LIFE ON THE EDGE:

STRUCTURAL ANALYSIS OF FOREST EDGES TO AID URBAN MANAGEMENT

by

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Dedicated to my wife and daughter. I could not have done this without them.

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ABSTRACT

The accelerating expansion of agricultural and urban areas fragments and degrades forests and their capacity to provide essential ecosystem services while increasing physiological stress and mortality rates of trees growing near forest edges. Previous studies have documented that edges are hotter and drier than forest interiors and trees nearer the edge grow slower. However, the physical structure of a forest's canopy may serve to mitigate to these effects. This study quantifies forest fragmentation across the Central Hardwoods Region (CHR; containing Missouri, Illinois, and Indiana) and characterizes structural differences between the canopies of forest edges and forest interiors. Importantly, we distinguish between edges that neighbor developed land and agricultural lands since these landcover types may impose distinct effects on forest structure. We characterized forest canopy structure in a subset of the CHR region using the 2016-2020 Indiana 3DEP Lidar Program data. Our findings indicate edge forest (forests within 30m of an edge) makes up 29.8% of the total forest in our study extent, with urban and agricultural edges accounting for 17.8% and 72.8% of the edge edges in the region, respectively. Analysis of 15 separate structural metrics derived from aerial laser scanning (ALS) showed no significant structural differences between developed and agricultural edge canopies but did find differences between structure of canopies in forest cores and those in forest edges of any kind. As developed and agricultural lands increase so too will forest fragmentation and the creation of new forest edges. If there are no significant differences between forest edge types, then we could begin to treat edges without distinction. This could lead to simplified management practices for foresters and urban foresters alike to protect and preserve forest fragments.

CHAPTER 1. LIFE ON THE EDGE: STRUCTURAL ANALYSIS OF FOREST EDGES TO AID URBAN MANAGEMENT

1.1 INTRODUCTION

Conserving habitat quality and ecosystem services requires natural landscapes including intact forests (Fynn & Campbell, 2018) but expansion of agricultural and urban lands has caused global forest cover to decline by one third (Reinmann & Hutyra, 2017a; Williams, 2006), fragmenting the remaining areas of natural forest cover. Fragmentation is the breaking apart of habitat into smaller separated pieces; expansion of developed and agricultural lands from human activity is a leading cause of fragmentation (Haddad et al., 2015). Of the total forest cover globally, greater than 70% is within 1 km of a forest edge and about 20% is within 100m; edges are exposed to cover types other than forest including agriculture, developed, and developing, or other landcover types altered by humans (Haddad et al., 2015; Smith et al., 2018). A forest edge is an area that is protected from the effects of climate and neighboring land classes from above and at least all but one side (Matlack, 1993; Smith et al., 2018). In the 54 million hectares of the northeastern United States, 23% (12.42 million ha) is within 100m of an edge, 12% (6.48 million ha) border agricultural cover types, and 11% (5.94 million ha) border developed areas or roads (Smith et al., 2018). As human activities expand these land cover types forests become more fragmented leading to decreases in forest interiors while increasing forest edges and changing the type, quantity, and distribution of ecosystem services these forests provide.

Forest fragmentation imposes a wide array of structural and functional changes. These include decreases in biomass and changes in nutrient cycling (Haddad et al., 2015; Reinmann & Hutyra, 2017a; Smith et al., 2018), which negatively impacts ecosystem functions and reduces biodiversity levels. As fragment size decreases, the magnitude of these effects increases (Haddad et al., 2015). Trees growing at edges are exposed to different environmental conditions than trees in the interior including higher exposure to light, wind, and larger temperature gradients (Smith et al., 2018). Depending on the forest type and the neighboring land cover types, other factors may include changes in soil N and C, nitrogen deposition from fertilizer applied to agricultural fields and residential lawns, traffic emissions (Decina et al., 2017; Reinmann & Hutyra, 2017a, 2017b; Remy et al., 2016, 2017), wildfire vulnerability as well as breaks in fuels (Cochrane & Laurance, 2002; Laurance & Curran, 2008; Smith et al., 2018), and in increase chance of pest infestations

(Smith et al., 2018; Weathers et al., 2001). In temperate broadleaf forests, edge effects have been shown to boost forest growth rates, increasing carbon uptake (Reinmann & Hutyra, 2017a). Depending on a biome though, forest growth can either increase or decrease from the same edge effects (Smith et al., 2018). Expansion from landscape changes and fragmentation in urban areas has been shown to alter canopy cover, stem density, and aboveground biomass (Briber et al., 2015) changing the structure of the forests.

