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Using lidar to approximate keystone structure and evaluate management practices in potential habitats of the endangered Karner blue butterfly (Lycaeides melissa samuelis)

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ABSTRACT

Using lidar to approximate keystone structure and evaluate management practices in potential habitats of the endangered Karner blue butterfly (*Lycaeides melissa samuelis*)

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Keystone structure is the spatial structure required by a given species, at a scale that is determined by that species' needs and mobility. The endangered Karner blue butterfly (*Lycaeides melissa samuelis*, hereafter KBB) has a keystone structure that incorporates trees and bushes to provide the mixture of sun and shade required to fulfil its life functions. Airborne light detection and ranging (lidar) is a potentially invaluable tool for characterizing keystone structures. However, lidar has yet to be utilized to evaluate structural suitability of KBB habitats. Therefore, I investigated the use of lidar for characterizing critical attributes of KBB habitat structure, and its use in the evaluation of management practices. Structural diversity was summarized from lidar using two approaches: one that attempted to test the canopy cover criteria used in the field-based Glacial Lake Albany habitat mapping (hereafter GLA heterogeneity), and a second based on the texture of the lidar-derived canopy cover imagery. These lidar-derived measures were calculated at five scales, using kernels (moving windows) with areas of 0.05 ha to 19.2 ha. The lidar heterogeneity measures derived at 0.9 ha or less were highly correlated with density of field observations of KBB presence, with the highest correlation at 0.2 ha. Larger kernels were poorly correlated with KBB presence. Notably, the 0.9 ha scale corresponds to more than 75% of KBB mobility range observations, as reported in a previous field study. GLA heterogeneity was also found to be consistently more correlated with KBB observations than the texture measure. The criteria used to establish the four GLA heterogeneity classes appear to be useful, based on rank correlation relationships with the classes that were combined or evaluated individually. The 0.2 ha kernel GLA heterogeneity was used to evaluate the effects of prescribed burning on structural suitability, and was found to be significantly correlated with burn intensity.

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1. Introduction

1.1 Driving question

This thesis is driven by the overarching question: can lidar be used to characterize critical attributes of Karner blue butterfly (*Lycaeides melissa samuelis*), hereafter KBB, habitat structure and aid in the evaluation of management practices?

1.2 Approach

To address the driving question, I first focused on using lidar to detect the most appropriate scale at which to characterize shade heterogeneity for the KBB, hereafter referred to as its *keystone structure*—defined by Tews et al. (2004) as the spatial structure required by a given species, at a scale that is determined by that species' needs and mobility. I then explored how a spatially continuous structural suitability coverage can inform the effectiveness of prescribed burning in maintaining KBB's keystone structure.

All approaches to describing heterogeneity are implicitly scale-dependent (McGarigal, 2015; Ferro and Warner, 2002). In their review of 85 publications on structural heterogeneity from 1960 to 2003, Tews et al. (2004) note an overarching commonality: habitat suitability of a species is affected by structural heterogeneity at specific spatial scales, which vary by their needs and mobility. They define this as a species' "keystone structure," (p. 86). McGarigal (2015) reiterates this, explaining that habitat heterogeneity requirements vary by organism, and likely have characteristic spatial scales dependent upon its ability to obtain resources.

2. Background

2.1 The Karner blue butterfly

The KBB is an endangered species native to the Midwest and Northeastern United States. It thrives in oak savanna and pine barren habitats, an early-successional ecological stage that requires regular disturbance events, such as fires, to maintain a unique canopy structure. Over the past century, KBB's habitat has been steadily degraded or destroyed by human development and fire suppression policies (Kilgore, 1989; Nowacki, 2008; Gifford et al., 2010). Therefore efforts to restore viable KBB populations prioritize the protection of critical habitat requirements and the ecological processes that sustain them (Bried et al., 2014).

The primary objective of habitat monitoring for the KBB is to focus on a set of environmental indicators that represent KBB's most critical requirements. One such indicator that accounts for a significant amount of management expenditure is vegetation structure, with particular emphasis on the shade heterogeneity that results from variations in canopy cover (Bried et al., 2014; Grundel et al. 1998).

2.2 The Albany Pine Bush Preserve

The study site for this project the Albany Pine Bush Preserve, which is home to a globally rare inland pitch pine-scrub oak barren ecological community (Edinger et al. 2014) in the capital region of upstate New York (*Figure 1*). It is one of the last remaining examples of this early-successional community type (Albany Pine Bush Commission, 2017), and is one of several KBB metapopulation recovery areas designated in the Glacial Lake Albany Federal Recovery Unit (Bried et al., 2014). The preserve's relatively small size (~1300 hectares), and proximity to dense urban centers (Albany and Schenectady) make it a prime example of the wildland-urban interface that is vulnerable to development pressure and habitat fragmentation.

2.3 Structural requirements of KBB habitat

Wild lupine (*Lupinus perennis*), the only known food source for larvae of the KBB, grows most abundantly in open-canopy barrens and savanna. Nectaring by adult butterflies occurs primarily in such areas, where direct sunlight is available. However, females prefer moderately shaded lupine under 30-60% canopy cover for oviposition, as shade and habitat structure play a major role in lupine "quality," affecting larval growth rate (Grundel et al. 1998). The canopy structure of oak savanna and barrens habitats typifies KBB shade heterogeneity requirements (Grundel et al. 1998).

Because shade is a direct function of canopy cover, it is frequently used as a proxy measure of shade (Grundel et al., 1998; Bried et al., 2014). As such, it is generally recommended that conservation planning for KBB habitat incorporate canopy heterogeneity and subsequent shade availability. Knutson et al. (1999) elaborates that the KBB is not known to travel particularly long distances during their short life span. In their study of KBB movement patterns and population dynamics, more than 75% of movements were less than 100 m. This indicates that horizontally heterogeneous canopy should be available within a threshold adjacent area of at least 1 ha to sustain healthy KBB populations, which may reflect KBB's keystone structure. Providing a healthy mix of open grassland and forest also enables connectivity of KBB metapopulations, as dense forest can act as a barrier to their movement (Bried et al., 2014).

The Albany Pine Bush Preserve Commission utilizes transect field methods to measure vertical canopy cover and derive heterogeneity. Measurements are obtained using a periscope densitometer at one-meter increments along transects that vary in length and number, by the size and shape of the management unit in which they were sampled. After completing each transect, the number of points with canopy coverage is divided by the total number of points sampled, resulting in a canopy cover percentage for that area. Shade heterogeneity is then derived from these transects by interpolation to distinct habitat patches, as outlined in *Table 1*, using criteria that were qualitatively derived from previously published literature (Bried et al., 2014). Differentiating good from very good heterogeneity for the KBB habitat requires that vertical structural distribution is also taken into account, which requires the presence of both shrubs and trees. Rankings of poor and fair are seen as low potential suitability, while rankings of good and very good are seen as high potential suitability (Bried et al., 2014). This approach to defining heterogeneity is hereafter referred to as the Glacial Lake Albany (GLA) heterogeneity.

2.4 Potential of lidar

An ongoing challenge in remote sensing for conservation is how to utilize spatially continuous environmental data at scales that are optimal for the objectives at hand. Typically this is accomplished in one of two ways: by simplifying the data into classes, an approach known as the patch matrix model, or by leaving the data unclassified to allow for gradational boundaries rather than explicit ones, known as the gradient model. The simplicity of the patch matrix model has proven useful in studies that pertain to relatively homogenous landscape elements, and for characterizing landscape-scale relationships between patterns and processes. It also has the advantage of utilizing statistical approaches that are widely accepted and understood (McGarigal et al., 2009; Turner, 2005). However, many landscape ecologists tout the superior strength of the gradient model, as it embraces the nuances of soft transitions that tend to manifest in the landscape (Cushman et al., 2010; McGarigal et al., 2009; Seto et al., 2004).

Lidar interpreted via the patch matrix and gradient models potentially captures critical aspects of habitat structure. However, only recently have surface metrics been developed that are applicable to heterogeneity measurements of gradational data (Cushman et al., 2010; McGarigal et al., 2009). One example is how structural heterogeneity might manifest as image texture. Texture can be described in several different ways (e.g. tonal variation or distribution at the pixel level, interrelationships between groupings of similar pixels, etc.) (Ferro and Warner, 2002). For example, a 2010 study by Gomez et al. used image texture analysis to study canopy heterogeneity as it pertains to habitat suitability for different coffee plant species, but only after the imagery was generalized to the geographic extents of tree crowns.

McGarigal et al. (2009) drew from concepts in the field of surface metrology to describe and evaluate several surface metrics that may relate to different aspects of landscape patterns. They found that metrics pertaining to first-order surface roughness (e.g. average roughness, root mean square roughness, and ten-point height) were most analogous to patch matrix approaches that quantify landscape diversity.

As previously stated, shade and subsequent shade heterogeneity are a direct function of canopy cover. There is no single broadly accepted method for estimating canopy cover from lidar data. However, the most straightforward methods utilize return ratios to calculate directly from lidar point clouds (Posilero et al., 2016). Ratio modeling involves counting the number of returns (or, in some cases, finding the sum of the intensities) reflected from the canopy and dividing this number by the total number of returns (or sum of intensities) in a given geographic extent (e.g. a pixel size of 5 meters). Hopkinson and Chasmer (2009) compared four canopy ratio models: first return, all return, return intensity, and return intensity modified by Beer's law. They compared all four ratio models to ground-based canopy cover measurements across several forest ecozones, and found that intensity-based ratios were the least sensitive to changes in canopy type and resulted in more stable measurements, but all ratio approaches were reasonably accurate.

Smith et al. (2009) compared landscape-scale lidar estimates of canopy cover to plot-based field measurements and found them to be correlated ($r^2 = 0.78$). This demonstrates that lidar facilitates the collection of reasonably accurate canopy data at fine resolutions over broad geographic extents, where manual plot and transect methods are limited in their scope. Zellweger et al. (2014) evaluated the utility of lidar data in a landscape-scale habitat suitability model of hazel grouse, an avian species that is heavily affected by forest structural characteristics, and concluded that lidar is highly effective in quantifying species-habitat relationships at this scale.

