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A Social-Ecological Analysis of Urban Tree Vulnerability for Publicly-Owned Trees in a Residential Neighborhood

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Abstract. The urban forest is a valuable ecosystem service provider, yet cities are frequently degraded environments with myriad stressors and disturbances affecting trees. Vulnerability science is increasingly used to explore issues of sustainability in complex social-ecological systems, and can be a useful approach for assessing urban forests. The purpose of this study was to identify and explore drivers of urban forest vulnerability in a residential neighborhood. Based on a recently published framework of urban forest vulnerability, a series of indicators of exposure, sensitivity, and adaptive capacity that describe the built environment, urban forest structure, and human population, respectively, were assessed for 806 trees in Toronto, Ontario, Canada. Tree mortality, condition, and diameter growth rates were then assessed using an existing 2007/2008 inventory. A bivariate analysis was first conducted to test for significant relationships of vulnerability indicators with mortality, condition, and growth. A multivariate analysis was then conducted using multiple linear regression for the continuous condition and growth variables and a multilayer perceptron neural network for the binary mortality variable. Commercial land uses and commercial buildings adjacent to trees consistently explained higher mortality rates and poor tree conditions. However, at finer spatial scales it is important to differentiate between different causes and correlates of urban forest decline within commercial land uses. Tree species, size, and condition were also important indicators of vulnerability. Understanding the causes of urban forest change and decline are essential for developing planning strategies to reduce long-term system vulnerability.

Key Words. Condition; Growth; Mortality; Neighbourwoods; Urban Forest; Vulnerability Assessment.

The urban forest is a valuable ecosystem service provider and represents essential green infrastructure for many cities. However, cities are highly altered, densely settled, and frequently degraded environments with myriad stressors and disturbances that create difficult conditions for tree establishment and growth (Nowak et al. 2004; Trowbridge and Bassuk 2004; Steenberg et al. 2017a). Consequently, urban trees are often in poor condition and frequently have reduced longevity (Roman and Scatena 2011; Koeser et al. 2013), both of which translate to a reduction in ecosystem services (Nowak and Dwyer 2007). Cases and causes of decline in urban forest structure and function need to be identified, assessed, and modeled. Such research can inform the processes of urban design and policy development, as well as urban forest management, so that unnecessary tree decline and mortality are avoided and the benefits that urban inhabitants receive from trees are maximized.

The built environment is a source of stress for urban trees, especially in higher-density neighborhoods. Building density, height, and type affect irradiation (i.e., sunlight available for photosynthesis and plant growth), the physical growing space for trees, and the microclimate of urban areas (Jutras et al. 2010). Moreover, construction activities and conflicts with above- and belowground utilities and other gray infrastructure are common sources of urban tree decline and mortality (Randrup et al. 2001; Koeser et al. 2013; Steenberg et al. 2018). Land use is highly influential on urban forest ecosystems (Nitoslawski et al. 2017), and is indeed indicative of the presence of many of these stressors. Land uses with higher human populations and building densities, as well as abundant

Table 1. Description of exposure, sensitivity, and adaptive capacity indicators used to assess urban forest vulnerability and the direction of their assumed relationship with vulnerability, where a positive assumption means an increase in indicator value translates to an increase in vulnerability and a negative assumption means the opposite. Descriptive statistics are given for the 2014 data only, and where denoted by an asterisk (*), data represents the count of occurrences and percent of total measurements for the binary (0/1) indicators.

Indicator description	Vulnerability assumption	Mean/Count*(standard deviation/percent*)
Exposure		
Built environment		
Population density (persons/km^2)	Positive	14,834 (±8,146)
Built area intensity (%)	Positive	50.2 (±21.2)
Land use[z] (categorical)		
Site type (categorical)		
Site size (m^2 of growing environment)	Negative	136.7 (±383.4)
Type of nearest building (categorical)		
Height of nearest building (storeys)	Negative	4.1 (±4.5)
Distance to nearest building (m)	Negative	6.7 (±14.2)
Distance to street (m)	Negative	4.1 (±3.0)
Width of sidewalk (m)	Positive	2.7 (±1.9)
Width of street (m)	Positive	11.2 (±6.7)
Impervious cover (%)	Positive	47.3 (±32.1)
Light availability[y] (ordinal rank; 0-5)	Negative	2.7 (±1.1)
Conflicts		
Conflict of overhead utilities (0/1)[x]	Positive	416 (51.6)*
Conflict with sidewalk (0/1)	Positive	76 (9.4)*
Conflict with buildings (0/1)	Positive	259 (32.1)*
Conflict with building foundation (0/1)	Positive	47 (5.8)*
Conflict with other infrastructure (0/1)	Positive	294 (36.5)*
Social stressors		
Poor management (0/1)	Positive	172 (21.3)*
Vandalism (0/1)	Positive	92 (11.4)*
Sensitivity		
Species (categorical)		
DBH class (categorical)		
Tree condition index (Neighbourwoods)[w]	Positive	0.30 (±0.17)
In-grown tree (0/1)[x]	Positive	41 (5.1%)*
Adaptive capacity		
Social adaptive capacity		
Median family income ($)	Negative	54,194 (±11,676)
Average dwelling value ($)	Negative	734,451 (±152,682)
Homeownership (%)	Negative	44.0 (±14.8)
Population with a university degree (individuals/10,000 people)	Negative	4,313 (±1,130)
Signs of stewardship (0/1)[v]	Negative	162 (20.1)*
Environmental adaptive capacity		
Open green space (%)	Negative	16.7 (±13.4)
Existing canopy cover (%)	Negative	18.0 (±20.3)

[z] Land-use designation is based on categories described in the i-Tree Eco v. 5.0 manual. Land uses present in Harbord Village include commercial/industrial, institutional, multi-unit residential, park, residential, and vacant.
[y] Light availability was measured using crown light exposure, which is a component of the i-Tree Eco measurement protocol.
[x] 0/1 measurement denotes a binary indicator, where 0 represents absence and 1 represents presence.
[w] An aggregate index that has a maximum value of 1.0 indicating extremely poor tree condition, which is based on the Neighbourwoods assessment protocol (Kenney and Puric-Mladenovic 2001).
[v] Signs of stewardship include direct and obvious actions taken to protect trees or enhance growth (e.g., mulch, bicycle guards, pest protection; Lu et al. 2010). 0/1 measurement denotes a binary indicator, where 0 represents absence and 1 represents presence.

