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Supplementary material

Appendix 1

Supplement A1. Extended methods, results, and discussion.

Figure A1. Box plot summaries of habitat attributes among bird groups from the New York study area.

Figure A2. Box plot summaries of Bray-Curtis dissimilarities calculated from habitat attributes variables from the New York study area.

Figure A3. Semivariograms of the residuals of independent variables from the New York study area.

Figure A4. Semivariograms of the residuals of independent variables from the Pennsylvania study area.

Supplementary Figure Captions

Figure A1. Box plot summaries of the distributions of habitat attributes found to differentiate territory occupancy by Blue-winged Warblers (BWWA), phenotypic hybrids, cryptic hybrids (Cryptic), and Golden-winged Warblers (GWWA) (column one); and BWWA, hybrids (phenotypic and cryptic hybrids combined), and GWWA (column two) in the St. Lawrence Valley, New York, USA. The boxplot figures display the median values, the first and third quartile, and the minimum and maximum values, while circles denote outliers.

Figure A2. Box plot summaries of Bray-Curtis dissimilarities calculated from habitat-attribute variables that were quantified within five spatial extents (see Table 1) for differentiating among sites occupied by Blue-winged Warblers (BWWA), cryptic hybrids, phenotypic hybrids, and Golden-winged Warblers (GWWA) in the St. Lawrence Valley, New York, USA. Following the calculation of the Bray-Curtis dissimilarity matrices, we performed analyses of similarities tests (ANOSIM) to identify the spatial extent over which to quantify habitat characteristics in order to best differentiate among sites occupied by the four groups of birds. For each spatial extent, we display the ANOSIM *R* statistic (values further from 0 indicate larger dissimilarity among groups), and the associated *p*-value.

Figure A3. Semivariograms of the residuals of *Solidago* spp. % cover [a measure of territory-level (50 m) vegetation composition], microedge [a measure of territory-level (50 m) vegetation structural variability], proportion of deciduous forest cover [a measure of remotely sensed vegetation composition from 2011 National Land Cover Data (NLCD)], and 1st order standard deviation image texture (a measure of remotely sensed habitat structure quantified at 122 bird capture locations throughout the St. Lawrence River Valley, New York, USA. We quantified deciduous forest cover and image texture within four spatial extents (50-m, 100-m, 250-m, and 500-m radius circles) surrounding bird capture locations. The semivariance at each lag is denoted as a black dot. The dashed lines represent the maximum and minimum semivariances observed based on 99 random permutations of the original data. Semivariance values falling within the maximum and minimum semivariance envelopes indicate little evidence of spatial correlation of a habitat attributes among capture locations.

Figure A4. Semivariograms of the residuals of microedge [a measure of territory-level (50 m) vegetation structural variability], proportion of deciduous forest cover [a measure of remotely sensed vegetation composition from 2011 National Land Cover Data (NLCD)], and 1st order standard deviation image texture [a measure of remotely sensed habitat structure] quantified at 28 bird capture in central Pennsylvanian Appalachian Mountains, USA. We quantified deciduous forest cover and image texture within four spatial extents (50-m, 100-m, 250-m, and 500-m radius circles) surrounding bird capture locations. The semivariance at each lag is denoted as a black dot. The dashed lines represent the maximum and minimum semivariances observed based on 99 random permutations of the original data. Semivariance values falling within the maximum and minimum semivariance envelopes indicate little evidence of spatial correlation of a habitat attributes among capture locations.