The spatially continuous nature of lidar products facilitates the generation of grid-format heterogeneity outputs, which may highlight geographic patterns and areas of potentially suitable habitat that had previously been overlooked. Estimates of heterogeneity derived in this fashion may also more accurately reflect the effects of disturbances, allowing for a more nuanced and unbiased study of the relationships between canopy patterns, management activities, and ecological function (e.g. KBB density).

3. Study I: Deriving shade heterogeneity from lidar to approximate the Karner blue butterfly's keystone structure

3.1 Aims

Study I seeks to determine KBB's keystone structure using lidar-derived heterogeneity products. In addressing this aim, the following questions are investigated:

1. Which model(s) and scale(s) of spatially continuous heterogeneity coverages successfully characterize critical attributes of KBB habitat structure (e.g. its keystone structure)?
2. Are the lidar-derived GLA heterogeneity ranking criteria correlated with KBB observations?
3. Do the observed relationships support the proposition by Tews et al. (2004) that keystone structure is a function of a species' mobility range?

3.2 Methods

3.2.1 Field data: 2007 - 2009 transects of KBB observations

In this study three years of KBB observation data were used: 2007 – 2009. By including multiple years, the effective sample size was greatly increased (*n* = 105). Minimal structural disturbance during these three years was assumed because all data were collected in management units that were not burned during this time period. The data were acquired in the form of transects that vary in length from 13.3 m to 256 m several times throughout the year (exact number of visits varied by transect) by Albany Pine Bush Preserve staff.

The exact location of observations along each transect were not recorded, thus the areas of observation along the transects reflect the inherent resolution of the data. "During a survey, observers walked slowly along each transect and searched for butterflies directly on the transect line and on either side of the line [at a maximum distance of 4 m]." (Campbell, 2018). Because observations were limited to a maximum distance of 4 m from each transect, a buffer of 4 m was generated to create polygon features (*Figure 1*). The sum of KBB observations per polygon was then normalized by the number of surveys in which KBB observations were recorded, and polygon area. Because KBB is a rare species, it was assumed that it had not completely fulfilled its niche within the landscape. Therefore differences in density were considered only for transect surveys where the butterfly was observed; transects without KBB observations were ignored.

3.2.2 Lidar analyses

Lidar data were acquired in late April, 2008 over 1168 km² in the capital region of upstate New York, including over the Albany Pine Bush Preserve. The data were acquired by The Sanborn Map Company, Inc. on behalf of the New York State Department of Environmental Conservation. The point density is approximately 1.7 points m^{-2}, and comprises first and last returns along with the associated intensity value for each (NYSDEC, 2008). This point density is not sufficient to resolve many individual small bushes. However, while studying the relationships between point density and forest metric estimation, Jakubowski (2013) found that root mean square error of canopy cover estimation plateaus at a threshold of roughly 1 point m^{-2}. 1.7 points m^{-2} was therefore accepted as sufficient for this purpose.

In order to derive continuous canopy cover and estimate GLA heterogeneity rankings, percent canopy cover from shrubs and trees was calculated in addition to total canopy cover from the lidar data. Shrubs were differentiated using a height threshold of 2 m, and ground points were differentiated by a height threshold of 0.5 m. Toolbox for Lidar Data Filtering and Forest Studies (TIFFS) (Chapman et al., 2010) was used to produce canopy cover estimates on a 5 m grid using the all returns ratio approach, for two reasons: (1) it is the most straightforward method available, and (2) the lidar data were found to have unreliable return number information, making methods that require that information unfeasible.

Impervious surfaces, such as roads, buildings, and parking lots, are generally considered unsuitable habitat. Therefore such areas were masked in the canopy cover products. The mask was developed by applying a maximum likelihood classification of impervious surfaces using high resolution four-band visible and near-infrared orthographic imagery (NYS-OCS, 2011). The imagery was collected in April, 2011, by the New York State Division of Homeland Security and Emergency Services—Office of Cyber Security at a pixel resolution of 6 in. A building footprint shapefile was also obtained from Microsoft and incorporated into the mask. The building footprint map was created through a deep neural network algorithm performed on nation-wide aerial imagery, and is available on GitHub as a free download (Open Data Commons Open Database, 2018).

3.2.3 Generating heterogeneity models at various test scales

To create spatially continuous outputs of heterogeneity, rasters were generated at various scales in which each pixel represents a summary measure of its surrounding environment. Five test scales were generated for each of two models: a gradient model based on first-order image texture, and a patch matrix model based on the definition of GLA heterogeneity by Bried et al. (2014). Knutson et al. (1999) describe a benchmark of 100 meters within which more than 75% of all KBB travel was observed. A 0.9 ha moving kernel, with values designed to approximate a circular region, and adjusted to allow for a single center pixel (*Figure 2*), was generated based on this finding. The kernel was then bracketed by scales on either side, each one approximately 5x the area of the last, for a total of five test scales: 0.05 ha., 0.2 ha., 0.9 ha., 4 ha., and 19.2 ha (*Table 2*).

Focal standard deviation was used for the gradient model to provide a preliminary overview of canopy variation, followed by categorical raster grids of GLA heterogeneity rankings (*Table 1*). To generate GLA heterogeneity, a binary layer was generated, identifying areas with > 30% canopy cover. The focal mean operator in IMAGINE was then used to calculate the proportion of a specified kernel with canopy cover greater than 30%. These proportions were then reclassified as: (1) poor; (2) fair; and (3) good, based on *Table 1*. To address the final stipulation in a ranking of very good, several more layers of binaries were created from aforementioned shrub and tree cover lidar products:

Layer 2: > 5% Shrub Canopy.

Layer 3: > 5% Tree Canopy.

Layers 2 and 3 were then multiplied, resulting in a fourth binary (layer 4) to identify areas with shrub and tree contributions > 5%. This was combined with the good areas in the first raster to separate out very good. This resulted in a final output of four classes: (1) poor; (2) fair; (3) good; and (4) very good. This analysis was repeated using each of the five kernels to produce GLA heterogeneity products at each of the five scales.

3.2.4 Evaluating model and scale performance

The lidar-derived GLA heterogeneity and texture values at each scale were summarized by finding the mean per field transect of KBB observations. Because GLA heterogeneity is a nominal measure, the rankings were converted to an index on a scale of 1 - 4 (*Table 3*). Scatter plots were generated to compare the mean GLA and focal standard deviation values to each polygon's corresponding KBB density. The data failed parametric tests, so a non-parametric Spearman correlation analysis was conducted for each plot, and *r* values were compared. In order to evaluate the association of KBB mobility trends with heterogeneity and texture, *r* values were plotted against scale diameter. The graph was then overlaid onto KBB mobility observations performed by Knutson et al. (1999) ($n = 1499$), to facilitate comparison.

The best-performing GLA scale was then analyzed to evaluate whether the qualitatively-derived ranking criteria are associated with the density of KBB field observations, or whether a smaller number of classes would be appropriate. The spearman analysis was repeated to explore the relationship between average KBB density and average GLA rank with: (1) poor/fair combined; (2) good/very good combined; and (3) poor/fair and good/very good combined (representing an aggregation to low potential and high potential habitats). Spearman analyses were also run on the relationship between KBB density and each individual rank by percentage of coverage in each transect, as well as percent coverages of poor/fair habitat combined and good/very good habitat combined.

3.3 Results & Discussion

3.3.1 Lidar analysis

As expected, there is notably more tree cover than shrub cover in the Albany Pine Bush Preserve and surrounding region (*Figure 3*). Shrub cover is concentrated along corridors, roadsides, and forest edges (*Figure 3 (e) and (f)*), while tree cover is concentrated in clusters of varying density throughout the study area (*Figure 3 (c) and (d))*. The general pattern of tree cover is typical of an oak savanna, with sparse clusters of tree cover surrounded by grassland and/or low shrub land.

3.3.2 Heterogeneity model and scale performance

Figure 4 shows that for the larger the kernel size used, the more generalized the representation of the landscape. Furthermore, the larger kernel sizes resulted in increasing dominance of high texture values. The most significant *p*-values for correlation with KBB field densities were associated with kernel sizes at or below 0.9 ha. The 0.2 ha kernel size yielded the highest *r* value (0.59), indicating that the strongest relationship between KBB density and first-order canopy variation exists at this scale, notably lower than the approximately 1 ha reported threshold by Knutson et al (1999).

The GLA heterogeneity maps (*Figure 5*) show generally similar trends to those of the texture maps. As the kernel size increases, the patches become larger, resulting overall in a more homogenous map. The most significant *p*-values were associated with kernel sizes at or below the 0.9 ha scale, and the 0.2 ha kernel size yielded the highest *r* value (0.69), indicating the strongest relationship between KBB density and GLA heterogeneity.

The scatter plots of lidar-derived measures versus field observed KBB densities for the 0.2 ha scale of both models (*Figure 6*) show a general increase in kernel standard deviation and average GLA rank. The increasing spread of KBB densities at higher standard deviation and GLA rank is consistent with the assumption that the KBB does not entirely fill its potential habitat. Furthermore, this spread could be a consequence of the model not considering lupine presence. The higher *r* value for the GLA model suggests that it is a more effective measure of habitat suitability than standard deviation.

These observations are underscored by a comparison of the KBB densities overlaid onto maps of both models at the 0.2 ha scale (*Figure 7*). Generally, though not always, transects with lower KBB densities tend to be located in areas with lower standard deviation values and lower GLA rankings, while higher KBB densities tend to be associated with higher standard deviation values and higher GLA rankings. However, although the spatial patterns appear similar between the two models, comparing them in a more spatially heterogeneous area (*Figure 8*) highlights some differences. In many isolated pockets of poor and fair GLA rankings, standard deviation calculations infill with higher values, thus minimizing or missing these areas completely.

The standard deviation coverage is a simple first-order texture analysis that does not explicitly require both trees and shrubs. Nevertheless, the texture approach holds promise as a simplified alternative to the GLA heterogeneity metric. Incorporating vertical structure through separate consideration of tree and shrub cover might further strengthen this model.

3.3.3 Performance of the GLA ranking

Figure 9 graphs field observations of KBB density verses average GLA rank for various combinations of the GLA classes. Combining the good and very good ranks to produce a classification with just three classes slightly strengthened the relationship between modeled GLA heterogeneity and observed KBB densities. However, combining poor and fair (producing three classes) or combining poor and fair as well as combining good and very good (producing two classes) slightly weakened the relationship.