impervious surfaces (e.g., commercial land uses), have higher rates of tree mortality and urban forest decline (Nowak et al. 2004; Lu et al. 2010). Cities are also characterized by high rates of commercial trade and shipping that can expose urban trees and forests to invasive insects and pathogens (Laćan and McBride 2008; Vander Vecht and Conway 2015), such as the emerald ash borer (*Agrilus planipennis*; EAB), Asian longhorned beetle (*Anoplophora glabripennis*; ALB), and butternut canker (*Sirococcus clavigignenti-juglandacearum*). These stressors and disturbances can be interactive and cumulative, and their ultimate effect on individual trees and urban forest ecosystems is dependent on tree condition, species, age, and overall species and structural diversity.

The influences of the human population and socioeconomic variability on urban forest structure and function are complex, dynamic, and uncertain. There are a number of social stressors, ranging from vandalism and poor management practices, affecting individual trees (Lu et al. 2010; Jack-Scott et al. 2013; Koeser et al. 2013), to citywide issues of urban forest policy and governance affecting the maintenance of the entire urban forest resource (Conway and Urbani 2007). Furthermore, there is a growing body of research that has investigated the influence of the socioeconomic characteristics of residents and their association with urban forest condition as well as the spatial distribution of city trees and their provision of benefits (Grove et al. 2006; Jack-Scott et al. 2013; Shakeel and Conway 2014; Moskell et al. 2016). This research points to strong positive relationships between resident affluence and urban tree cover, where higher levels of resident income, education, and homeownership are spatially associated with urban tree cover. Moreover, several studies highlight direct relationships of these resident socioeconomic attributes with participation in urban forest stewardship activities (Conway et al. 2011; Greene et al. 2011).

Research investigating the rates and causes of tree mortality and declines in urban forest structure and function is an important resource for urban forest practitioners. The disciplines of ecology, urban planning, and geography continue to explore the dynamics of urban forests and their relationship with human populations. However, there is a considerable knowledge gap on the combined effects of these stressors and their interaction with urban forest structure. Moreover, there are comparatively few empirical field studies investigating the effects of socioeconomic variability on urban forest ecosystem decline.

Vulnerability science can offer a useful theoretical framework for addressing these gaps and for bridging the potential contributions of different disciplines that investigate urban forests and their benefits (Steenberg et al. 2017a). Vulnerability science in social-ecological systems is a useful approach for exploring issues of sustainability and environmental change in both theoretical and applied research (Turner et al. 2003; Füssel 2010). Examples of applied vulnerability research have ranged from agricultural systems and regional land-use change to arctic systems and climate change (Turner et al. 2003; Adger 2006). It was used in the recent development of an urban forest vulnerability framework (Steenberg et al. 2017a), where vulnerability is defined as the likelihood of decline in urban forest ecosystem service supply in response to stress, and is comprised of exposure, sensitivity, and adaptive capacity.

Exposure refers to the magnitude, frequency, duration, and spatial extent of stressors and disturbances that affect a system (Burton et al. 1993; Adger 2006). These are the external causes of tree decline and mortality associated with the urban environment. Sensitivity is the relative level of response by a system to stressors or disturbances, and is determined by intrinsic characteristics of the system itself (Turner et al. 2003). Urban forest sensitivity is the internal structure of urban tree species assemblages, such as species, size/age, condition, and diversity. Adaptive capacity is the capacity for a system to shift or alter its state to reduce its vulnerability or accommodate a greater range in its ability to function while stressed (Adger 2006; Füssel 2010). For urban forests, this refers to associated human populations and their behaviors regarding urban forest stewardship, as well as the environmental capacity for increasing and maintaining tree cover. By shifting research focus away from external agents of stress and disturbance only (i.e., impacts-only research), vulnerability analysis may allow for a more comprehensive and integrative mechanism for assessing urban forest structure, function, and change.

The purpose of this study was to explore the processes of urban forest vulnerability for trees in the public right of way in a residential neighborhood. Specifically, a conceptual framework of urban forest vulnerability (Steenberg et al. 2017a) was used to assess 2014 data describing 806 public trees in a residential neighborhood in Toronto, Ontario, Canada. The framework consists of a series of quantitative indicators of exposure, sensitivity, and adaptive capacity that describe the built environment and associated stressors, urban forest structure, and the neighborhood's human population, respectively. Tree mortality, condition, and diameter growth rates were then assessed using an existing tree inventory from 2007/2008. A bivariate analysis was first conducted to test for significant relationships of vulnerability indicators with mortality, condition, and growth. A multivariate analysis was then conducted using multiple linear regression for the continuous condition and growth variables and a multilayer perceptron neural network for the binary mortality variable. With much of the global population increasingly living in cities and urbanization rates on the rise, ongoing research and science-based tools for understanding the causes of urban forest change and decline are essential for developing planning strategies to reduce long-term system vulnerability.

METHODS

Study Area

The study was conducted in a centrally located, downtown residential neighborhood, Harbord Village, in Toronto, Ontario, Canada. The neighborhood was selected because of its existing, spatially-referenced tree inventory. As of 2011, Harbord Village had 8,583 residents, a population density of 13,484 persons/km^2, and total area of 0.6 km^2, and was predominately comprised of semi-detached residential dwellings, with approximately 1,600 households (Keller 2007; Statistics Canada 2012). There are commercial land uses along main street sections, with several larger multi-unit and institutional parcels, and three small public parks. Urban forest researchers and Harbord Village residents conducted a tree inventory in 2007 and 2008 to inform their strategic urban forest management plan (Keller 2007). Dominant tree species in the neighborhood include Norway maple (*Acer platanoides*), green ash (*Fraxinus pennsylvanica*), honeylocust (*Gleditsia triacanthos*), white cedar (*Thuja occidentalis*), silver maple (*Acer saccharinum*), and horsechestnut (*Aesculus hippocastanum*). Naturalized species that have grown from seed (in-grown) that are common include white mulberry (*Morus alba*), tree-of-heaven (*Ailanthus altissima*), and Manitoba maple (*Acer negundo*). Toronto has a continental climate with hot, humid summers and cold winters, with a mean annual precipitation is 834 mm and a mean annual temperature of 9.2°C (Environment Canada 2015). The city is within the Deciduous Forest Region and Mixedwood Plains Ecozone (Ontario Ministry of Natural Resources 2012).