Forest canopy structure (CS) is the arrangement of leaves, branches, and empty space at a given time (Atkins, Fahey, et al., 2018; Fotis et al., 2018). Analysis of structure derived from LiDAR (Light Detection and Ranging) data can provide insights into forest ecosystem characteristics. These include increased soil respiration and evaporation due to leaf clumping and open space in the canopy allowing light to reach the forest floor, differences in air temperature and moisture content from leaf arrangement variations and gas diffusion through the canopy from wind penetration measured from total leaf area, canopy height, and gap fraction (Bohrer et al., 2008, 2009; Fotis et al., 2018; Fotis & Curtis, 2017; Iio et al., 2005; Law et al., 2001; Maurer, Bohrer, et al., 2013). Canopy structure analysis can also help our understanding of understory development from light infiltration through deep canopy gaps and altered recruitment rates from seed dispersal affected by size and fraction of gaps in the canopy and density of leaves (Maurer, Hardiman, et al., 2013; Oliver & Larson, 1996). These structural characteristics include height, area and density, arrangement, cover and openness, and variability in the canopy, each of which can be quantified using a variety of structural metrics (Atkins, Fahey, et al., 2018). These metrics of canopy structure are indicative of and can be used to predict forest characteristics including disturbance and successional status, net primary production (NPP) and carbon storage, and aboveground biomass (Gough et al., 2019; Hardiman et al., 2013; Parker et al., 2004). When applied to forest edges these indicators may inform management practices including, but not limited to, removal of invasive species to reduce stress on native species' growth and planting of native species to increase local diversity.

Portable canopy lidar (PCL) systems have been used successfully to collect data on canopy structural complexity in non-urban forests (Atkins, Bohrer, et al., 2018a; Gough et al., 2019; Hardiman et al., 2011, 2018). PCL and other terrestrial laser scanning systems can analyze fine scale details of structural complexity on a site basis, but a recent study has found that aerial laser scanning (ALS) can quantify similar structural components on a larger scale (LaRue et al., 2020).

Significant correlations were found between TLS and ALS for metrics of height, cover and openness, external and internal heterogeneity, and vegetation area (LaRue et al., 2020). We can utilize ALS to analyze forests canopy structure across multiple forests in both urban and rural areas.

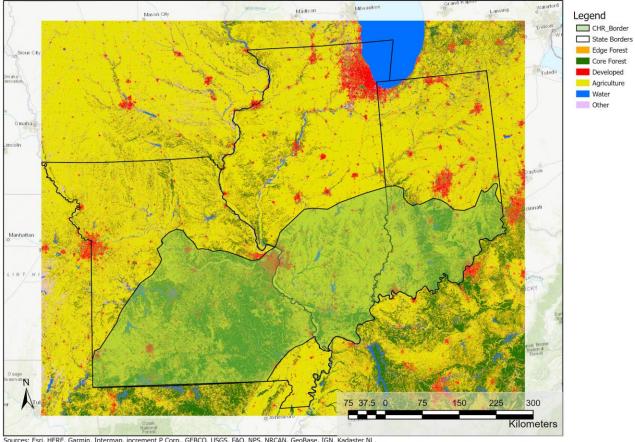
The goal of this study was to quantify edge effects on forest canopy structure. Specifically, we ask if canopy structure differs significantly between forest edges and cores and if there is a significant difference between forest edges neighboring developed and agricultural land cover classes. Since canopy structure is an indicator of forest growth, edges are exposed to a different magnitude of factors compared to the interior, and ALS can be applied to measure differences in structure at larger landscape (sub-continental) scales, then remote sensing analysis can reveal differences in structure between edge and interior at different neighboring cover types. We focus on lands in the Central Hardwoods Region (CHR) of the North Central Midwest. Utilizing remote sensing analysis of NLCD land cover and tree canopy data at 30m resolution, we found from a forest area of about 24.7 million ha, 3.3 million patches ranging in size from 0.9 ha to 3.7 million ha and a mean patch size of 7.4 ha. We expected to see a larger number of small, fragmented patches compared to fewer intact large forests across our study area and that within those areas we hypothesized that canopy structure will be significantly different between forest edges and cores and structure will differ significantly between developed and agricultural edges due to the variety of conditions that forest edges are exposed to depending on neighboring land class types (Smith et al., 2018).

1.2 METHODS

1.2.1 Area of Interest (AOI)

The Central Hardwoods region is a well-studied area that spans Indiana, Illinois, Missouri, and portions of the surrounding states. At nearly 17 million hectares, it consists of a mix of ecosystems including forests, woodlands, and savannas (Handler et al., 2014). The study region contains 15 metropolitan statistical areas (MSAs) with populations ranging from 9.4 million people in the Chicago MSA to approximately 160,000 in the Bloomington, IN MSA (U.S. Census Bureau, 2020). Previous analyses that have examined edge effects on forest structure and functioning have focused on other forest types (e.g., norther temperate mixed deciduous), other regions (e.g., New England, where agriculture is not a dominant driver of landcover change), and other forest

characteristics than canopy structure (e.g., growth rates and biogeochemistry). Analyses across this region can improve our understanding of forest fragmentation and canopy structural patterns from developed to undeveloped forest areas within the forest edge and interior.