Table 4 summarizes the regression relationship between the average proportion within the transects of each rank (poor, fair, good and very good) and KBB density, as well as combinations of the classes (poor and fair combined, and good and very good combined). The strongest negative correlation was with the proportion of poor (r = -0.69); the strongest positive correlation with very good (r = 0.59). Correlations of KBB density with the proportion of each rank were significant at the α = 0.005 level, except the good class, which was not significant (r = 0.18, *p*-value = 0.065). The proportion of the combined poor and fair classes, and the combined good and very good, produced intermediate r-values.

These results indicate that the GLA ranking scale uses criteria that are strongly related to KBB densities, and therefore are a suitable tool for characterizing the butterfly's structural relationships. The result are, however, ambiguous regarding the value of differentiating good from very good. The fact that combining good and very good in the average GLA rank for the transects improved the correlation with KBB density from $r = 0.59$ (Figure 6) to 0.72 (Figure 9) suggests that the classes should not be separated. On the other hand, results from table 4 suggest that the very good class is a useful differentiation, as shown by the fact that proportion of the very good habitat in a transect was significantly correlated with KBB density, wheareas the proportion of good was not significantly correlated with KBB density, and that combining good and very good slightly weakened the relationship compared to very good on its own.

It is perhaps not surprising that the results are ambiguous with respect to the benefit of differentiating the good and very good habitat. In the absence of location information for the KBB observations within each transect, aggregate measures such as average GLA heterogeneity or proportion of a single GLA class in a transect are likely to be weakened by considerable noise. Therefore, in summary, I assume that the generally significant correlations, and in particular, the strong positive correlation of the proportion of very good habitat with KBB density is evidence that the GLA heterogeneity classes are useful. Furthermore, the vertical structure criteria used for separating the very good class from good appear to be useful and appropriate.

3.3.4 Keystone structure and KBB mobility

Figure 10 plots the *r* values of both models against kernel diameter. To enable comparison, KBB travel distances observed by Knutson et al. (1999) have also been included, represented by the bars. Each bar has been labeled with the total proportion of KBB observations at or below that distance range.

Both models show similar trends, with the GLA heterogeneity almost always higher than the standard deviation measure (*Figure 9*). The *r* values increased from the 0.05 ha scale (25 m diameter) to a peak at 0.2 ha (45 m diameter), then followed a sigmoid curve decrease to near-zero *r* values at 19.2 ha (495 m diameter). Peak performance occurred within the range of 50% of all observed KBB travel, and the only significant *p*-values occurred within the range 90% observed KBB travel. Thus the KBB's keystone structure appears to be captured by the kernel scale of 0.2 ha (45 m diameter), and its relationship to KBB mobility appears to be supported.

These results highlight a scale that is notably lower than the approximately 1 ha benchmark underscored by Knutson et al. (1999). However, while the benchmark represents the diameter within which more than 75% of KBB were observed to travel, most individuals did not approach that limit. Therefore, in hindsight, a strong relationship between KBB densities and a smaller geographic extent of 0.2 ha is a logical outcome.

3.3.4 Key findings of Study I

The lidar derived products were significantly related to KBB densities, particularly at smaller kernel sizes, suggesting that they do successfully characterize critical attributes of KBB habitat structure. The strongest association, and thus apparently the most appropriate scale at which to quantify heterogeneity for KBB, is 0.2 ha. While these findings are limited to this particular case study, the results are consistent with the notion that keystone structure is a function of a given species' mobility. Therefore, I infer that spatially continuous representations of structural diversity are most meaningfully calculated at scales that approximate the keystone structure of the species in question. GLA heterogeneity resulted in stronger associations than the simple texture measure, perhaps due to the explicit consideration of trees and shrubs in the GLA measure. However, while the relevance of GLA heterogeneity is generally supported.

These findings have potential implications in KBB habitat monitoring. For example, the strongest correlation between GLA heterogeneity and KBB density is at a diameter notably smaller than any of the patch sizes evaluated in Bried et al. (2014). This suggests that conservation planners should carefully consider the scale at which they are monitoring structural aspects of KBB habitat. Furthermore, the use of remote sensing to characterize KBB habitat structure in future studies has the potential to reduce physical labor and increase objectivity.

4. Study II: Evaluating prescribed burning as a management practice in the Albany Pine Bush

4.1 The role of fire in maintaining keystone structure

Fire has historically played a major role in maintaining North American landscape heterogeneity. Native Americans recognized and maintained pyrogenic (e.g. fire-dependent) communities with deliberate (e.g. prescribed) burning. This resulted in a pre-settlement patchwork mosaic of open-canopy pine and oak woodlands, savannahs, and closed-canopy forests, which supported diverse communities of organisms (Nowacki et al., 2008). The Albany Pine Bush Preserve Commission uses prescribed burning as one of its primary management techniques to create and maintain suitable habitat for the KBB, and reestablish the heterogeneous ecological patchwork that was commonplace at the time of natural and Native American burn regimes (Albany Pine Bush Commission, 2017). However, the 2010 recovery plan indicated that of the approximately 105 ha of abundant wild lupine within the preserve, most sites have poor shade heterogeneity (Gifford & O'Brien, 2010), making heterogeneity a priority for improvement. The development of methods that utilize lidar-derived heterogeneity products could potentially aid in this endeavor by providing detailed insight into the spatial distribution of KBB-suitable shade heterogeneity that can be used to target management action and improve functional metapopulation dynamics.

4.2 The benefit of a spatially continuous GLA coverage

The spatially continuous nature of GLA heterogeneity derived from lidar allows for a more detailed evaluation of management practices than is possible from field data. The lidar data facilitates an evaluation of the *extent to which* that score is realized—for example, the proportion of very good heterogeneity in each management unit, without the need to interpolate. The lidar approach also provides valuable insight for designing future prescriptions at the management unit and landscape scales. Sites or units that have suitable structure, but no or little larval or adult food resources, are places to target for restoration.

4.3 Aims

This aspect of the study seeks to determine whether a spatially continuous coverage of GLA heterogeneity, at a scale related to the KBB's keystone structure, can be used to evaluate prescribed burning as a management practice in the Albany Pine Bush. This is accomplished by evaluating the relationship(s) between proportion of very good GLA heterogeneity per management unit and the associated burn history.

4.4 Methods

Albany Pine Bush Preserve management units and associated fire history information, including burn years, burn frequency, and relative burn severity, were obtained from the Albany Pine Bush Preserve Commission. Relative burn severity was qualitatively evaluated as low, medium, or high, based on a post-fire field assessment of average crown scorch, bark scorch, crown consumption, and percent killed. All burn data were recorded as an average value at the management unit scale.

The 0.2-ha GLA heterogeneity model created in Study I was used to summarize the proportion of very good rank coverage per management unit. A series of box plots was then created to investigate relationships between proportion of very good rank coverage per management unit and several critical characteristics of burn history. Statistical differences between bivariate medians were evaluated using the Wilcoxin test, and between multivariate medians using the Kruskal Wallace test.

4.5 Results & Discussion

Percent of very good rank coverage per management unit ranged widely from 0% - 50% (*Figure 11*). Many of the higher percentages occur at the preserve's center, southwestern, and mid-northwestern portions. The far southeast and far northwest portions of the preserve were generally less suitable. This distribution is a reflection of development pressure (and fire suppression) at the fringes of the preserve, where its flanks are more heavily urbanized by the cities of Schenectady and Albany, as well as the management history within the core of the preserve that focused on restoring/maintaining remnant high quality pitch pine-scrub oak barrens and Kbb habitat.

Figure 12 provides an overview of the relationships between proportion of very good heterogeneity and prescribed burn history characteristics. *Figure 12 (a)* compares plots never burned during the period of preserve fire recording (1991 – 2008) to plots that have been burned. While the Wilcoxon analysis did not yield a statistically significant difference in the medians, the box plots indicate that burned sites show a greater range, and slightly higher proportions of very good heterogeneity. The lack of statistical significance is probably due to confounding variables that remain unaccounted for in this simplistic approach, such as total number of burns, burn intensity, and time elapsed since the last burn.

Figure 12 (b) details the relationship between proportion of very good heterogeneity and total number of burns. The categories of four and six burns have only one example each, and therefore can be disregarded. Overall a higher proportion of very good heterogeneity is associated with a greater number of up to three burns, and a statistically significant Kruskal-Wallis analysis at 95% confidence underscores that there is a difference between the medians.

Differences in burn severity may also have an impact on forest structure and suitability. *Figure 12 (c) and (d)* explore the association between proportion of very good suitability, and severity of last burn and average burn severity (averaged over all fires), respectively. The box plots indicate that greater proportions of very good heterogeneity tend to coincide with higher intensity burns. Statistically significant Kruskal-Wallis *p*-values show that the medians are indeed statistically different for each intensity rating. However, it is noteworthy that the medium average severity has lower proportions of very good heterogeneity than the low-medium average severity.

Finally, *Figure 12 (e)* summarizes the potential relationship between very good heterogeneity and years since last burn. The box plots suggest a peak in suitability three years after a burn. The Kruskal-Wallis test indicates a lack of statistical significance, which is perhaps not surprising given the variation within the graph between individual numbers of years. Nevertheless, the overall pattern is notable.

An examination of the burn intensity maps compared to the average very good rank coverage underscores the associations between these variables (*Figure 13*). Higher proportions of suitability ranking tend to coincide with higher intensity burns, particularly near the center of the preserve.

While results of these comparisons were generally only marginally significant, it is important to note that this investigation did not account for confounding variables. For example, *Figure 12 (e)* shows a peak in suitability after a threshold of three years following a burn. This could introduce noise into consideration of other variables, such as intensity and number of burns, since any single unit could have been burned any number of years ago. A followup study might examine the relationships between these variables to create a customized burn index. Nevertheless, the results support the notion that a spatially continuous representation of GLA heterogeneity is indeed capable of picking up on differences that result from various characteristics of fire history.

4.5.1 Key findings

Spatially continuous coverages show differences in heterogeneity within management units, enabling objective evaluations into the effectiveness of management practices at high levels of detail. GLA heterogeneity appears to be strongly related to burn intensity. While most results were not statistically significant, the box plots suggest that this may be due to confounding variables.