Data Collection and Processing

Data collection took place during the growing season of 2014. A total of 806 publicly-owned trees (i.e., street trees and trees in front-yard rights-of-way, parks, and schoolyards) were re-inventoried and matched with data from the existing 2007/2008 tree inventory. Of the 806 trees inventoried in 2007/2008, 672 were still living in 2014 during field data collection. Residential backyard trees were omitted from the study due to access constraints. The 806 trees represent a full survey of 24 city blocks covered in the original inventory. In addition to the standard tree inventory metrics of species, diameter at breast height (DBH), and location, a series of indicators of urban forest vulnerability were assessed for each tree (Table 1). Newly planted trees were also measured for descriptive purposes but were not used in subsequent statistical analysis.

The design of the urban forest vulnerability assessment framework and selection of indicators are described in Steenberg et al. (2017a). Specific indicator selection and design were further refined according to the study's scale of assessment (i.e., individual trees), data availability, and feasibility. Indicators in the framework are assigned to the vulnerability subcategories of exposure, sensitivity, or adaptive capacity. Exposure indicators (Table 1) represent external stressors and disturbances that cause tree decline and mortality, and subsequently a decline in ecosystem service supply. While some of the exposure indicators represent direct stressors (e.g., vandalism), most characterize indirect relationships between stress and the surrounding environment, all of which have been previously identified as important causes and correlates of tree decline and/or mortality (Randrup et al. 2001; Nowak et al. 2004; Trowbridge and Bassuk 2004; Jutras et al. 2010; Lu et al. 2010; Lawrence et al. 2012; Koeser et al. 2013; Steenberg et al. 2018). The main data source for exposure indicators was field data collected during this study. Additionally, 2011 census data were used to measure population density, and a combination of 2013 orthorectified aerial photography and 2013 City of Toronto property map data were used to measure built area intensity (assessed as building site coverage; the ratio of building footprint to parcel area), distances to nearest buildings, and widths of streets. The binary exposure indicators resulting from the presence/absence of conflicts with infrastructure (Kenny and Puric-Mladenovic 2001), vandalism, and poor management were measured in the field.

Sensitivity indicators (Table 1) represent the internal structure of the system, in this case the tree species measured in the study and its relative response to exposures. In other words, they are elements of urban forest structure that increase or decrease the likelihood of tree decline and mortality in response to stress. Species and DBH class were included to account for potential variation in the vulnerability of tree species and sizes (i.e., ages). A number of studies have found that mortality rates fluctuate by species and are elevated in younger and newly planted urban trees (e.g., Nowak et al. 2004; Roman and Scatena 2011; Koeser et al. 2013). Tree condition is another predictor of urban tree mortality (Koeser et al. 2013) and is itself an indicator of sensitivity to stress (Trowbridge and Bassuk 2004).

In this study, researchers derived tree condition using an aggregated index calculated from data collected as part of the Neighbourwoods assessment protocol (Kenney and Puric-Mladenovic 2001). This aggregate index has a maximum value of 1.0, indicating extremely poor tree condition. Neighbourwoods is a tool for community-based urban forest stewardship, which was developed by Kenney and Puric-Mladenovic (2001). It describes a standardized procedure for community members to inventory and monitor the location, composition, and condition of their urban trees. The protocol describes 15 ordinal metrics of tree condition (e.g., scars and cavities) and structure (e.g., included bark), ranging from 0 (best condition) to 3 (worst condition), giving a total possible score of 45, which researchers then standardized to produce the aggregate condition index. A Neighbourwoods assessment was conducted during the 2007/2008 Harbord Village tree inventory and was again conducted for all trees measured in 2014. The tree condition index was calculated for both 2007/2008 and 2014 data. All sensitivity indicators were measured using field data.

Adaptive capacity indicators (Table 1) represent components of the urban forest that enable it to reduce its own vulnerability or increase its capacity to tolerate greater change without adverse effects (Adger 2006). In the context of this study, indicators of adaptive capacity measure socioeconomic variables that are likely to increase or be positively associated with ecosystem service supply, or environmental ones that are likely to increase supply. All social adaptive capacity indicators were measured using 2011 National Household Survey data at the dissemination-area level, excluding presence/absence indicators that were assessed in the field. Dissemination areas are the smallest geographic unit for which census and National Household Survey data are available, and are delineated to contain between 400 and 700 people. The environmental adaptive capacity indicators were measured using 2007 land-cover data derived from QuickBird satellite imagery with 0.6-m resolution, quantified at the parcel scale (City of Toronto 2010). Additional satellite-derived land cover data for 2014 would have been desirable but were not available.

Analysis

Three metrics of ecological change were assessed by comparing field data collected for this study in 2014 with the existing 2007/2008 tree inventory. Tree mortality was measured as presence/absence using matched tree comparisons. Tree mortality was recorded for both tree removals and for dead trees still located on site. Annual mortality rates (Equation 1) were measured for the ten most abundant tree species with the equation used by Nowak et al. (2004) and adapted by Lawrence et al. (2012):

$$[1] \qquad m = 1 - (N_1/N_0)^{1/t}$$

where m is the annual mortality rate (%), N_0 is the number of living trees at the time of the first inventory, N_1 is the number of living trees at the time of the second inventory, and t is the number of years between inventories. Diameter growth rates (cm/yr) were measured by dividing the difference in DBH between matched trees by the time interval between inventories. The third ecological change variable was the Neighbourwoods-derived 2007/2008 and 2014 tree condition indices. However, change in tree condition between inventories was not analyzed due to the ordinal ranking method of Neighbourwoods and the corresponding likelihood of assessment subjectivity among different researchers collecting data at the two time instances.