Supplement A1

Extended Methods

Broad-scale habitat structure

Image texture calculations

To provide a description of habitat structure across broad extents, we calculated image texture, which is the spatial distribution (texture) of pixel values (tones) from raster-based imagery (Haralick et al. 1973). We calculated image texture from two image sources. The first were 1-m resolution aerial photographs acquired by the National Agricultural Imagery Program (NAIP, USDA-FSA, available from http://www.fsa.usda.gov/FSA/apfoapp?area=home&subject=prog&topic=nai). NAIP acquires multi-band, orthoimages during the summer growing seasons throughout the U.S. We used two images from 2011 (ortho_1-2_1n_s_ny089_2011_1 and ortho_1-1_1n_s_ny045_2011), which together covered our study area in New York. We used one image from Pennsylvania, which covered the extent of our study area (ortho_1-1_1n_s_pa027_2010_1). Second, we used two, 30-m resolution Landsat TM images acquired on 2 June, 2010 (path 15, row 29) and July 2, 2010 (path 15, row 30) for our New York study area, and one for our Pennsylvania study area from 2 June 2010 (path 16, row 31). All images were captured during the peak of the growing season and thus describe the state of vegetation for the avian breeding season in our study area. Both NAIP and Landsat are multi-band data sources, capturing information across different ranges of the visible and near-infrared spectrum. NAIP consists of four bands, whereas Landsat images are composed of seven bands, and image texture values likely vary based on which bands are used for calculation. We opted to convert the NAIP imagery from the natural color and near infrared to black and white. From the Landsat data, we choose to use Band 4 (near-infrared).

We computed 1^{st}-order standard deviation image texture to characterize patterns in habitat heterogeneity (Wood et al. 2012). To calculate texture, we used a moving window analysis in which, for each window size, the standard deviation of pixel digital number values within a given window size was computed, and assigned to the central cell of the moving window. This process was then repeated such that every pixel within the area of interest was in turn treated as the central cell. We calculated image texture in two window sizes from the aerial photograph (5×5 and 63×63), and one from Landsat (3×3). The combination of image grain size and window extent reflect a scale at which we computed image texture, and allowed for the evaluation of habitat structural heterogeneity at multiple spatial scales, which we summarized as the means and standard deviations at the four different spatial extents (50-m – 500-m radius circles).

In New Jersey, territories of Golden-winged Warblers ranged in size from 0.3 – 4 ha (Defalco and Dey 2003) and in Kentucky from 1.3 – 2.1 ha (Patton et al. 2010). The extents at which we calculated image texture ranged from 0.0005 to 0.0063 ha from the aerial photograph and 0.81 ha from Landsat. The extent of the 50-m radius circle in which we described habitat attributes, and computed remotely sensed metrics was 0.79 ha. The areas in which we summarized the remotely sensed variables were 2.4 ha (100-m radius circles), 18.8 ha (250-m radius circles), and 77.7 ha (500-m radius circles). Thus, we used remotely sensed data to quantify habitat structure at both fine- and medium-grain, and then summarized this structure at spatial extents similar to the breeding territory size of the study birds, and in larger landscapes surrounding the territories. This allowed for us to perform a comprehensive examination of the relationships of habitat structural variability on territory occurrence of Golden-winged and Blue-winged Warblers, and hybrids.

Statistical analysis

Assumptions

Aside from the analysis of similarities test (ANOSIM) and logistic regression best-subsets analysis (see manuscript text), prior to all other analyses we visually searched for outliers and assessed the assumptions of normality by constructing histograms and fitting normal *QQ*-plots of independent variables, and heteroscedasticity by performing Bartlett's tests. If our data met assumptions for parametric analyses, we conducted analysis of variance (ANOVA) or *t*-tests. If variables were not normally distributed, we applied log transformations. If log-transformed data did not meet normality assumptions, we used non-parametric Kruskal-Wallis tests or Wilcoxon-rank sum tests.