These findings have noteworthy implications in KBB habitat management. For example, the importance of high-intensity fires in maintaining structural suitability is underscored. Furthermore, results suggest that repeated, ongoing burns are necessary to maintain structural suitability. Past the threshold of three years since last burn, conditions steadily deteriorate. Therefore I speculate that high intensity burns conducted at three-year intervals would be ideal in maintaining structural suitability for the KBB.

5. Conclusion

This research has demonstrated that lidar can be used to characterize critical attributes of KBB habitat structure in ways that aid in the evaluation of habitat management practices. The lidar derived products were significantly related to KBB densities, particularly at smaller kernel sizes. The strongest association, and thus apparently the most appropriate scale at which to quantify and monitor heterogeneity for KBB, is 0.2 ha. Key findings support the notion that spatially continuous representations of structural diversity are most correlated with field observations of KBB densities at scales that approximate its keystone structure, which is a function of its mobility and host plant availability. The relevance of qualitatively-derived GLA heterogeneity criteria is supported. GLA heterogeneity is also significantly related to burn intensity, and shows promising potential relationships to other aspects of fire history as well, including number of years since last fire. However, noteworthy limitations of this study include: (1) the presence or absence of lupine was not considered, which may have confounded some correlations and introduced noise to the data; and (2) the field transects of KBB observations were not spatially explicit within the transects. Therefore absence of statistical significance does not necessarily mean the structural properties themselves are insignificant.

The findings herein have several noteworthy implications in KBB habitat management. Products generated from lidar can be useful in evaluating management practices by finely quantifying differences in environmental variables across the landscape that may have previously been overlooked. Furthermore, the strong correlation between GLA heterogeneity measured at 0.2 ha and KBB densities suggests that it would benefit conservation planners to carefully consider the scale at which they characterize and manage KBB habitats. Finally, the importance of high intensity fires at regular intervals is supported.

Overall, in the interest of increasing reproducibility, reducing physical labor, and potentially reflecting the nuances of spatial variation in the landscape, structural diversity models should utilize lidar technology wherever possible, at scales that typify a species' preferred mobility range. It is my hope that this method will be applied to future lidar acquisitions at the Albany Pine Bush and other critical KBB habitats.

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7. Tables & Figures

7.1 Tables

Table 1: Shade heterogeneity ratings

Shade Heterogeneity	Proportion of transects with > 30% shade density (%)	Minimum shrubs (%)	Minimum trees (%)
Poor	< 5.1 or > 80	0	0
Fair	5.1 - 20 or 60.1 - 80	0	0
Good	20.1 - 60	0	0
Very good	20.1 - 60	5	5

(Bried et al., 2014, p. 1388)

Table 2: Kernel areas and diameters

Square kernel area (ha)	Rounded kernel area (ha)	Kernel diameter (m)	Kernel Diameter (pixels)
0.06	0.05	25	5
0.2	0.2	45	9
1.1	0.9	105	21
5.1	4	225	45
24.5	19.2	495	99

Table 3: Conversion of GLA heterogeneity rankings to indices

Ranking	Index
Poor	1
Fair	2
Good	3
Very good	4

Table 4: Correlation coefficients and p-values of percent coverage of individual and combined GLA ranks vs. average KBB densities

Rank	***r***	***p***
Poor	-0.69	< 0.001
Fair	-0.3	0.002
Good	0.18	0.065
Very good	0.59	< 0.001
Poor and fair combined	-0.58	< 0.001
Good and very good combined	0.58	< 0.001

7.2 Figures

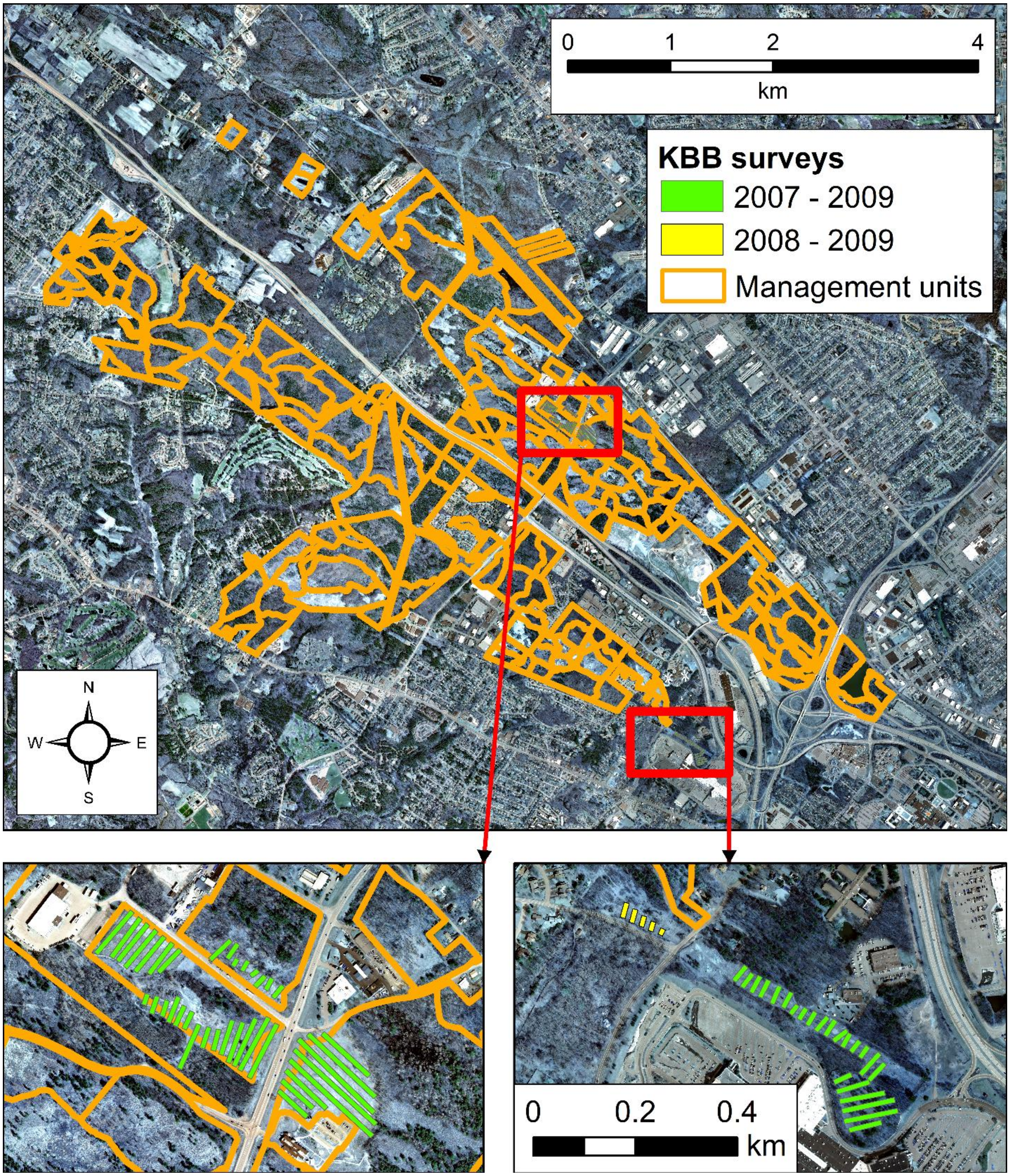


Figure 1: Albany Pine Bush Preserve and locations of KBB transects.

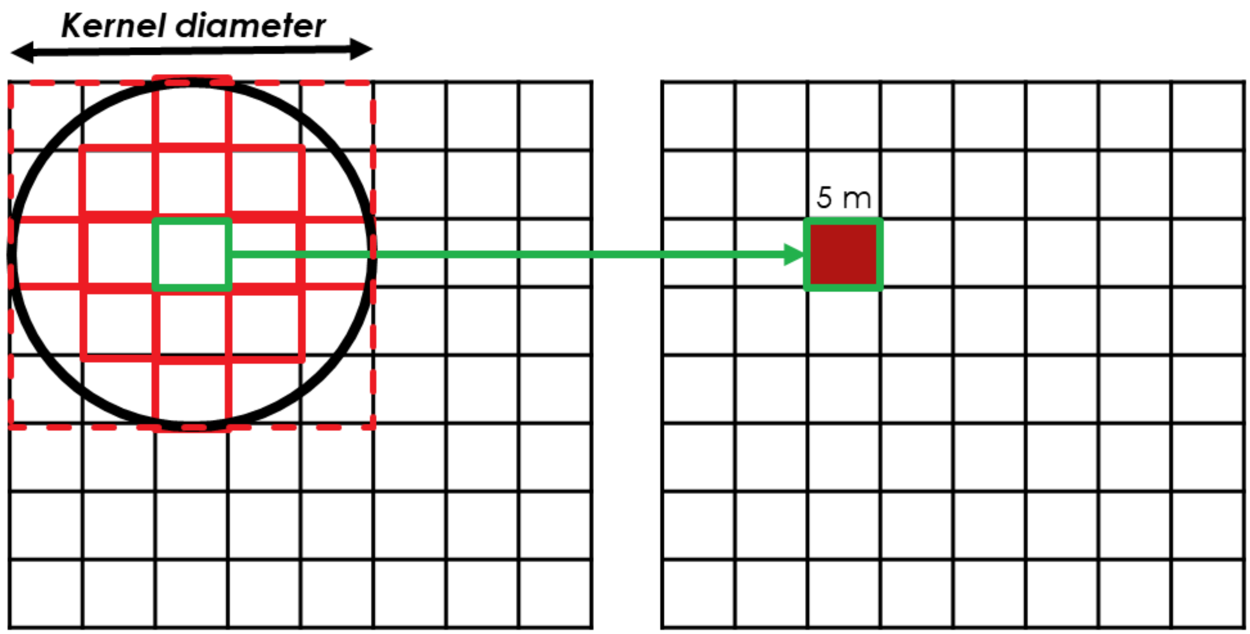


Figure 2: Diagram of a kernel application as used to generate test scales. The black grid represents the pixels. Dashed red lines indicate the square kernel, pixels outline in solid red are selected within the kernel to approximate a circle, as indicated. The value from the kernel is written to the pixel outline in green in the new image.