Researchers first conducted a bivariate analysis to get an understanding of the influence of individual vulnerability indicators (i.e., exposure, sensitivity, and adaptive capacity indicators in Table 1) on the three ecological change variables, and insight into their utility for vulnerability framework refinement. The analysis included simple significance testing on relationships between vulnerability indicators and mortality, condition, and growth, using the appropriate nonparametric statistical test based on data type. Spearman's Rho was used for tests between continuous variables and Pearson's chi-squared (χ^2) test was used for tests between categorical/binary variables. The Mann-Whitney U test was used for tests between continuous and binary variables, while the Kruskal-Wallis rank test was used for tests between continuous and categorical variables with more than two groups.

A subsequent multivariate analysis was conducted to evaluate the predictive capacity and explanatory power of the vulnerability indicators on urban forest ecological change in Harbord Village. Only those vulnerability indicators that were found to have statistical significance at the $\alpha = 0.05$ level in the bivariate analysis were included. Multiple linear (i.e., ordinary least squares) regression was used to predict the continuous tree condition and growth rate variables. Condition and growth were used as dependent response variables in separate regression models using the reduced selection of vulnerability indicators as independent predictor variables. These two models were run on the 672 living trees only, as condition and growth cannot be measured on dead/removed trees. The site size (i.e., m^2 of growing environment), height of nearest building, distance to nearest building, distance to street, width of street, and width of sidewalk variables were log transformed to meet normality assumptions for regression analysis. Tolerance values indicated no issues with multicollinearity (i.e., tolerance values above 0.1; Hair et al. 2010) for all variables except for some of the groups (i.e., dummy variables) of the land use and building type categorical variables. While this multicollinearity was to be expected to some degree, it does reduce the effectiveness of the models and is a source of uncertainty. Only the top five most abundant species were included in the analysis as dummy variables.

Lastly, to analyze the possible effects of the vulnerability indicators on the binary variable describing tree mortality, researchers used a multilayer perceptron neural network using IBM® SPSS® Statistics 24 (Hastie et al. 2009; Jutras et al. 2009). Multilayer perceptron neural networks are artificial neural networks comprised of a collection of data structures and algorithms in a network meant to loosely mimic a biological brain. They fall within the discipline of machine learning that has been growing in importance with the rise of computational power and large data sets (Hastie et al. 2009). The mixed structure, noisy, and highly variable nature of the vulnerability data—and of urban social-ecological systems in general—negate the use of many traditional inferential statistics. While logistic regression has been used to predict tree mortality in urban forests (e.g., Koeser et al. 2013), researchers opted not to use this approach because of the many categorical variables used in the analysis and comparatively small sample size (Hair et al. 2010). Neural networks have their origin in computer science and artificial intelligence, but have been applied successfully in tree mortality research in both rural (Guan and Gertner 1991; Hasenauer et al. 2011) and urban settings (Jutras et al. 2009). For example, Jutras et al. (2009) used them to investigate morphological parameters of street trees in Montreal, Québec, Canada. Multilayer perceptron neural networks use a number of neurons (i.e., units) in one or more layers, which communicate with each other via weighted connections, or links (Hastie et al. 2009). The independent variables (i.e., inputs) in the input layer communicate to neurons in one or more hidden

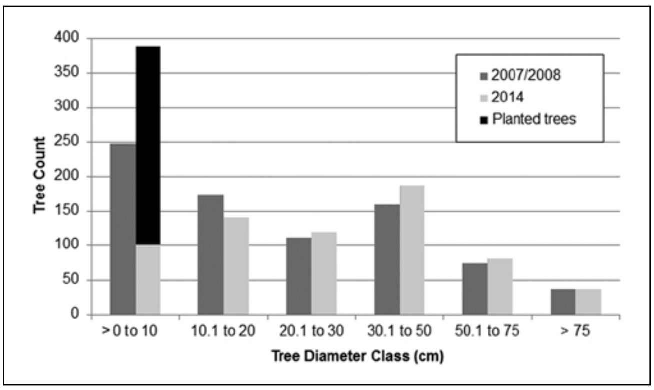

Figure 1. Change in size-class distribution of measured trees between the 2007/2008 (*N* = 806) and 2014 (*N* = 672; *N* = 1,056 with newly planted trees) inventories in the Harbord Village neighborhood in Toronto, Ontario, Canada.

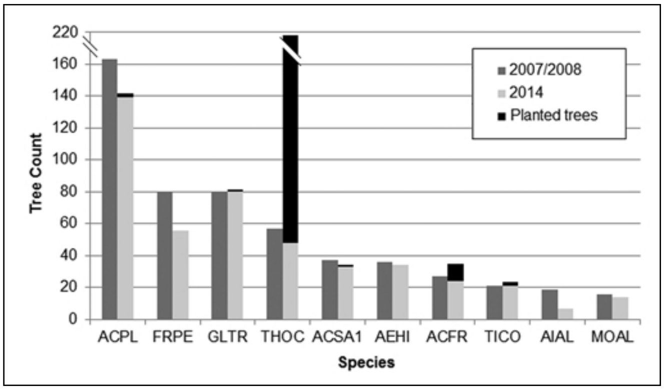

Figure 2. Change in tree species distribution of the 10 most abundant species measured between the 2007/2008 and 2014 inventories in the Harbord Village neighborhood in Toronto, Ontario, Canada. ACPL: Norway maple; FRPE: green ash; GLTR: honeylocust; THOC: white cedar; ASCA1: silver maple; AEHI: horsechestnut; ACFR: Freeman maple; TICO: littleleaf linden; AIAL: tree-of-heaven; MOAL: white mulberry.

layers (i.e., one or more neurons in between the input and output layers), which ultimately communicate to the output layer. Supervised learning is used to train and adapt the network using error values to identify final weight values and ultimately optimize its predictive capacity (Hastie et al. 2009). In this study, the neural network used the vulnerability indicators identified in the bivariate analysis as inputs to predict mortality outcomes (0/1). A single hidden layer with six neurons was used. Two-thirds of the data records ($N = 565$) were used as the training sample, and the remaining one-third ($N = 241$) as the testing sample. Training samples are important to use to avoid overfitting of the model, which can lead to incorrect generalizations of the results.