Spatial autocorrelation

Because many of the capture locations were located close to one another, we checked for statistical independence of habitat data among the plots by fitting semivariogram models (Legendre and Fortin 1989) to data from selected habitat attributes within each spatial extent from both the New York and Pennsylvania study areas using the geoR package (Ribeiro Jr and Diggle 2001) in the R statistical program. We tested for the presence of non-independence of field-collected habitat data using microedge as our representative variable. Additionally, we selected *Solidago* spp. % cover (New York only), which captured a component of floristic composition important to our study species (Confer et al. 2011). For the data from the four remotely sensed spatial extents (50 – 500m), we selected image texture (aerial photograph, 1st-order standard deviation, 5×5 moving window) and deciduous forest cover because we assumed these variables captured habitat structure and floristic variability throughout our study sites. We detected slight evidence for spatial dependence of *Solidago* spp. % cover among capture locations in New York (Fig. A3). However, we did not detect a similar pattern for any of the other nine habitat attribute in New York, and thus treated the capture locations as independent in our statistical analyses (Fig. A3). We detected evidence for slight spatial dependence among capture locations in Pennsylvania for deciduous forest quantified within 100-m and 250-m buffers (Fig. A4). Again, because these effects were small, and since all other habitat attributes did not show considerable evidence of spatial dependence, we treated capture locations in Pennsylvania as statistically independent (Fig. A4).

Testing for sources of bias in the data-collection process

Three additional sources of variability in the data that we analyzed - observer, year, and bird capture location - might have introduced biases into analyses. In New York, we checked for differences in the typical values of ground collected habitat variables based on observer (two groups of observers) or year (2009 and 2010) by fitting Wilcoxon-rank sum tests. We used a non-parametric procedure here due to the presence of outliers in the data. We found systematic differences in % bare ground cover ($W_{122} = 1112$, $p < 0.01$) and snag density ($W_{122} = 895$, $p < 0.01$) between observer groups, and microedge ($W_{122} = 2312$, $p < 0.01$), % bare ground ($W_{122} = 2838$, $p < 0.01$), and tree cover ($W_{122} = 2545$, $p < 0.01$) between years. Because we found few differences of habitat attributes between observer groups, and since we assumed the differences in attributes among years represent structural components of habitat unique to each capture location rather than due to major differences in growing conditions between years, we did not include observer or year as random effects in our models.

Further, because the general shifting distribution pattern of Blue-winged Warblers into Golden-winged Warbler territories is northward, we checked in New York for evidence that the bird groups were clustered on a latitudinal gradient, using a Kruskal-Wallis test. We found slight evidence for differences among avian groups due to latitude (H_3 = 8.6, *p-value* = 0.4). To understand which avian groups may be driving this trend, we performed a nonparametric multiple comparisons test that is based on relative contrast effects (Konietschke 2011). We used a Bonferroni corrected alpha-value (0.05/6 = 0.008) to assess significance. The two groups with the greatest observed difference in spatial location were Golden-winged Warbler and cryptic hybrids (*p-value* = 0.9). Otherwise, we did not find evidence for a north-south distribution of avian groups based on capture latitude. We performed a similar set of analyses in Pennsylvania using a Kruskal-Wallis test to examine differences in the ground collected habitat variables among four groups of observers and four years of data collection (2008-2011). We found no differences in habitat attributes for either of these factors and similarly did not include observer or year as random effects in our models.

Extended Discussion

Habitat associations: differences of habitat attributes among extents

The majority of studies of habitat selection at breeding sites of Golden-winged Warblers have been conducted at the territory scale (see references within Roth et al. 2012). Yet, it is relatively well established that birds can respond to differences in habitat attributes at multiple spatial extents (Wiens et al. 1987). Thus, we were interested in identifying dissimilarities in habitat occupancy by Golden-winged and Blue-winged Warblers, and hybrids relative to habitat attributes quantified at extents larger than the territory itself. The largest separation of the bird groups based on habitat attributes came from variables quantified at the landscape extent (500-m radius circles). Further, when only comparing habitat attributes quantified at the territory scale (50 m), we found no apparent differences in avian groups. Recent investigations have begun to elucidate the importance of broader-scale habitat features in influencing foraging behavior and abundance of Golden-winged Warblers (Thogmartin 2010, Streby et al. 2012), and these results have been adapted into conservation plans (Roth et al. 2012). We extend these findings to also highlight the importance of spatial extent in determining territory habitat occupancy by Golden-winged and Blue-winged Warblers, and hybrids.