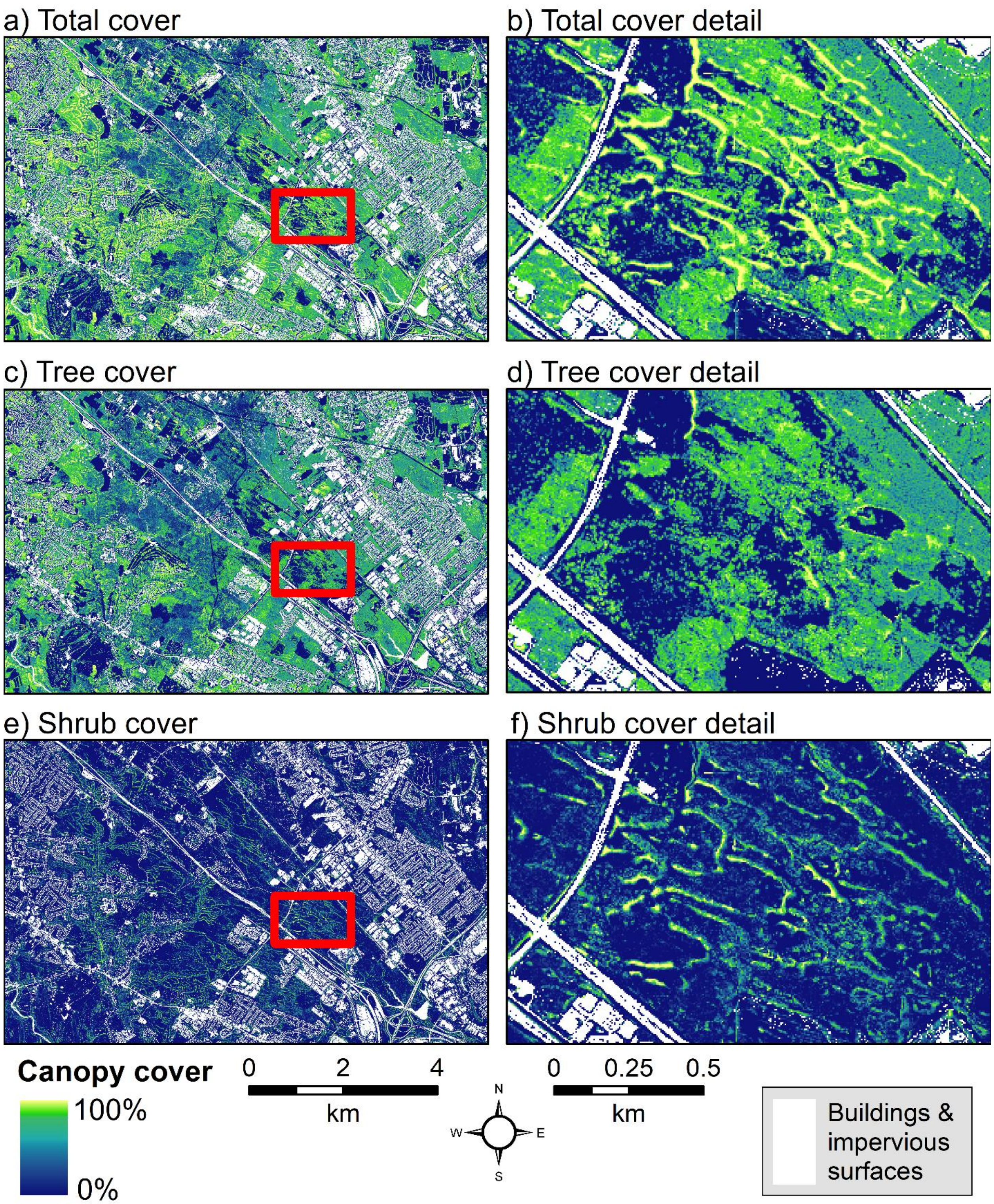


Figure 3: Canopy cover with trees and shrubs separated, and region highlighted to show detail.

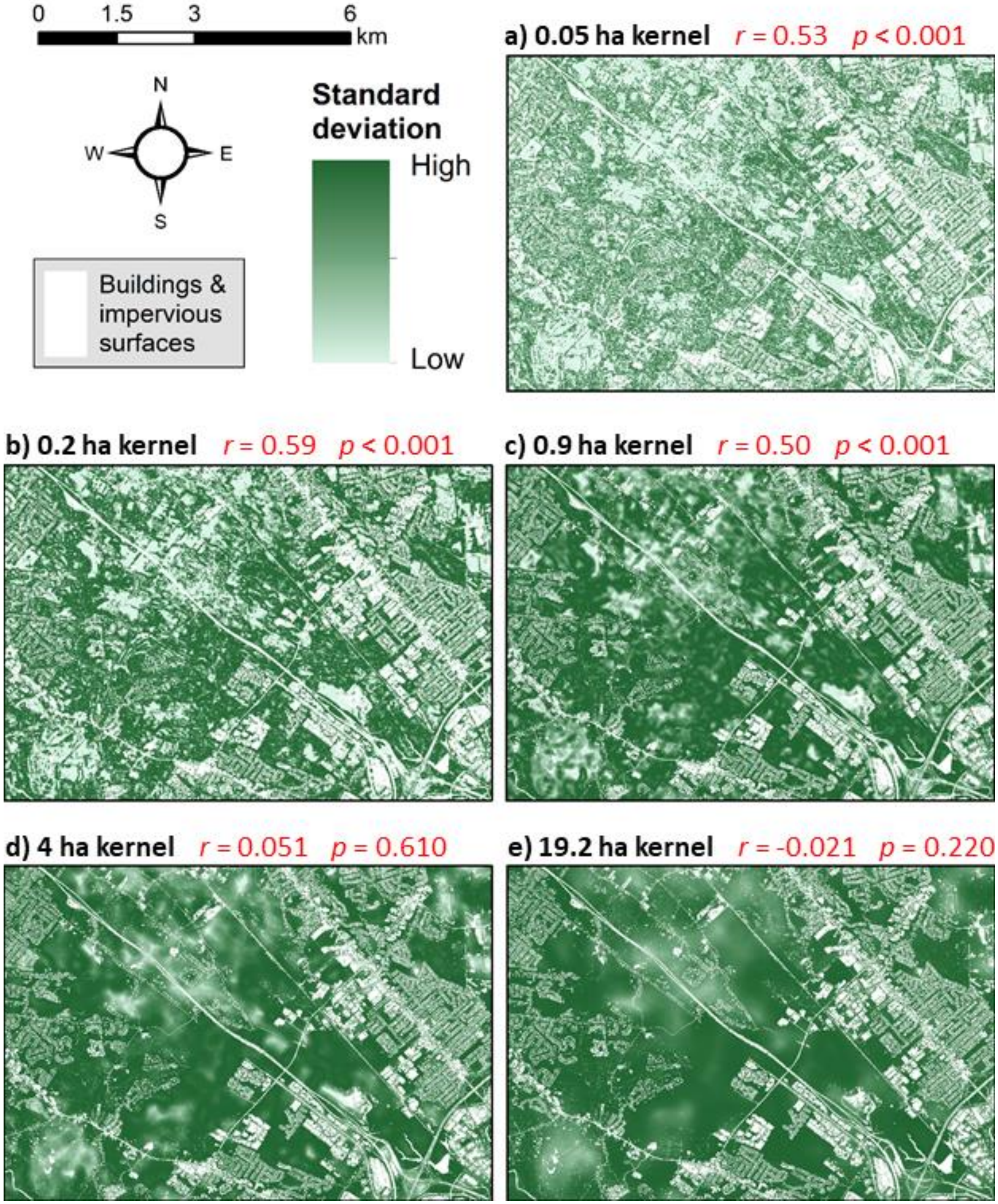


Figure 4: Gradient model of kernel standard deviation at various scales, with Spearman coefficient relating each to KBB density.

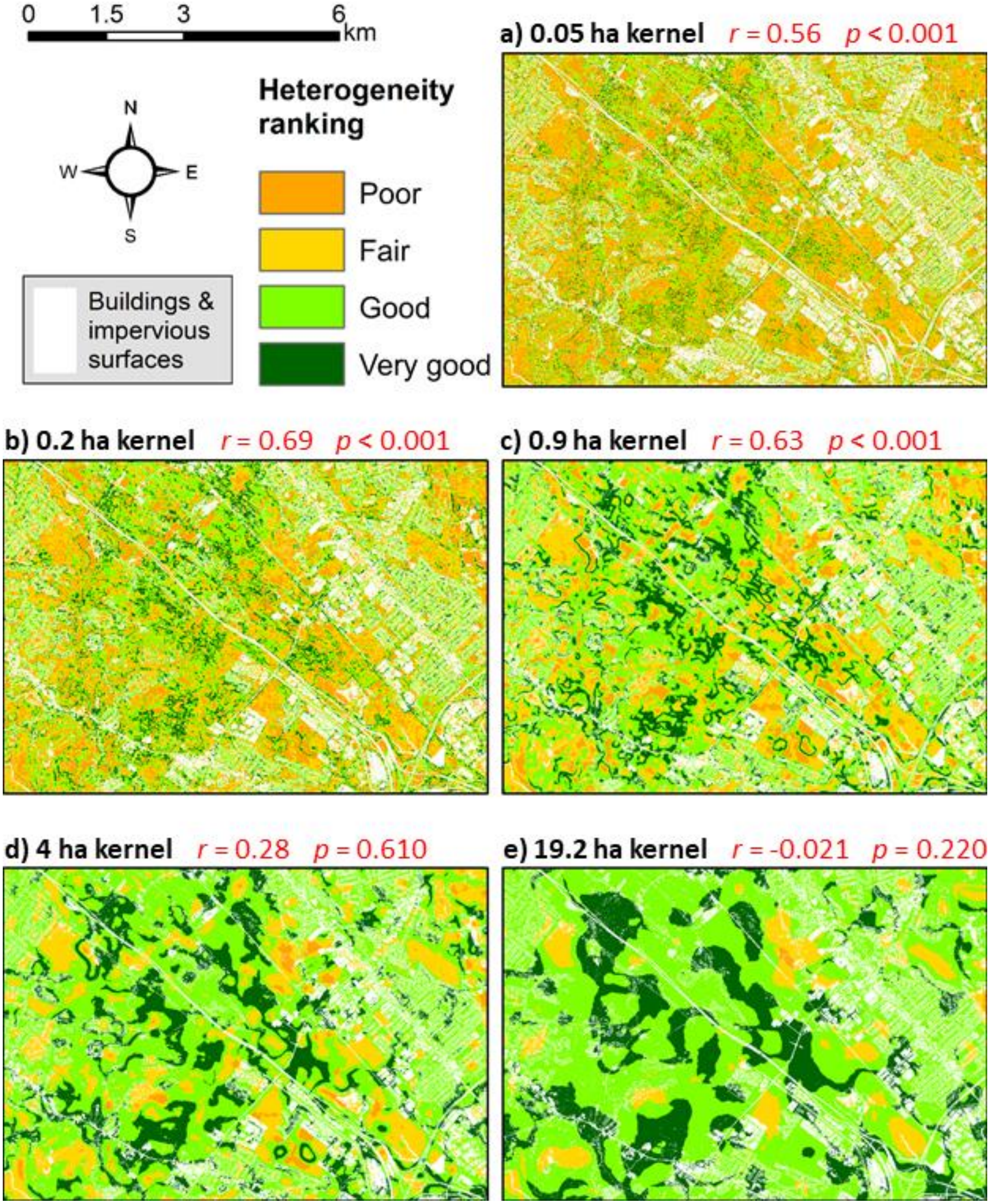


Figure 5: Patch matrix model of kernel GLA heterogeneity at various scales, with Spearman coefficient relating each to KBB density.