Land Classes and Fragmentation Across the Central Hardwood States and Surrounding Areas

Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), (c) OpenStreetMap contributors, and the GIS User Community

Figure 1: Study area in the Central Hardwoods region states of Illinois, Indiana, Missouri and the surrounding areas, reclassified from 2016 NLCD landcover and tree canopy to visualize forest fragmentation. Forest edges and cores = NLCD codes 41, 42, 43, 52, and 90; developed land = NLCD codes 21, 22, 23, and 24; agriculture = NLCD codes 81 and 82, water = NLCD code 11; and other = NLCD codes 31 and 95. NLCD tree canopy was based on canopy cover from 20 - 100%

1.2.2 Landcover Analysis

To assess effects of forest fragmentation on canopy structure across the Central Hardwoods Region states we combined a spatial analysis of landcover patterns throughout the region with an assessment of canopy structure using aerial lidar surveys from Indiana. We followed the classifications used by Smith et al. (2018), reclassifying the NLCD landcover (Dewitz, 2019) classes to create Forest, Developed, Agriculture, Water, Other, Developed Edge, Agriculture Edge, Water Edge, and Other Edge. To get a better view of canopy in developed areas we used the 2016 NLCD tree canopy (Dewitz, 2019) data set to the land cover data. First, we reclassified the NLCD land cover data to create the five main classes. We also reclassified the NLCD tree canopy data to forest (20 - 100% cover) or non-forest (0 - 19% cover) based on the canopy cover classifications from The Nature Conservancy (TNC) (R. C. Anderson et al., 1999). Next, we did a raster calculation in ArcGIS Pro to combine the land cover and tree canopy layers together. The NLCD landcover does not account for tree canopy cover in developed areas (Hardiman et al., 2017) so we added the reclassified canopy layer to give a more accurate estimation of tree cover in developed areas. With the new land cover canopy layer created, we converted to unsmoothed polygons to begin the edge creation. We created individual shapefiles for each class (forest, developed, agriculture, water, and other) which output 1,885,570 forest features and of that 1,499,573 were less than 8,100 m². Any area less than this would return a forest area that is all edge and has no core effect on the edge. These polygons were removed from the canopy analysis but were retained for the fragmentation study. To create the edge polygons, we buffered the total forest to -30 m following (Reinmann & Hutyra, 2017a) and used symmetrical difference with the total forest and buffered forest to create our total edge forest.

To separate the edge polygons into developed edge and agriculture edge we used the polygons created for developed and agriculture land use and ran feature to point. We created Thiessen polygons on the points and spatial joined them to get the land use attributes on the Thiessen polygons. Next, we intersected the edge forest polygons with the joined Thiessen polygons. Then we selected for each land use to export them as separate layers and dissolved them into a single feature in order to create 300 random points each within developed edge, agriculture edge, and core forest for LiDAR analysis.

1.2.3 Forest edge structure analysis

Within our study area, Indiana had the only complete statewide aerial LiDAR dataset, so we focused the analysis of canopy structure to Indiana. Compared to the region at large, Indiana landcover is typical of the region: forests make up 28.6% of the total area (31.4% of the region total), developed land 8.7% (7.0% of the region total), agricultural lands 59.9% (57% of the region total), water 1.8% (region total 3.4%), and other 0.9% (1.3% overall). Aerial LiDAR was downloaded from public sites (Jung & Oh, 2021) to assess a random sampling of 15m radius plots in developed and non-developed edge forests and core forests. The LiDAR was clipped to a 15 m radius using the points created in ArcGIS Pro. The clipped point clouds were analyzed using the lidR (Roussel et al., 2020; Roussel & Auty, 2021), leafR (Ameida et al., 2019), and gstat (Gräler et al., 2016; Pebesma, 2004) packages in RStudio to assess 15 canopy structural complexity parameters for height, cover and openness, external and internal heterogeneity, and vegetation area (Atkins, Bohrer, et al., 2018b; LaRue et al., 2020). Height metrics included q100, q75, q50, q25, mean maximum canopy height, and the Gini index coefficient (Gini). The metrics analyzed for cover and openness were deep gap fraction (DGF) and gap fraction profile (GFP). External heterogeneity metrics were rumple and top rugosity, while internal heterogeneity metrics were vertical standard deviation (vertSD), standard deviation of the standard deviation of heights (sd.sd), vertical complexity index (VCI) and vertical coefficient of variation of heights (vertCV). Vegetation density was examined using vegetation area index (VAI). All structural metrics and their method of calculation are explained in greater detail in (Atkins, Bohrer, et al., 2018a).

A total of 693 plots across both agricultural and urban edge as well as core forest were analyzed. Some plots (n=224) were removed due to point cloud densities less than 0.4 pts per ft² (4 pts per m²) and one plot from the forest core (plot 97_Core_E) was removed due to a plot size of 81.8 ft². A power analysis for an ANOVA comparing 3 groups indicated that a minimum sample size of 75 plots per group needed to obtain a power of 0.80, when the effect size is moderate (0.25) and a significance level of 0.001 is employed. Final plot totals were 99 developed edge plots, 174 agricultural edge plots, and 195 core plots for a total of 468 plots. Statistical analyses in R included a multivariate analysis of variance (MANOVA), followed by individual ANOVAs with Tukey tests to check for significance.