Pervious investigations of territory site selection for Golden-winged Warblers indicated the importance of early-successional, structurally complex breeding habitats often situated within a forested mosaic (Klaus and Buehler 2001, Confer et al. 2003, 2010, Bulluck and Buehler 2008, Thogmartin 2010, Streby et al. 2012). Our results for Golden-winged Warblers individuals in New York were nearly identical to these findings. However, extending these previous investigations, we also discovered an apparent aversion to urban areas by Golden-winged Warblers, which has not been previously described. Blue-winged Warblers displayed almost the exactly opposite associations for these habitat attributes.

An interesting finding from our analysis was the importance of remotely sensed habitat structure (image texture) for characterizing territory habitat occupancy by Golden-winged Warblers. In our case, Golden-winged Warblers occupied territories where the habitat structure was relatively homogenous surrounding territories. This is most likely related to the presence of contiguous deciduous forest, which is an important attribute for breeding Golden-winged Warblers (Streby et al. 2012). These findings also echo those from studies in the Upper Midwest portion of the U.S, were Golden-winged Warbler abundance was lower in areas with high broad-scale habitat edge density, and in patchy, transitional forests (Thogmartin 2010). Image texture, particularly when calculated from high resolution imagery, is valuable for characterizing fine-grained habitat features important to avian density and richness (St-Louis et al. 2006, Wood et al. 2012, 2013). Our findings provide a new application for the use of image texture in biodiversity studies where we were able to characterize habitat occupancy for Golden-winged Warblers from that of Blue-winged Warblers, phenotypic hybrids, and cryptic hybrids.