RESULTS

The change in size-class distribution (Figure 1) and species composition (Figure 2) between the 2007/2008 and 2014 inventories illustrates the demographic change of public trees in the study area. The most abundantly planted trees were white cedar, Japanese maple (*Acer palmatum*), serviceberry (*Amelanchier* spp.), Freeman maple (*Acer* × *freemanii*), dogwood (*Cornus* spp.), eastern red cedar (*Juniperus virginiana*), and mugho pine (*Pinus mugo*), which are considerably different from the current dominant species and are nearly all smaller-sized trees at maturity. The total tree planting rate in the study area was 1.42

Table 2. Annual mortality rate (%), mean diameter growth rate (cm/yr), and mean condition index value of measured trees, stratified by diameter class and 10 most abundant species.

Category	N	Annual mortality rate (%)	Mean growth rate (standard deviation)	Mean condition index value (standard deviation)
All trees	806	2.40	0.59 (±0.57)	0.30 (±0.17)
Size class				
>0.1-10.0 cm DBH	168	6.56	0.27 (±0.25)	0.23 (±0.17)
10.1-20.0 cm DBH	174	2.67	0.64 (±0.42)	0.28 (±0.17)
20.1-30.0 cm DBH	133	1.36	0.72 (±0.47)	0.29 (±0.13)
30.1-50.0 cm DBH	200	0.75	0.69 (±0.49)	0.29 (±0.15)
50.1-75.0 cm DBH	89	1.09	0.56 (±1.08)	0.39 (±0.20)
>75.0 cm DBH	42	1.33	0.37 (±0.33)	0.43 (±0.15)
Species				
Norway maple	163	2.10	0.46 (±0.23)	0.36 (±0.19)
Green ash	80	4.64	0.50 (±0.33)	0.40 (±0.16)
Honeylocust	80	0	0.59 (±0.44)	0.28 (±0.13)
White cedar	57	2.27	0.59 (±0.53)	0.17 (±0.14)
Silver maple	37	1.51	0.48 (±0.58)	0.39 (±0.13)
Horsechestnut	36	0.76	0.28 (±0.60)	0.37 (±0.16)
Freeman maple	27	1.56	1.10 (±0.70)	0.23 (±0.13)
Littleleaf linden	21	0	0.82 (±0.44)	0.29 (±0.12)
Tree-of-heaven	19	12.47	1.11 (±0.59)	0.18 (±0.10)
White mulberry	16	1.75	1.05 (±2.14)	0.33 (±0.12)
Other	270	2.93	0.65 (±0.56)	0.26 (±0.16)

trees/ha/yr, and white cedar, which was frequently planted along fence lines, represented 43% of all new trees planted. Diameter growth rates slowed with increases to tree size; the condition of measured trees also consistently worsened with greater tree size (Table 2). However, the lower diameter growth rate

Table 3. Bivariate analysis of the exposure, sensitivity, and adaptive capacity indicators with tree mortality, condition, and growth rate, showing test statistic values and significance levels.

Independent variable	Mortality	Condition	Growth
Exposure			
Built environment			
Population density (persons/km^2)	42,919[z]	-0.15[y],***	-0.01[y]
Built area intensity (%)	42,112[z]	0.02[y]	-0.12[y],**
Land use (categorical)	33.89[x],***	23.99[w],***	25.20[w],***
Site type (categorical)	9.78[x]	17.69[w],*	24.55[w],**
Site size (m^2)	40,486[z]	0.01[y]	0.14[y],***
Type of nearest building (categorical)	16.487[x],*	13.52[w]	20.71[w],**
Height of nearest building (storeys)	43,545[z]	0.08[y],*	-0.04[y]
Distance to nearest building (m)	39,449[z],*	0.14[y],***	0.06[y]
Distance to street (m)	44,949[z]	-0.16[y],***	0.16[y],***
Width of sidewalk (m)	44,826[z]	0.11[y],**	-0.07[y]
Width of street (m)	43,203[z]	0.10[y],**	-0.04[y]
Impervious cover (%)	41,420[z]	0.22[y],***	-0.06[y]
Light availability (ordinal rank; 0-5)	7.52[w]	0.03[y]	0.02[y]
Conflicts			
Conflict of overhead utilities (0/1)	142.98[x],***	49,752[z]	46,913[z]
Conflict with sidewalk (0/1)	6.11[x],*	14,756[z],*	18,497[z]
Conflict with buildings (0/1)	59.45[x],***	44,628[z],**	39,982[z],***
Conflict with building foundation (0/1)	6.24[x],*	9,381[z]	8,456[z]
Conflict with other infrastructure (0/1)	5.45[x],*	47,964[z]	44,596[z],*
Social stressors			
Poor management (0/1)	N/A	30,348[z],***	36,580[z]
Vandalism (0/1)	N/A	18,189[z],***	21,593[z]
Sensitivity			
Species (categorical)	67.69[x],***	95.77[w],***	164.32[w],***
DBH (cm)	95.76[x],***	0.25[y],***	0.04[y]
Tree condition index (Neighbourwoods)	40,988[z]	N/A	-0.21[y],***
In-grown tree (0/1)	32.22[x],***	5,175[z]	5,670[z]
Adaptive capacity			
Social adaptive capacity			
Median family income ($)	44,798[z]	-0.03[y]	-0.03[y]
Average dwelling value ($)	43,134[z]	-0.09[y]*	0.03[y]
Homeownership (%)	43,693[z]	0.05[y]	-0.03[y]
Population with a university degree (individuals/10,000 people)	43,985[z]	0.09[y]*	-0.03[y]
Signs of stewardship (0/1)	N/A	35,058[z]	32,406[z],*
Environmental adaptive capacity			
Open green space (%)	40,491[z]	-0.08[y],*	0.11[y],**
Existing canopy cover (%)	40,833[z]	-0.01[y]	0.01[y]

[z] Mann-Whitney U test.
[y] Spearman's Rho.
[x] Pearson's chi-squared (χ^2) test.
[w] Kruskal-Wallis rank test.