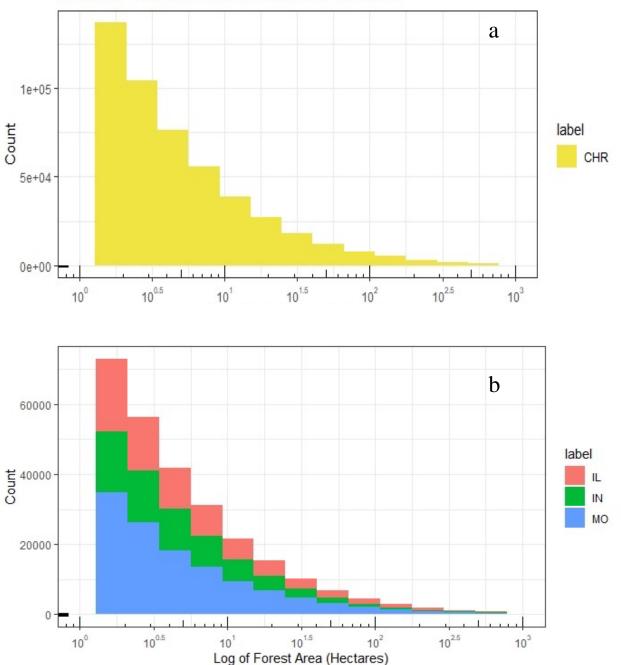
1.3 Results

1.3.1 Forest Fragmentation

Our analysis of landcover within the study region identified a total area of about 78,648,000 ha. Of that, the total forest area of encompassed about 31% of the land, developed land totaled about 7%, agriculture equaled 57%, water was 3%, and other totaled 1%. Edge forest makes up 29.8% of the total forest with a total edge length of 3,371,000 km. Urban edges account for 17.8% of the edge forest (5.3% of the total forest) and 600,000 km. Agricultural edges account for 72.8% of the edge forest (21.5% of the total forest) and 2,428,000 km. Water edges account for 3.9% of the edge forest (1.1% of the total forest) and 133,000 km. Other edges (including barren land, herbaceous, and emergent herbaceous wetlands) account for 6.2% of the edge forest (1.9% of the total forest) and 209,000 km. Across all three states and the study area as a whole, numbers of forest fragments decreased as fragment area increased (Fig. 2). An analysis of forest area to perimeter length (Fig.3) found that as patch size decreases so too does forest edge length, however, there are fewer large forest patches that are edgier compared to smaller patches.

	Landcover								
	% Edge Forest	% Total Forest	Perimeter (km)	Area (ha)					
Total Forest Area			3,371,000	24,699,000					
Total Edge Area		29.8%	3,371,000	7,357,000					
Urban Edge	17.8%	5.3%	600,000	1,309,000					
Agriculture Edge	72.0%	21.5%	2,428,000	5,299,000					
Water Edge	3.9%	1.2%	133,000	290,000					
Other Edge	6.2%	1.8%	209,000	456,000					

Table 1: Total forest (24,699,175 ha) and forest edge areas (7,357,059 ha). Percent edge forest (29.79% of total forests) and total forest for urban (5.3%), agriculture (21.46%), water (1.18%), and other land classes (1.85%). Perimeter in kilometers and area in



Distribution of CHR Forest Patches in Hectares

Figure 2: Distribution of forest patches across our study area and individual states (IL, IN, and MO). Number of forest fragments in each area increases as patch size decreases.

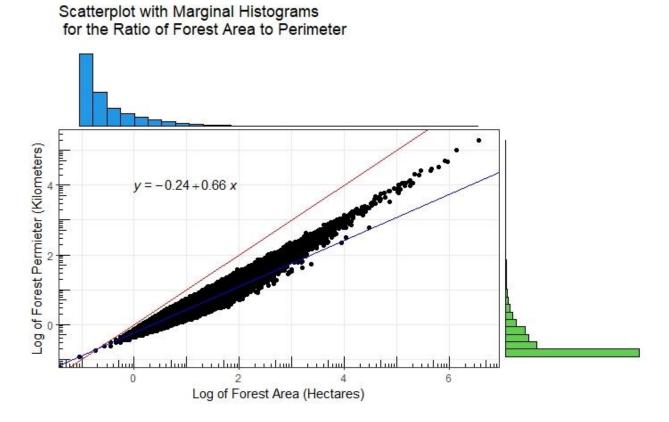


Figure 3: Plot of forest patch area (x-axis) to forest edge perimeter length (y-axis) with marginal histograms showing the distributions of each show that as patch size decreases edge length decreases. As larger patches are fragmented more edge is created forest edges become shorter.