Additional Literature Cited

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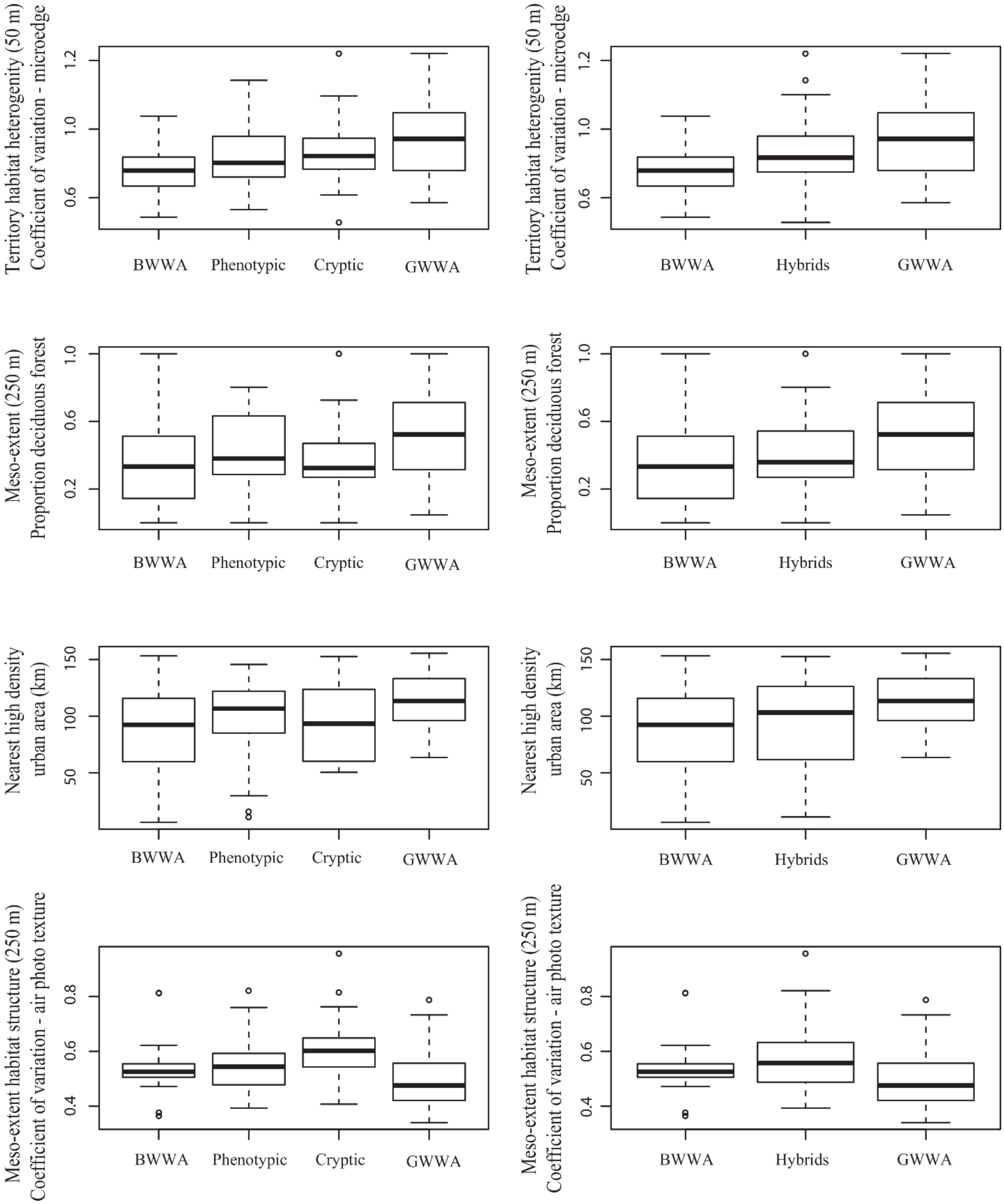
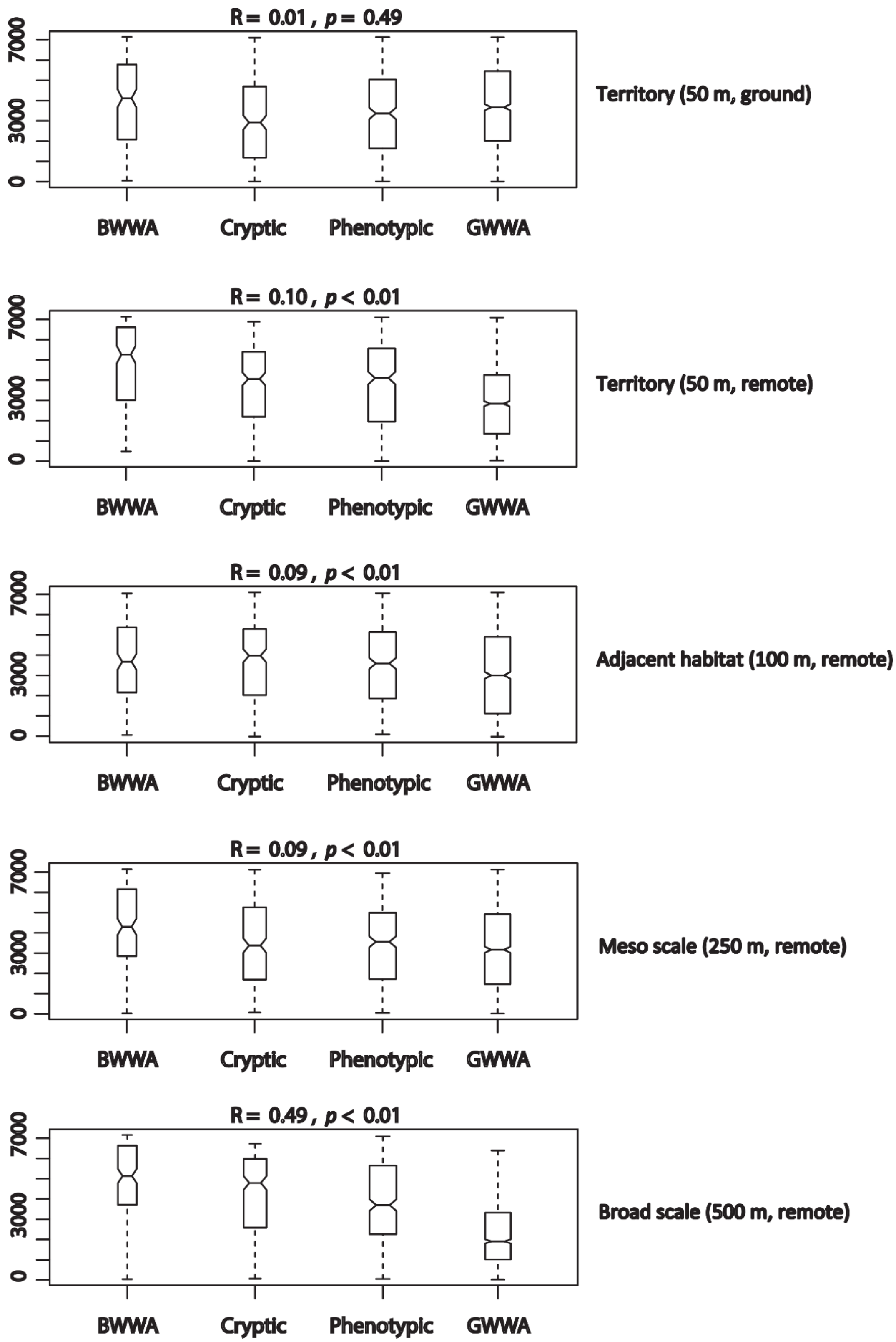