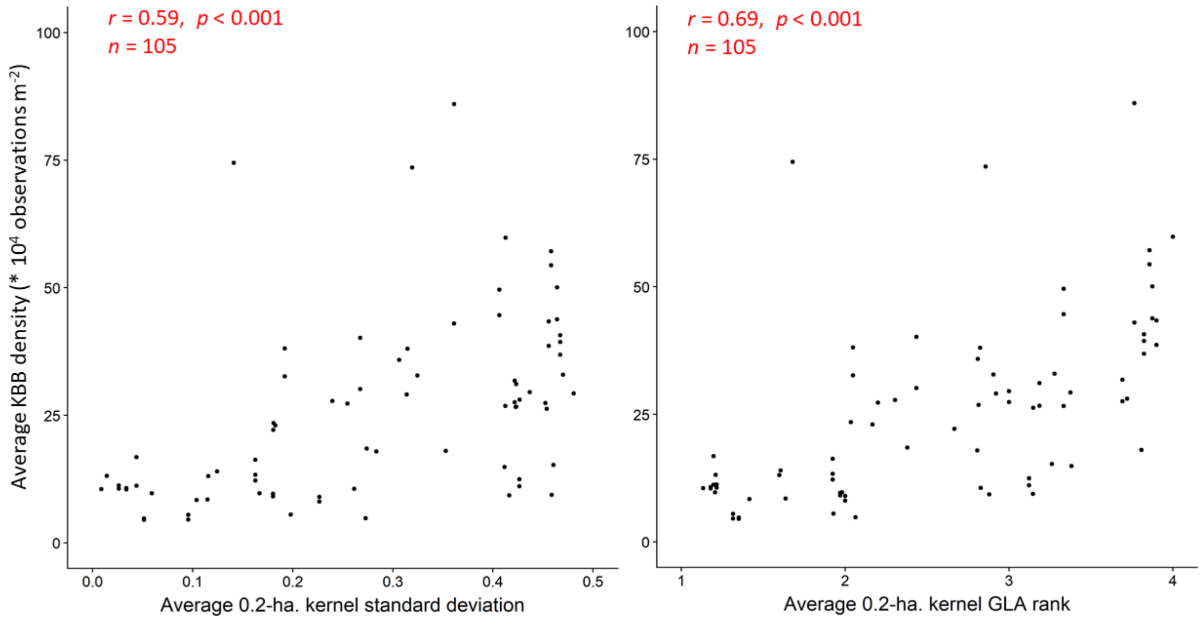


Figure 6: Scatter plots of KBB densities vs. standard deviation and GLA rank per field transect with Spearman correlation.

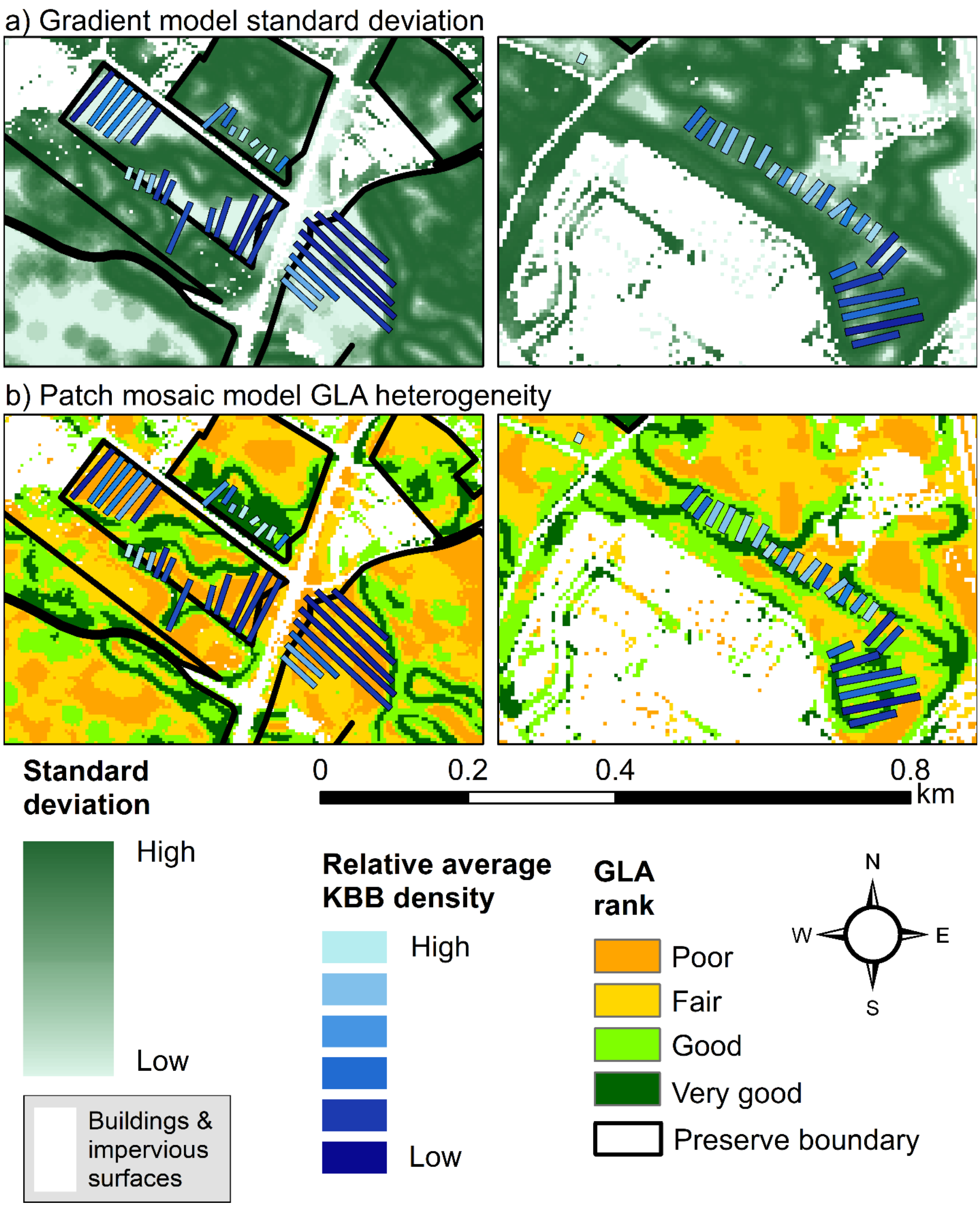


Figure 7: Field-mapped average KBB densities overlaid onto (a) standard deviation and (b) GLA heterogeneity at 0.2 ha. scale.

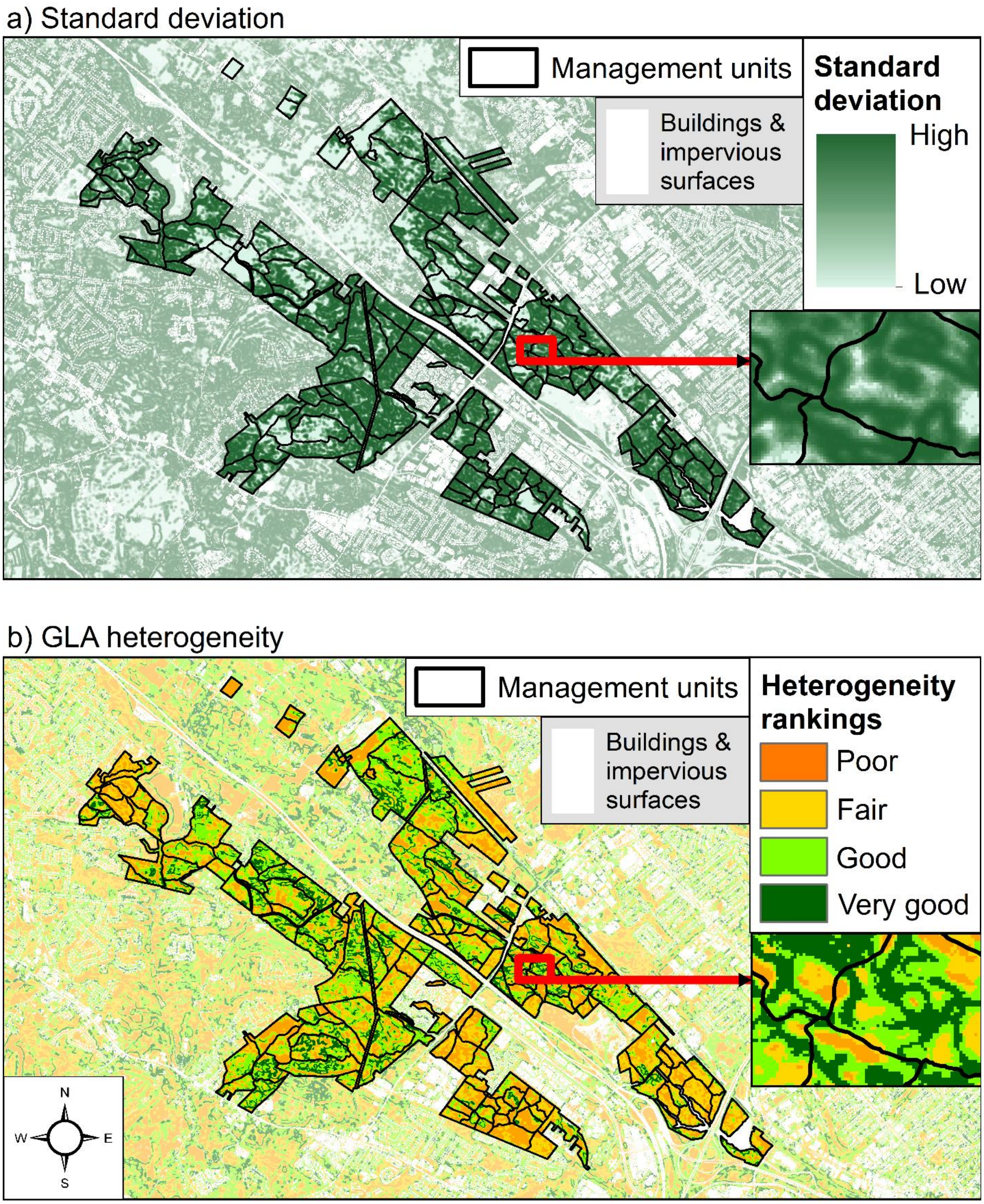


Figure 8: GLA heterogeneity and standard deviation side by side.