Notes: single asterisk (*) indicates significant at the $\alpha = 0.05$ level; double asterisk (**) indicates significant at the $\alpha = 0.01$ level; and triple asterisk (***) indicates significant at the $\alpha = 0.001$ level.

of the >0.1-10.0 cm tree size class was anomalous. It should be noted that multiple-year DBH measurements and growth rates derived from there are likely to have high measurement error, which is a potential explanation for this anomaly.

Of the measured trees present in both the 2007/2008 and 2014 inventories, Norway maple was the most abundant (Figure 2). White cedar exceeded Norway maple in 2014 in abundance when trees planted during the time between inventories were incorporated. Honeylocust, white cedar, Freeman maple, and littleleaf linden (*Tilia cordata*) all increased in population size when planted trees were incorporated, while Norway maple, green ash, silver maple, horsechestnut, tree-of-heaven, and white mulberry decreased. No planted green ash, horsechestnut, tree-of-heaven, or white mulberry were observed. Tree-of-heaven had a substantially higher mortality rate than other trees (Table 2), followed by green ash, both of which were higher than the study area average annual mortality rate of 2.4% (Table 2). Green ashes were in the worst condition, which was likely attributable to the ongoing EAB infestation in the study area, while white cedar were consistently in better condition. Tree condition of other species was generally reflective of tree size, where consistently larger species (e.g., silver maple and horsechestnut) were in worse condition.

The bivariate analysis revealed a number of significant relationships between vulnerability indicators and tree mortality. Land use is known to be an influential driver of urban forest structure and function, which was corroborated by the findings (Table 3). The χ^2 test revealed that commercial land uses had a high occurrence of tree mortality (36 observed versus 22 expected), while institutional land uses had a lower occurrence (15 observed versus 20 expected). Distance to the nearest building and building type were other significant built environment indicators, with shorter distances being associated with higher mortality. The five conflict with infrastructure indicators all had significant relationships with mortality, yet some were counter to *a priori* vulnerability assumptions (i.e., increased mortality with conflict). In particular, the presence of conflicts with overhead utility wires had an observed 6 incidences of mortality compared to the expected value of 69. Tree mortality was much higher for trees in the smallest DBH class (67 observed versus 28 expected) and for green ash compared to other species (Table 3). Additionally, in-grown trees were far more likely to experience mortality than planted trees. There were no significant relationships between mortality and adaptive capacity indicators.

Tree condition had the highest number of significant relationships with the vulnerability indicators, many of which were associated with increasing intensity of the built environment, like land use and site type (Table 3). More impervious surface cover and larger sidewalks and streets were all associated with poor tree condition. Incidences of poor management (e.g., improper pruning, unremoved tethers causing damage), vandalism (e.g., torn branches), and conflicts with sidewalks were also associated with poor tree condition, while conflicts with buildings were associated with better condition. Tree condition declined consistently with increasing DBH (Table 3). Green ash, silver maple, and horsechestnut were in worse condition, while white cedar and tree-of-heaven were in better condition. There were significant but fairly weak correlations of dwelling value, education, and open greenspace with tree condition (Table 3), although the relationship between education and tree condition was counter to vulnerability assumptions.

With tree diameter growth rates, land use, site type, and building type were again found to have significant relationships (Table 3), with slower growth rates associated with higher-density commercial areas (i.e., commercial land uses and buildings). Multi-family residential land uses and apartment towers were associated with faster growth rates. Built area intensity was also associated with lower growth rates and greater distances from streets with higher ones. Similar to the counterintuitive mortality results, trees in conflicts with buildings and other types of infrastructure were associated with faster growth rates. As expected, trees in poor condition had slower growth rates and growth rates declined with increasing DBH class (Table 3). The exception to the latter were trees in the smallest DBH class, which combined with the high mortality rate of these trees, is likely explained by transplant shock and establishment failure (Trowbridge and Bassuk 2004). Open greenspace was associated with faster growth rates while the presence of stewardship activities (e.g., watering bags) were associated with lower growth rates (Table 3).

The regression models predicting tree condition and growth rates in the multivariate analysis yielded some additional insight (Table 4). The condition model explained 32.1% of the variation in tree condition. Evidence of poor management and DBH were strong predictors of poorer condition. Norway maple and green ash were strongly associated with poor tree condition, while white cedar was associated with better condition. Both park land uses and exposure to vandalism were associated with poor tree condition as well. The regression model predicting diameter growth rates did not perform as well, explaining only 17.5% of the variation in growth rates with several counterintuitive relationships. Additionally, DBH was measured manually using diameter tapes by different researchers and at different time periods, so sampling error resulting from variability in measurements was likely. Institutional land uses were strong significant predictors of faster tree growth rates,

Table 4. Beta coefficients (β) and *P*-values for the multiple linear regression analysis predicting individual 2014 tree condition index values and diameter growth rates (cm/yr) of individual trees using the urban forest vulnerability indicators.