Territory habitat heterogenity (50 m)
Coefficient of variation - microedge
0.6
1.0
1.2
BWWA
Phenotypic
Cryptic
GWWA
Territory habitat heterogenity (50 m)
Coefficient of variation - microedge
0.6
1.0
1.2
BWWA
Hybrids
GWWA
Meso-extent (250 m)
Proportion deciduous forest
0.2
0.6
1.0
BWWA
Phenotypic
Cryptic
GWWA
Meso-extent (250 m)
Proportion deciduous forest
0.2
0.6
1.0
BWWA
Hybrids
GWWA
Nearest high density
urban area (km)
50
100
150
BWWA
Phenotypic
Cryptic
GWWA
Nearest high density
urban area (km)
50
100
150
BWWA
Hybrids
GWWA
Meso-extent habitat structure (250 m)
Coefficient of variation - air photo texture
0.4
0.6
0.8
BWWA
Phenotypic
Cryptic
GWWA
Meso-extent habitat structure (250 m)
Coefficient of variation - air photo texture
0.4
0.6
0.8
BWWA
Hybrids
GWWA

Figure A1



R= 0.01 , p= 0.49
Territory (50 m, ground)
R= 0.10 , p< 0.01
Territory (50 m, remote)
R= 0.09 , p< 0.01
Adjacent habitat (100 m, remote)
R= 0.09 , p< 0.01
Meso scale (250 m, remote)
R= 0.49 , p< 0.01
Broad scale (500 m, remote)
0
3000
7000
BWWA
Cryptic
Phenotypic
GWWA