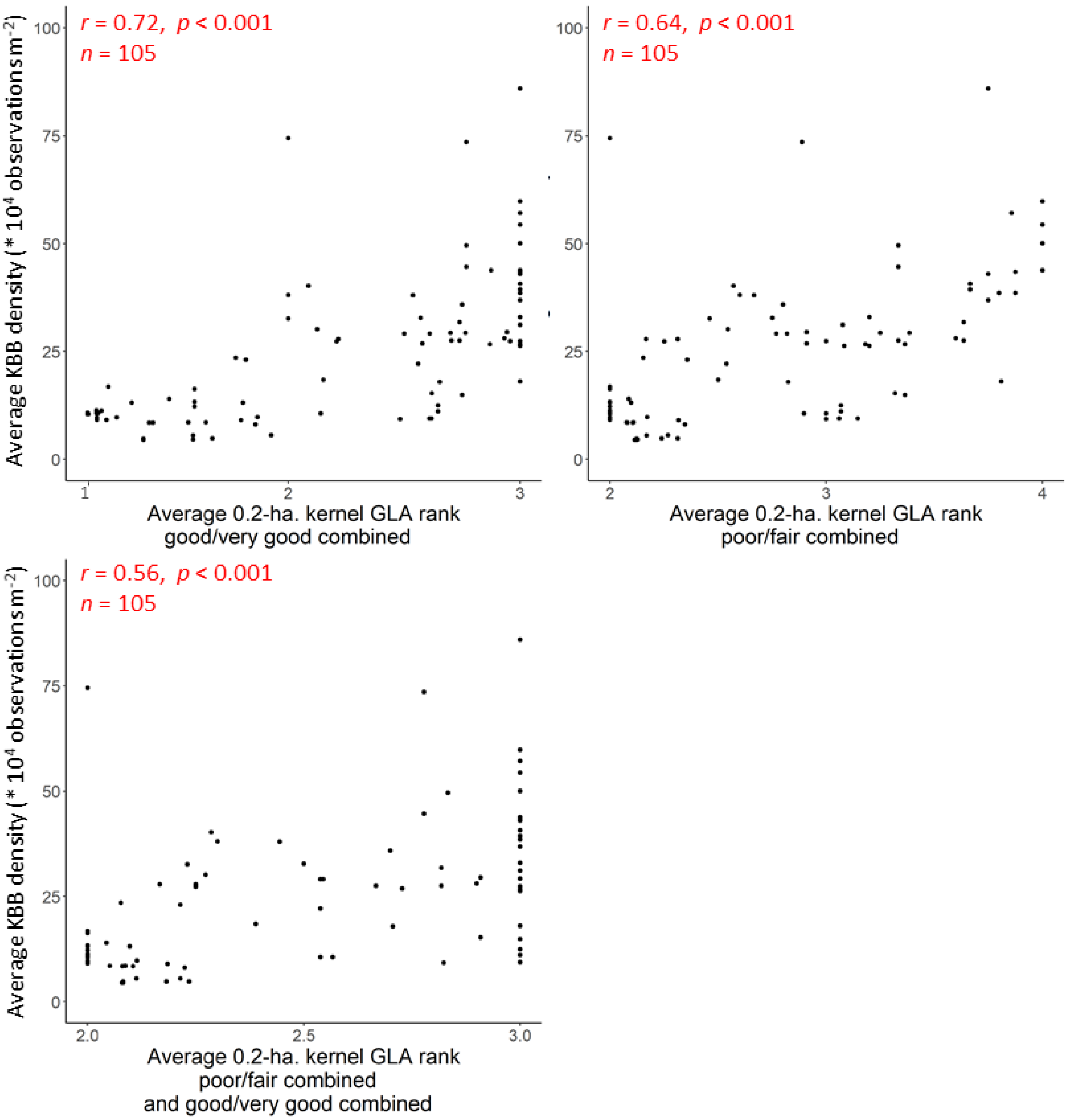


Figure 9: Scatter plots of average KBB density vs. average GLA rank, with good/very good combined into index 3 (top left), poor/fair combined into index 2 (top right), and poor/fair and good/very good combined into indices 2 and 3 respectively (bottom).

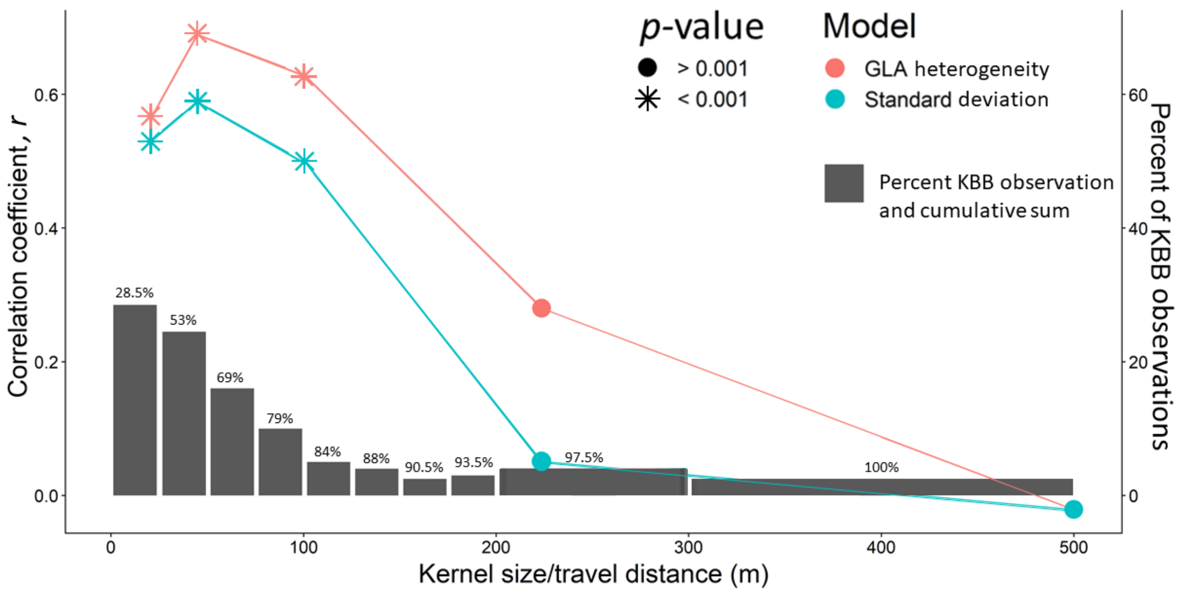


Figure 10: Scale performance vs. scale diameter, overlaid onto observed KBB travel distances from Knutson et al. (1999).