1.3.2 Forest Structure

Across all categories of canopy structural metrics, edge forests adjacent to developed or agricultural landcover types were more like each other than either was to core/interior forests (Figures 4-8, violin plots of canopy structural metrics are grouped into categories including: height, internal complexity, external complexity, vegetation density, and openness, respectively, following (LaRue et al., 2020)). Forests adjacent to both agricultural and developed landcover types were shorter than forest cores. The 25th, 50th, 75th, and 100th quantiles of height measurements (Fig. 4a-d) show that density of lidar returns skews towards the lower canopy for agriculture and developed compared to forest cores. Mean maximum canopy heights (Fig. 4e) are also lower for both edge types compared to cores. Means for each quantile and the mean maximum canopy height are similar for edge canopy heights adjacent to ag and developed landcover but were about a third less than forest cores. Gini coefficient values (Fig. 4f) for our study are higher for agriculture and developed edges compared to forest cores. Distributions tend to be more positively skewed for edge forests (Fig. 4a-c) with long tails and outliers across each landcover type. Ag and core forests are negatively skewed for q100 (Fig. 4d) with outliers in the lower tails.

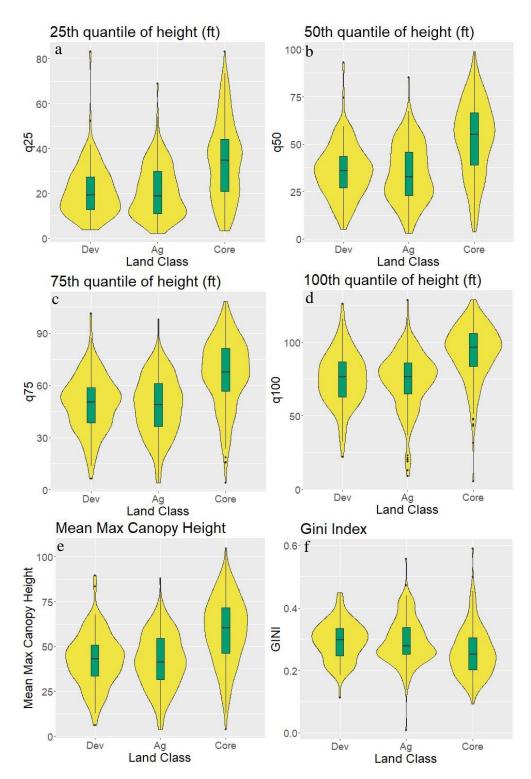


Figure 4: Forests adjacent to both agricultural and developed landcover types were shorter than interior forests. Plots were created in R studio using ggplot2 (Wickham, 2016) and include boxplots to help visualize the median and quartiles of the data. Kernel density estimation, shown in yellow, represents the distribution of data for each metric, while boxplots are displayed in green.

Edge forest canopies were on average less internally complex than canopies of forest interiors. Vertical standard deviation (Vertical SD, the standard deviation of heights within the plot), standard deviation of the vertical standard deviation (sd.sd, variability of the vertical SD across the plot), and vertical complexity index (VCI, the normalization of diversity and evenness) (Fig. 5a-c) all had mean values lower than those of core forests with distributions generally higher around the medians. Distributions are negatively skewed and unimodal with outliers present for each land class type (Fig. 5a-c). Interquartile ranges (IQR) are similar across all three land classes for Vertical SD and sd.sd but about 50% smaller for forest cores in VCI. VCI also had long tails with outliers across all classes. The vertical coefficient of variation (Fig. 5d) distributions were less skewed for developed edges (slightly bimodal) while ag and core were more skewed with outliers.

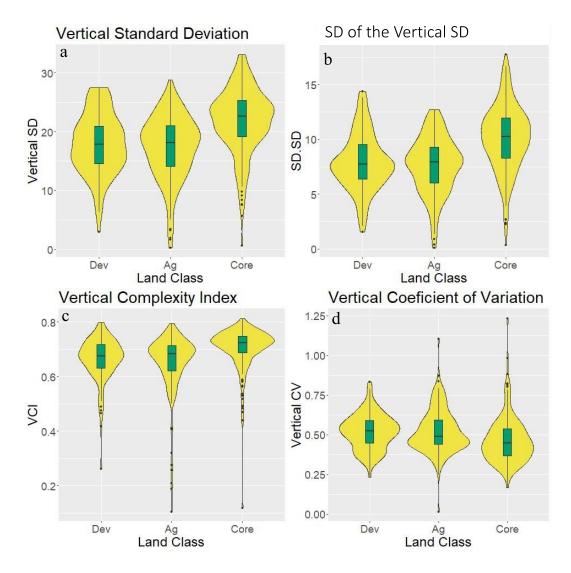


Figure 5: Edge forests were on average less internally complex compared with forest cores. Our study found lower means for vertical standard deviation (a), standard deviation of the vertical standard deviation (b), and vertical complexity index (c) with higher values for the vertical coefficient of variation.

Edge forests were on average less complex as indicated by metrics of external complexity than interior forests (Fig. 6a&b). Rumple (Fig. 6a), the area of canopy surface relative to the plot area, had lower means on edges with the distributions of those measurements skewed slightly downward. Top rugosity (Fig. 6b), the standard deviation of outer canopy heights, also showed lower means at the edges but with higher distributions closer to the mean. Mean rumple values for edge canopies adjacent to ag and developed landcover were similar but were about half of the mean rumple value for forest cores. Forest core rumple values were approximately normally distributed about the mean but were strongly positively skewed in both ag and developed edges.