Figure A2

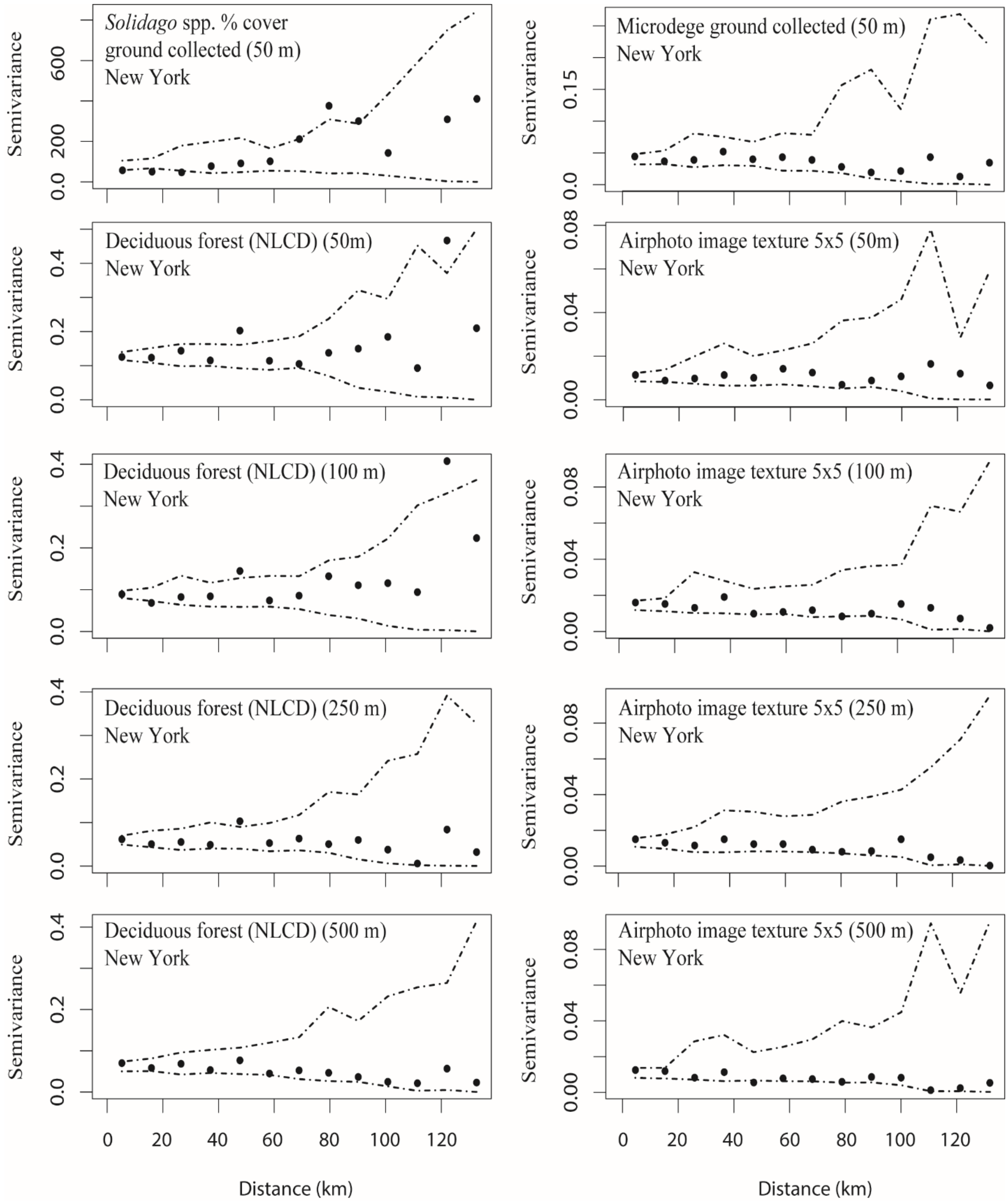
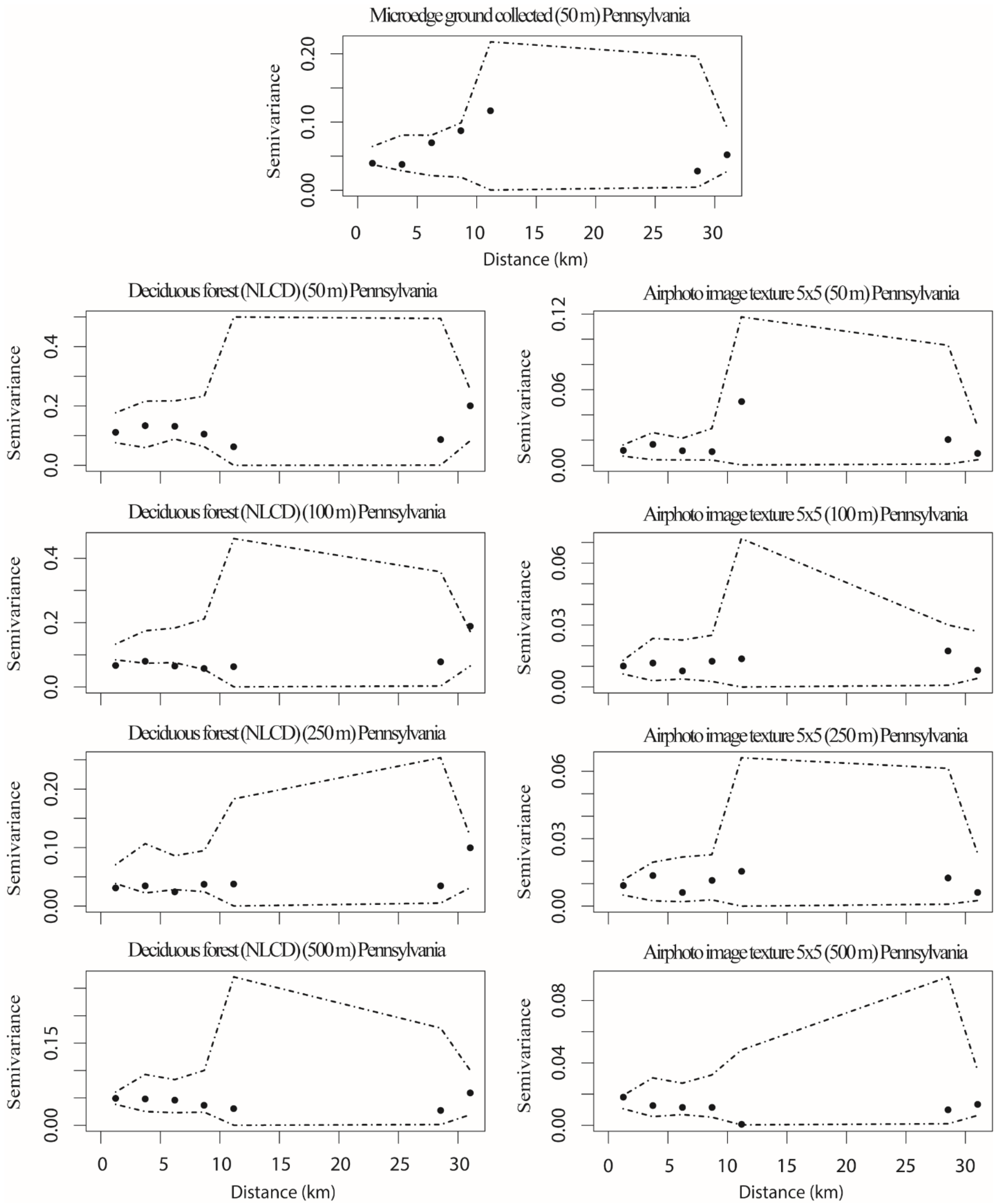

Solidago spp. % cover
ground collected (50 m)
New York
Microdege ground collected (50 m)
New York
Deciduous forest (NLCD) (50m)
New York
Airphoto image texture 5x5 (50m)
New York
Deciduous forest (NLCD) (100 m)
New York
Airphoto image texture 5x5 (100 m)
New York
Deciduous forest (NLCD) (250 m)
New York
Airphoto image texture 5x5 (250 m)
New York
Deciduous forest (NLCD) (500 m)
New York
Airphoto image texture 5x5 (500 m)
New York
Semivariance
Distance (km)

Figure A3



Microedge ground collected (50 m) Pennsylvania
Deciduous forest (NLCD) (50 m) Pennsylvania
Airphoto image texture 5x5 (50 m) Pennsylvania
Deciduous forest (NLCD) (100 m) Pennsylvania
Airphoto image texture 5x5 (100 m) Pennsylvania
Deciduous forest (NLCD) (250 m) Pennsylvania
Airphoto image texture 5x5 (250 m) Pennsylvania
Deciduous forest (NLCD) (500 m) Pennsylvania
Airphoto image texture 5x5 (500 m) Pennsylvania
Semivariance
Distance (km)

Figure A4