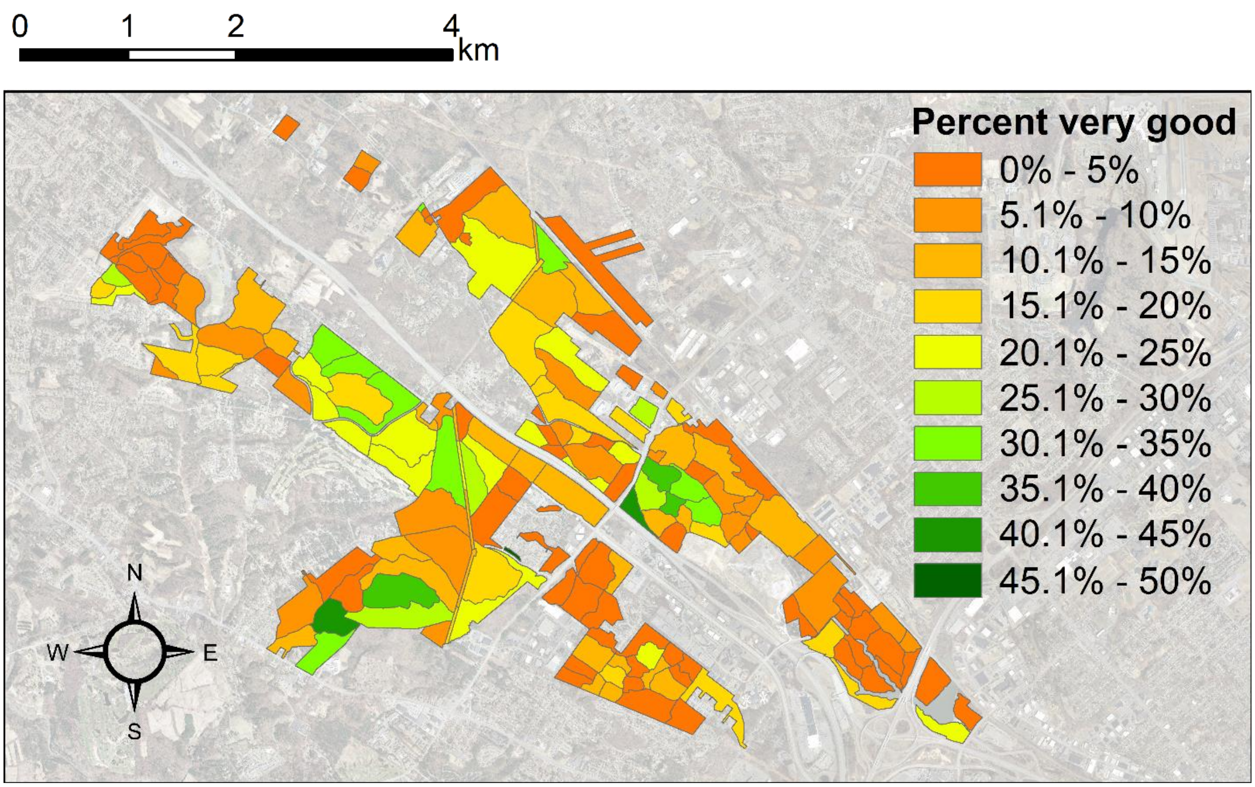
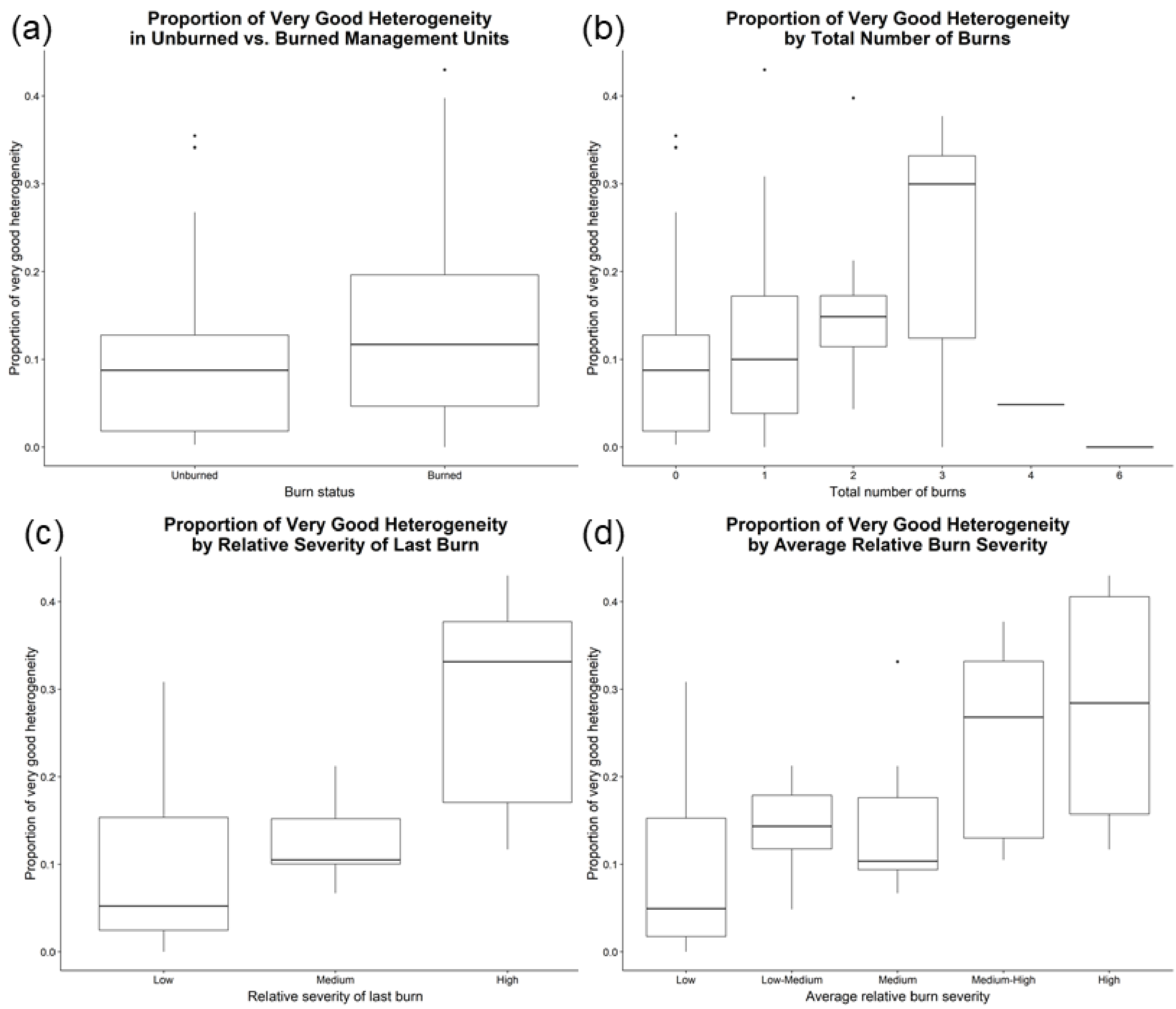
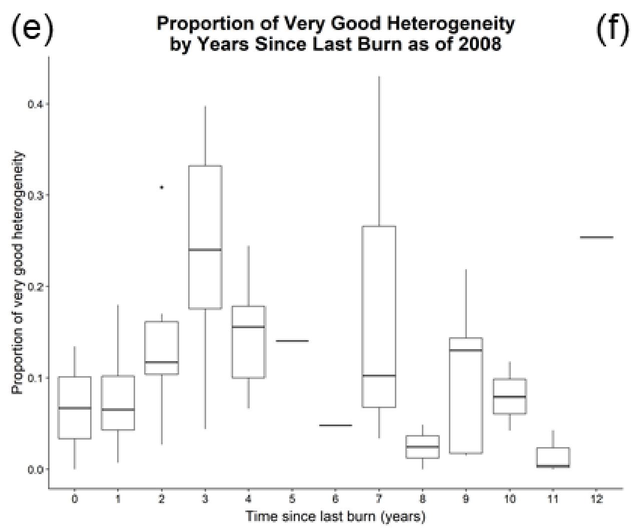


Figure 11: Percent very good GLA rank coverage per management unit.





(f)

Graph	Significance test	*p-value*
(a)	Wilcoxon	0.088
(b)	Kruskal-Wallis	0.047
(c)	Kruskal-Wallis	< 0.001
(d)	Kruskal-Wallis	0.014
(e)	Kruskal-Wallis	0.053

Figure 12: Box plots summarizing the relationship between proportion of very good GLA rank and: (a) burn status; (b) total number of burns; (c) relative severity of last burn; (d) average relative burn severity; and (e) time since last burn. (f) Table of values summarizing the significance of the statistical test of differences between the means.

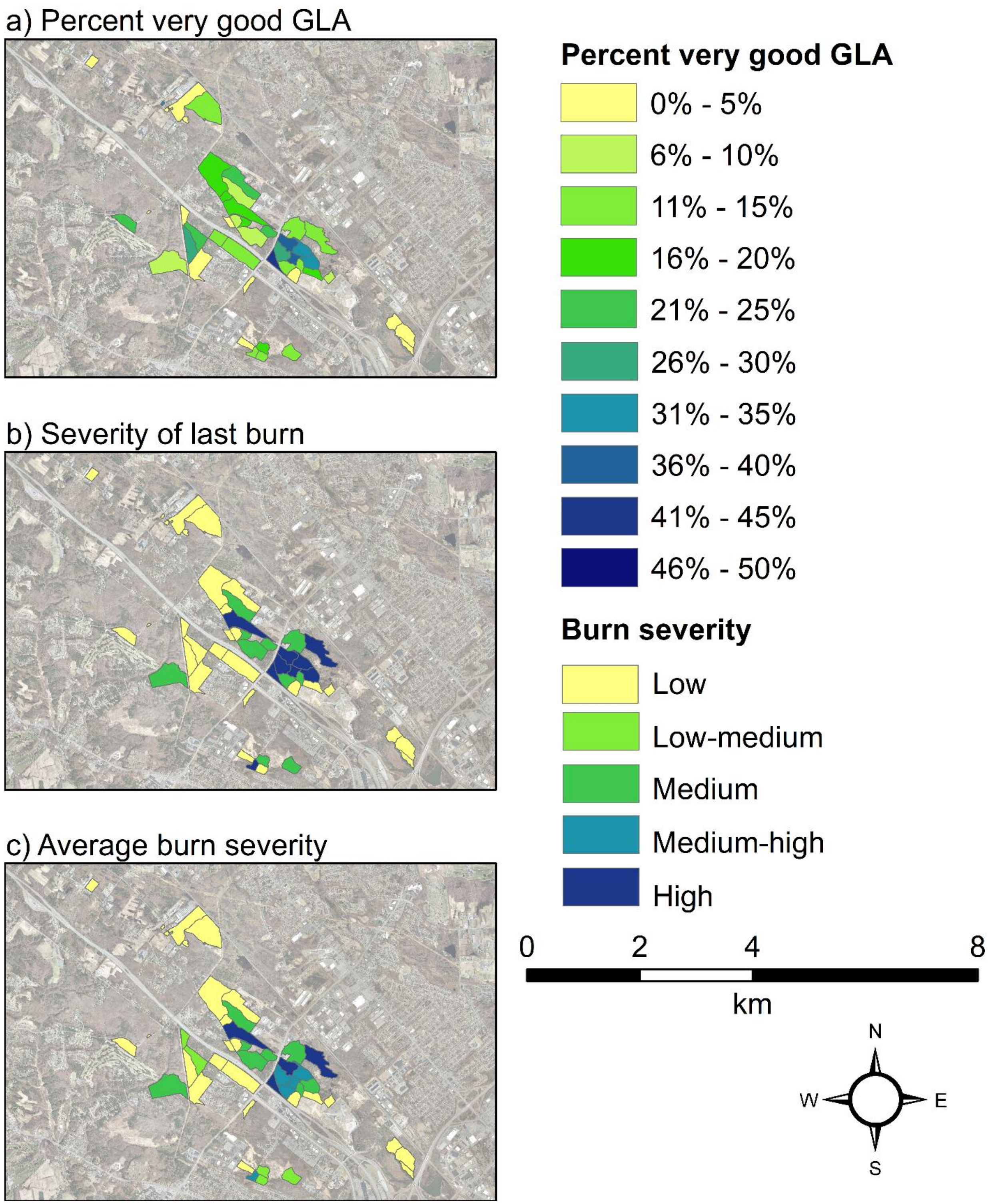


Figure 13: (a) Percent very good GLA vs. (b) severity of last burn and (c) average burn intensity.