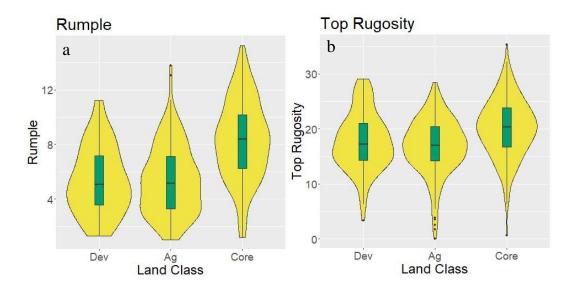


Figure 6: Rumple (a) and top rugosity (b), metrics for external complexity, were lower in both edge forest classes compared to cores indicating edge forests are less externally complex.

Edge forests on average had more open canopies that interior forests (Fig. 7). Higher deepgap fractions (Fig. 7a), the fraction of open spaces in the canopy in $\geq 1 \text{m}^2 (10.8 \text{ft}^2)$ gaps in the plot, were found in both developed and agricultural edges and were negatively skewed for all three land classes. IQR for edges were about three times as large as cores with multiple outliers in core forests. Mean values for gap fraction profile, the distribution of gaps in the point cloud, (Fig. 7b) were similar between all classes, skewed positively, and long tails with outliers (the longest in Ag).

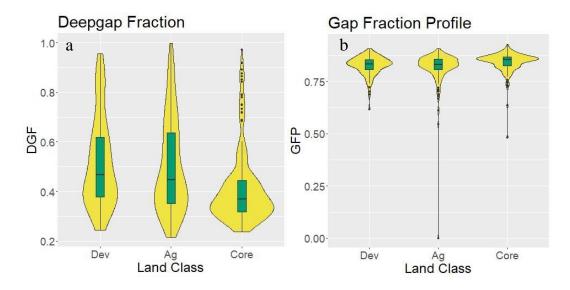


Figure 7: Forests adjacent to both developed and agricultural landcover types were on average more open than interior forests. Forest edges had higher deepgap fractions (a) with similar values between edges and core for gap fraction profile (b).

Vegetation area index (VAI) is the sum of leaf area density within the plot. Forest cores on average had more dense vegetation than edge forests (Fig.8). VAI medians were similar for developed and agricultural edges with a positively skewed distribution for developed edge and negatively skewed distribution for Ag edges, while all land classes had similar IQRs.

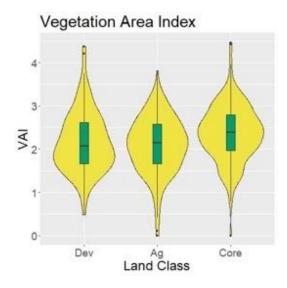


Figure 8: Vegetation area index values showed edge forests were less dense than core forests overall.

Table 2: One-way MANOVA analysis indicated a significant difference between at least one land class and the metrics.

one-way MANOVA summary										
	Df Pillai approx F num Df den Df Pr(>F)									
Land_Class	2.0	0.4	5.7	38.0	896.0	< 2.2e-16	* * *			
Residuals	465.0									
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1										

While forest cores were significantly structurally different from edges, there were no significant differences in the mean values for metrics between developed edges and agricultural edges. A one-way MANOVA test for the effects of land class (developed edge, agriculture edge, and core forest) on our 15 metrics showed a significant effect between at least one land class and the metrics (approx. F 5.73, Df = 2, 465, P = < 0.001) (Table 2). A univariate ANOVA showed significant effects (P = < 0.001) for all 15 metrics (Table 3). Tukey test analysis showed that for core forest vs. developed edge, 13 metrics returned P values less than 0.01, 2 metrics returned p values less than 0.05, and 1 returned a p-value less than 0.1. For core forest vs. agricultural edge, all metrics returned p-values <0.001 and no significant difference was found between agricultural edge and developed edge (Table 4).

Table 3: Univariate ANOVA test showed significant differences between at least two land class types across all metrics with p-values all <0.01.

Category			Univariate ANOVAs using summary.aov()								
		Metric	Test Stat								
			Df	Sum Sq	Mean Sq	F value	Pr(>F)	P-Value			
		Mean Max Canopy Height	2	30879.0	15439.3	55.6	< 2.2e-16	***			
ht t	Ĩ	Q100	2	39254.0	19626.8	53.3	< 2.2e-16	***			
Haiaht	D D	Q75	2	38127.0	19063.6	58.5	< 2.2e-16	***			
д		Q50	2	35915.0	17957.3	61.6	< 2.2e-16	***			
		Q25	2	20230.0	10114.8	49.3	< 2.2e-16	***			
		GINI	2	0.1	0.1	12.8	0.0	***			
	Ir	Vertical SD	2	2207.2	1103.6	37.5	0.0	***			
	rns	SD.SD	2	677.7	338.8	44.0	< 2.2e-16	***			
city	External Internal	VCI	2	0.3	0.1	16.3	0.0	***			
alex		Vertical CV	2	0.4	0.2	10.1	0.0	***			
Complexity		Rumple	2	975.5	487.7	67.7	< 2.2e-16	***			
		Top Rugosity	2	1067.5	533.8	19.4	0.0	***			
Vegetation Density		VAI	2	7.7	3.9	8.9	0.0	***			
		Deep Gap Fraction	2	1.1	0.5	17.8	0.0	***			
		GFP	2	0.1	0.0	8.2	0.0	***			
		* P<0).1, **	P<0.05, *	** P<0.01						

$ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \$	Category						Core vs Dev			Core vs Ag		
$ {\rm Height} \ {\rm Height} \ {\rm Height} \ {\rm (-)} \ {\rm ($			Metric							Test Stat		
$ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \$				Lower	Upper	* ** ***	Lower	Upper	* ** ***	Lower	Upper	* ** ***
$ \frac{1}{100} = 1$	щ		Сапору	(-)	(-)	(-)	11.2	20.9	***	12.6	20.8	***
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$ \frac{Q25}{GINI} & (-) & (-) & (-) & 9.0 & 17.4 & *** & 9.9 & 16.9 & *** \\ \hline Q101 & (-) & (-) & (-) & (-) & 0.0 & *** & -0.1 & 0.0 & *** \\ \hline Q101 & (-) & (-) & (-) & (-) & 0.1 & 0.0 & *** & -0.1 & 0.0 & *** \\ \hline Vertical SD & (-) & (-) & (-) & 1.4 & 3.0 & *** & 1.9 & 3.2 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.1 & ** & 0.0 & 0.1 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.1 & *** & -0.1 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & (-) & 0.0 & 0.1 & *** & -0.1 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & (-) & 0.9 & 4.0 & *** & 2.3 & 3.6 & *** \\ \hline Vertical CV & (-) & (-) & (-) & (-) & 0.9 & 4.0 & *** & 2.0 & 4.6 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.4 & ** & 0.1 & 0.4 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & *** & 0.1 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & 0.4 & ** & 0.1 & 0.4 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & *** & 0.1 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & 0.4 & ** & 0.1 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & *** & 0.1 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & 0.0 & ** & 0.0 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & ** & 0.0 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & ** & 0.0 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & ** & 0.0 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & ** & 0.0 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & ** & 0.0 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & ** & 0.0 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & ** & 0.0 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & ** & 0.0 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & ** & 0.0 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & ** & 0.0 & 0.0 & *** \\ \hline Vertical CV & (-) & (-) & (-) & 0.0 & 0.0 & ** & 0.0 & 0.0 & ** \\ \hline Vertical CV & (-) & (-) & (-) & (-) & 0.0 & 0.0 & ** & 0.0 & 0.0 & ** \\ \hline Vertical CV & (-) & (-) & (-) & (-) & 0.0 & 0.0 & ** & 0.0 & $	-	-	Q50				11.9	21.8	***	14.0	22.4	***
$ \frac{1}{1000} \frac{Vertical SD}{SD.SD} (-) (-) (-) (-) 2.4 5.6 **** 3.3 5.9 **** \\ \frac{1}{1000} \frac{1}{1000}$			Q25				9.0	17.4	***	9.9	16.9	***
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Seep Gap Fraction (-) (-) (-) -0.2 -0.1 *** -0.1 0.0 *** GFP (-) (-) (-) 0.0 0.0 * 0.0 0.0 ***			Top Rugosity	(-)	(-)	(-)	0.9	4.0	***	2.0	4.6	***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Vegetation Density		VAI	(-)	(-)	(-)	0.0	0.4	**	0.1	0.4	***
GFP (-) (-) (-) 0.0 0.0 + 0.0 0.0				(-)	(-)	(-)	-0.2	-0.1	***	-0.1	0.0	***
* P<0.1, ** P<0.05, *** P<0.01			GFP	(-)	(-)	(-)	0.0	0.0	*	0.0	0.0	***
	* P<0.1, ** P<0.05, *** P<0.01											

Table 4: Tukey tests indicted significant differences for all metrics in core forests vs developed edges and core forests vs agricultural edges. No significant differences were found between agricultural and developed edges.

1.4 Discussion

Edges currently make up nearly 30% of the forests in our study area and will continue to increase as non-forest landcover types expand. This trend will likely drive decreasing numbers of large forest patches and increasing number of smaller fragments, increasing the proportion of forest edges relative to forest cores (Reinmann & Hutyra, 2017a; Williams, 2006). This increase in fragmentation will decrease the edge lengths of large forest patches leading to more edges but with shorter overall lengths, breaking up habitat and reducing ecosystem services. Edge forests are exposed to a variety of structural changes that include changes in biomass (Haddad et al., 2015; Reinmann & Hutyra, 2017a; Smith et al., 2018) due to both positive and negative inputs depending on neighboring land class. Conservation of ecosystem services like habitat quality will become more difficult without larger intact forests (Fynn & Campbell, 2018). Broadly, we found that while there are significant structural differences between forest core and edge canopies, there are no significant differences between developed edges and agricultural edges. For the case of fragmentation and management of urban forests in the CHR, our results indicate that forest edges can be treated without distinction based on neighboring land class, which should simplify planning practices for urban and non-urban foresters alike.