Independent variable	Condition β	*P*-value	Growth β	*P*-value
Tree condition index (Neighbourwoods)			**-0.161**	**<0.0001**
Population density (persons/km^2)	-0.073	0.160		
Built area intensity (%)				
Height of nearest building (storeys)	0.076	0.152		
Distance to nearest building (m)	-0.046	0.370		
Distance to street (m)	0.035	0.540	0.101	0.096
Width of sidewalk (m)	0.079	0.176		
Width of street (m)	0.037	0.587		
Impervious cover (%)	-0.040	0.418		
Conflict with sidewalk (0/1)	0.012	0.782		
Conflict with buildings (0/1)	-0.033	0.405	**0.206**	**<0.0001**
Conflict with other infrastructure (0/1)			**0.099**	**0.012**
Poor management (0/1)	**0.308**	**<0.0001**		
Vandalism (0/1)	**0.109**	**0.004**		
Land use – Commercial	-0.153	0.254	-0.272	0.066
Land use – Institutional	0.063	0.494	**0.366**	**<0.0001**
Land use – Multi-family	0.031	0.767	-0.094	0.355
Land use – Park	**0.118**	**0.011**	0.026	0.670
Site type – Fence Line	0.027	0.517	**-0.126**	**0.005**
Site type – Bare	0.040	0.272	-0.012	0.753
Site type – Lawn/grass	0.031	0.480	0.074	0.116
Site type – Grass median	**0.123**	**0.021**	0.044	0.380
Site type – Raised planter	0.053	0.330	0.075	0.211
Site type – Tree pit/sidewalk	0.163	0.086	-0.015	0.867
Building type – Apartment	-0.050	0.595	0.105	0.290
Building type – Commercial	0.208	0.099	0.212	0.138
Building type – Detached house	-0.017	0.642	-0.019	0.622
Building type – Institutional	<0.0001	0.996	**-0.264**	**0.003**
Building type – Row house	-0.071	0.057	-0.064	0.103
DBH (cm)	**0.335**	**<0.0001**		
Norway maple	**0.127**	**0.002**	**-0.206**	**<0.0001**
Green ash	**0.115**	**0.020**	0.054	0.288
Honeylocust	-0.085	0.058	0.038	0.435
White cedar	**-0.107**	**0.006**	-0.016	0.697
Silver maple	0.058	0.128	**-0.146**	**<0.0001**
Average dwelling value ($)	-0.013	0.785		
Population with a university degree	-0.041	0.353		
(individuals/10,000 people)				
Signs of stewardship (0/1)	-0.061	0.153	-0.002	0.962
Open greenspace (%)	-0.076	0.112	0.052	0.318
R^2	0.321		0.175	

Table 5. Classification accuracy of the multilayer perceptron neural network for predicting tree mortality (0/1) in the testing and training samples using the vulnerability indicators.

	Predicted no mortality (0)	Predicted mortality (1)	Percent correct
Training sample			
Observed no mortality (0)	454	20	95.8
Observed mortality (1)	41	50	54.9
Overall accuracy			89.2
Testing sample			
Observed no mortality (0)	183	15	92.4
Observed mortality (1)	17	26	60.5
Overall accuracy			86.7

though adjacency to institutional buildings was also a strong predictor and explained slower growth rates. This unexpected finding can be explained, in part, by the fact that land use was assessed in the field at the parcel level while building type was assessed for the building with the shortest distance to a given tree. Poor tree condition explained slower tree growth rates, as did tree species (i.e., Norway maple and silver maple). Conflicts with infrastructure again were associated with faster growth rates. Lastly, the multilayer perceptron neural network used to analyze tree mortality performed well using the selected vulnerability indicators, which reinforces the utility of these indicators in future vulnerability assessment. The network had an accuracy of 89.2% with the training sample and 86.7% with the testing sample, and was more effective in predicting living trees than dead trees (Table 5).

DISCUSSION AND CONCLUSIONS

The findings of this study suggest that the highest exposure and corresponding levels of urban tree decline and mortality were most influenced by the intensity of land use and the conditions encountered in the built environment. Trees growing in land classified as commercial land uses, and circumstances in which commercial buildings were adjacent to trees, consistently explained higher mortality rates and poor tree conditions. While studies have found varying effects of commercial land uses on urban trees (e.g., Lawrence et al. 2012), it is generally established that these influences are among the most detrimental for tree health (Nowak et al. 2004; Jutras et al. 2010). However, at finer spatial scales it is important to differentiate between different causes and correlates of urban forest decline for trees growing within commercial land uses. For example, street width (i.e., wider streets) can be a positive correlate of tree stress (Nagendra and Gopal 2010). Current findings also suggest that distance from streets and buildings are important indicators of urban tree vulnerability. While land use is a fairly established mechanism for stratifying urban landscapes and conducting urban forest research (Nowak et al. 1996; Steenberg et al. 2015), the results of this study suggest that at the household scale, differentiated indicators (e.g., building type, impervious cover, street geometry) are necessary components of urban forest vulnerability assessment.

There are myriad physical, biological, and social stressors and disturbances that afflict urban trees and forests (Trowbridge and Bassuk 2004; Steenberg et al. 2017a). Consequently, there are many opportunities to improve upon frameworks of urban forest vulnerability assessment. In this study, exposure indicators were mainly limited in scope to those stressors associated with the built environment and urban form. However, the intent was that the sensitivity indicators would, in part, address these other dimensions of exposure for which quantification and/or data availability were limiting factors for measurement.

For example, vulnerability to biological threats (e.g., EAB) or storm events can be captured in the sensitivity metrics of species composition (e.g., ash abundance and distribution; Laćan and McBride 2008; Vander Vecth and Conway 2015) and age structure (e.g., structural diversity and over-mature canopies; Staudhammer and LeMay 2001; Lopes et al. 2009). Additionally, it is possible that the widespread decline of ash might also inflate the influence of some other exposure indicators.

Nonetheless, this study's findings suggest that quantifying known biological exposures would be beneficial in future vulnerability assessments, given the high levels of decline and mortality of green ash attributable to EAB. One finding that ran contrary to the *a priori* vulnerability assumptions was the exceedingly high survival rate of trees in conflict with overhead utility wires, compared to those that were not. This may be due to the hardiness of the species selected for street tree plantings. However, the study authors offer the one theory requiring further investigation: that trees most often in conflict were the municipally-owned, larger trees in the public right-of-way. Despite the conflict with utility wires, more frequent maintenance of these trees by urban forest practitioners could potentially explain this trend, but this requires further research to be substantiated.