Based on our hypotheses, we expected to find significant differences between not only forest cores and edges, but also between developed edges and agricultural edges but, in regard to the means values of each metric, found the contrary to be true from our investigation. In terms of canopy structure, edges differ from forest cores, but the type of edge does not matter. This apparently "negative result" is highly intriguing because it indicates that forests respond similarly to both of the two main drivers of fragmentation within the CHR (e.g., urban expansion, agricultural clearing). This convergent structural response could indicate that the microclimatic conditions that developed and agricultural landcover types impose on edge forests are sufficiently similar to drive a similar structural response, or that forests structural responses are somewhat insensitive to the driver of the fragmentation. We did see substantial variability in the data (indicated by the range and variance) and there are some important differences in the distribution of the data. Heights were skewed towards the lower canopy in edges, internal and external complexity metrics were highly variable as were metrics of openness. The variability in the distribution of values for each of the structural metrics we observed indicated that while on average there are only small differences between canopy structure of edge vs. core forest canopies, there

is substantial heterogeneity across the landscape throughout our study area. Thus, while the structural similarity of forest edges adjacent to developed and agricultural lands may suggest these forests could be managed similarly, when developing management strategies land managers should carefully weigh other factors that are likely to affect forest structure and functioning. In either case, the results we observed could lead to development of more consistent management plans for maintaining or improving the conditions of edges to continue acting as buffers for core forests. This could include planting of not only native trees but shrubs and undergrowth species which in turn could mitigate edge conditions and reduce stress and mortality rates to maintain edge areas.

Edge forests were generally shorter than interior forests (Fig. 4a-d) with skewing below the means indicating denser canopies closer to the forest floor that could be accounted for by common invasive species including, but not limited to, Amur honeysuckle (*Lonicera maacki*), common buckthorn (*Rhamnus cathartica*), Autumn olive (*Eleagnus umbellata*), and multiflora rose (*Rosa multiflora*) which are known to occur in greater densities nearer edges (Dillon et al., 2018). Higher Gini coefficient values for both edge forest classes compared to cores (Fig. 4f) indicates there is more inequality of heights with most trees in the shorter range.

Generally, both internal and external complexity was lower in edge forests compared to forest cores. Lower vertical variation internally (Fig.5) might arise from lower mean heights and/or higher tree mortality rates from edge effects. Similarly, lower external complexity could also be due to shorter canopies that have more exposure to sunlight and are able to close the upper canopy more fully. Previous work demonstrated that canopy complexity is primarily limited by canopy height (Gough et al., 2020). Both developed and agricultural edges had higher deep-gap fractions and were less dense on average compared to forest cores, but gap fraction profiles appeared similar across all land classes. Increased fraction of deep gaps could come from canopy openings due to increased tree mortality from edge stresses. It could also stem from forest edges being more porous since edges don't necessarily follow straight lines. The boundary between forests and neighboring land classes often forms ragged or undulating shapes. Complexity and openness can also be affected by both the age of an edge and what, if any, management practices are being employed. For example, if edges are being periodically cut it would maintain an overall younger edge, which would continue to have lower canopy complexity.

Certain features of the two main datasets used in this study warrant special consideration as they may impact the interpretation of our results. First, Indiana ALS data used in our study was acquired during leaf off season but still enables valuable analysis of woody growth from branches and twigs in the canopy. Future studies using TLS scans and/or ALS scans from drones on a plotbased scale during leaf on season, which have higher resolution, more complete data coverage, and more accurately classed edge types, could improve analyses, but as leaves grow where branches are, results should not change dramatically between leaf on and leaf off. Second, the developed land class includes all paved roads from the study area due to the definitions of "developed" used by the NLCD classification (Dewitz, 2019). This could lead to having corridors of developed land in both agricultural and forested areas that might not lead to the same edge effects. From this we might see cumulative effects from both agricultural and developed land classes and could be a factor explaining the heterogeneity of data distributions.

1.5 Conclusion and Future Directions

Our study presents a landscape scale analysis that combines landcover data and aerial lidar to quantify structural differences between the canopies of forest edges and cores. While we found significant differences between the canopy of forest cores and that within 30m of edges, we found no significant differences between developed and agricultural edges, suggesting that similar management practices could be applied in both forest types to maintain the capacity of edge forests to provide ecosystem services. This study adds to our understanding of forest canopy structure and changes in edge forests associated with fragmentation to better understand life on the edge in urban forests. Future plot-based studies with TLS and/or ALS scans from drones could increase resolution of LiDAR data, facilitating characterization of tree species and size distributions differences between developed and agricultural edges, as well as age distribution of forest edges and any management practices already employed, which may lend to a better understanding of canopy structure. We hope that our efforts will lead to future scientific testing and help to advance our understanding of forest fragmentation and edge effects on canopy structure and function to better maintain and improve green spaces across the urban-rural gradient.

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