Urban forest structural elements that characterize sensitivity were found to be valuable in examining overall vulnerability. Specifically, tree condition was a highly influential predictor of mortality and diameter growth. This finding confirms existing research supporting condition as an effective predictor of mortality (Koeser et al. 2013). This finding also suggests that more detailed frameworks for assessing tree condition (i.e., not just percent crown dieback) are valuable. Conversely, the findings also highlight important drivers of condition decline, such as poor management and vandalism, where poor management was most often identified as improper pruning practices and vandalism as torn branches on smaller trees (Lu et al. 2010). Decline, mortality, and vulnerability of the studied trees were likely a function of the composition and age distribution of the neighborhood and tolerance of individual species to urban conditions (e.g., high tolerance of honeylocust, and therefore low sensitivity and minimal mortality; Burns and Honkala 1990). One notable species-level effect was the much higher likelihood of mortality for in-grown species (e.g., tree-of-heaven), which emphasizes the importance of differentiating between planted and in-grown trees in urban forest vulnerability assessment.

Tree size was a highly influential metric of urban forest sensitivity, both in its interaction with exposures and as a predictor of tree condition. Trees in the smallest size class had by far the highest mortality rates, as might be expected (Roman and Scatena 2011). Additionally, assessed trees were consistently in poor condition with increasing diameter. Larger sites with more open greenspace, and those that were farther from adjacent buildings, were more likely to have larger trees, and therefore trees in poor condition, despite more suitable growing conditions than higher-density commercial areas. Again this highlights the influence of specific conditions in Harbord Village, and subsequently limits further generalizations. However, declining tree condition with age is an established pattern (Nowak et al. 2004), which suggests higher sensitivity and subsequent vulnerability of mature urban forest ecosystems, often found in older, established residential neighborhoods. Importantly, it may also reveal that the processes driving decline in tree condition may sometimes differ from those driving mortality.

Overall, adaptive capacity indicators were less influential on ecological change and vulnerability than exposure and sensitivity indicators. For one, they were limited by the scale of available socioeconomic data (i.e., census dissemination areas as opposed to households). However, this limitation does not preclude them from being important in long-term urban forest vulnerability. Many studies support a strong positive relationship of both urban forest structure and stewardship with the socio-demographic characteristics of city residents at broader spatial scales (e.g., Grove et al. 2006; Troy et al. 2007; Conway et al. 2011; Greene et al. 2011; Schwarz et al. 2015). Political processes are also important drivers of urban forest distribution and stewardship. For instance, Kendal et al. (2012) found that income inequality in tree cover distribution was more pronounced in public streetscapes than in residential properties. Füssel (2010) emphasizes that while observed empirical data are more objective and reliable, they cannot reveal all aspects of system vulnerability, especially long-term risks. It is likely that the comparatively short time span (e.g., six to seven years) between tree inventories in this study, as well as the spatial scale of data used in the analysis, might explain this lower influence of adaptive capacity on ecological change. Importantly, the quantitative nature and specific indicators of the Steenberg et al. (2017a) vulnerability framework restrict the conception of adaptive capacity considerably, especially given its emphasis on census data, and might imply that adaptive capacity is restricted to affluent communities.

Research has shown that adaptive capacity is driven by an array of social processes not necessarily affixed to wealth, including place attachment, common concern for neighborhood improvement (e.g., crime reduction), and the presence of community leaders (Westphal 1993; Manzo and Perkins 2006; Tidball and Krasny 2007). Household-scale, qualitative research will provide valuable insight into these social processes in future work.

Given their longevity and stationary nature, trees and forests are generally vulnerable to environmental change, where manifestations of change in urban forest structure and function may lag considerably in their response to drivers of change (e.g., changes in management practices). Current urban forest structure is often a function of decades-old management decisions (Boone et al. 2010). The disparity between commonly-planted tree species and overstory species composition in the neighborhood, coupled with ongoing decline of green ash and its removal from tree planting schedules, points toward the likelihood of considerable future change in ecosystem conditions. Moreover, Norway maple, which was the dominant overstory species, was an extremely popular urban tree in previous decades but is now no longer favored in Toronto's urban forestry plan and planting schedules because of its potential to become invasive (City of Toronto 2013). In addition to these potential lag effects in species composition, the observed species-specific mortality and shifts towards smaller, ornamental species may also correspond to declines in future ecosystem service supply irrespective of urban stressors and disturbances. Many ecosystem services are strongly associated with larger, longer-lived tree species with large leaf areas (Nowak and Dwyer 2007), which may indicate future declines in ecosystem service supply due to changing planting preferences in tree species. Moreover, populations of mature urban trees, especially with low species and age diversity, may provide high levels of ecosystem services but also be highly vulnerable due to their sensitivity to pests, storms, and age-related decline (Steenberg et al. 2017a). These issues reinforce the temporal nature of vulnerability and associated impacts (Adger 2006; Steenberg et al. 2017a). Urban forest vulnerability assessments require both hindsight in the form of monitoring (Roman et al. 2013), but also foresight in the form of ecological modeling to explore future scenarios of management and disturbance (Steenberg et al. 2017b).

Vulnerability science offers an integrative lens through which to explore risk and loss of function in highly complex, social-ecological systems like the urban forest (Turner et al. 2003; Adger 2006; Grove 2009; Steenberg et al. 2017a). Vulnerability also has many synergies with the concept of resilience that is of increasing importance in urban planning, though Steenberg et al. (2017) argue that a vulnerability lens addresses drivers of change that are often external to resilience frameworks. Much of the research investigating mortality and decline in urban forests focuses primarily on stressors and disturbances. Moreover, vulnerability assessment might also be a useful supplement to existing assessments of tree safety and risk (Ellison 2005). This study affirms that there is a need to investigate how these stressors interact with urban forest structure and surrounding human populations to reduce or inflate vulnerability in order to reliably predict the likelihood of potential loss of ecosystem services. Moreover, many of the established relationships between urban forests and socioeconomic variability are based on two-dimensional tree canopy cover data at broader spatial scales. There are far fewer studies (e.g., Shakeel and Conway 2013) investigating urban forest ecological processes at finer scales using empirical field data from multiple time periods. However, further research is needed that tests both the reliability and validity of indicator design in different neighborhoods, cities, and scales. With increasing attention paid to urban forests by municipalities (Ordóñez and Duinker 2013) and community groups (Conway et al. 2011), the demand for management information that goes beyond quantifying ecosystem structure and function to assessing urban forest vulnerability is of increasing interest.

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