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Predictors of mortality for juvenile trees in a residential urban-to-rural cohort in Worcester, MA

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ABSTRACT

This paper explores predictors of juvenile tree mortality in a newly planted cohort in Worcester, MA, following an episode of large-scale tree removal necessitated by an Asian Longhorned Beetle (*Anoplophora glabripennis,* ALB) eradication program. Trees are increasingly seen as important providers of ecosystem services for urban areas, including: climate moderation and thus reduction in heating/cooling costs; air and water filtration; carbon uptake and storage; storm water runoff control; and cultural and aesthetic values. Many cities have initiated tree planting programs to receive these benefits, typically seeking to complement existing urban forest. Conversely, Worcester's reforestation program was necessary to offset the loss of approximately 30,000 trees removed to eradicate the invasive pest ALB. Since then, more than 30,000 juvenile trees have been planted to offset the loss, creating the opportunity to study a highly dynamic urban forest. Tree planting effectiveness is contingent on high survivorship rates, particularly during the establishment phase during the first five years after planting. Using a large data set including biophysical and sociodemographic variables, this research uses Conditional Inference Trees (CIT), a machine learning technique, to explore predictors of mortality. The most important variables as determined by CIT were used to create a logistic regression to predict mortality. This analysis was run for all trees, and for several subsets of the sample based on tree type and season and year of planting, yielding twenty individual models. Results indicated that the following variables are important predictors of mortality during establishment, in descending order: adjacent home/building age, proportion renter occupancy, days since tree planted, tax parcel size, number of trees planted on property, and tax parcel value. Of these variables, proportion renter occupancy and days since tree planted were most frequently found to be significant in the logistic regression modeling.

1. Introduction

Urban trees are receiving increased recognition for the important role they play in providing ecosystem services, including moderation of Urban Heat Islands (UHI) and thus offsetting energy consumption for cooling (Akbari, 2002; Donovan and Butry, 2009; McPherson and Simpson, 2003; Pandit and Laband, 2010), air and water filtration (Jim and Chen, 2008; Mcpherson et al., 1994; Nowak et al., 2014; Tratalos et al., 2007), carbon uptake and storage (Nowak et al., 2013), storm water runoff control (Xiao et al., 1998; Xiao and McPherson, 2002), and cultural, aesthetic, and property values (Pandit et al., 2013). To attain maximal ecosystem service benefits, and because the costs associated with planting or replanting trees are large (McPherson, 1992), planting success depends on low mortality rates over time so that mature aggregate canopy and basal areas are maximized, thus yielding the largest ecosystem service benefits (Ko et al., 2015a; McPherson et al., 2011). Survival is particularly important during the establishment phase of five years after planting, during which time mortality is generally highest (Miller and Miller, 1991; Richards, 1979; Roman et al., 2014a; Shermana et al., 2016).

Urban forest management would benefit from a nuanced and complete understanding of the predictors and causal agents of mortality during the establishment phase, so as to enhance survivorship. Biophysical causes of establishment-stage mortality include poor staking and tying techniques leading to trunk girdling, and physical damage from vandalism, vehicles and construction (Hauer et al., 1994; Koeser et al., 2013); tree guard girdling; soil compaction (Coder, 2000; Kozlowski, 1999) and water availability (Nielsen et al., 2007).

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Additionally, anthropogenic factors are often important in predicting mortality, including land-use (Lu et al., 2010), socioeconomic status and property values (Ko et al., 2015a; Nowak et al., 1990; Roman et al., 2014b). These variables capture a complex set of direct and indirect interactions between humans and trees, relating to potential maintenance, neglect, and overall stewardship potential. Tree stewardship actions such as municipal or community irrigation strategies and tree condition monitoring can promote tree survival (Boyce, 2010; Koeser et al., 2014; Roman et al., 2015; Vogt et al., 2015). It is important to understand the primary drivers and predictors of juvenile tree mortality, so that they may be mitigated, therefore allowing the largest possible cohort of trees to reach maturity with minimized initial investment in planting (McPherson, 1992; Richards, 1979). Using such knowledge, urban land managers and private homeowners can maximize long-term ecosystem benefits from planting programs (Roman et al., 2014b).

Previous studies have investigated urban forest mortality for juvenile and mature tree cohorts. For example, Nowak et al. (Nowak et al., 2004) found differences in mortality based on tree size, health condition class (excellent, good, fair, poor, critical, dying, dead) species, and land-use. Results indicated lowest mortality for trees in medium and low density residential areas, while high mortality was found for trees of small size, those previously rated with 'poor' condition, those in transportation or commercial/industrial land-uses, and trees of particular species (in this case *Morus alba* and *Ailanthus altissima*). In a similar study in Oakland, CA, Roman et al. (Roman et al., 2014a) corroborated the results that mortality rates are higher for small trees, particularly with poor foliage condition while also showing higher mortality for trees planted in sidewalk or strips as opposed to sidewalk cut-outs. Results from both of these studies are particularly relevant for tree planting efforts that include an urban gradient from dense urban to sparser residential land-uses, which represent an important contribution to overall urban canopy coverage (Nowak et al., 1996; O'Neil-Dunne, 2010; Rogan, 2009). Additionally, the relationship between tree condition and mortality is especially important in the context of juvenile trees, because it implies that foliage and trunk condition are significant predictors of mortality for recently planted trees, relative to larger, mature trees (Roman et al., 2014a). This reinforces the need to provide adequate care and stewardship of juvenile trees to prevent their mortality. While such stewardship requires an additional management cost, this investment is justified by the additional ecosystem services gained from mature trees (McPherson et al., 2011).

Roman and Scatena (2011) evaluated mortality rates and expected lifespans of street trees using a meta-analysis of previous research plus field data from Philadelphia, PA. Results indicated a wide range of survivorship rates reported previously in the urban forestry literature, with estimated annual survival rates typically between 80% and 99%, although the authors noted that a small number of survivorship studies have indicated much lower survival rates (e.g., Sklar and Ames, 1985; Yang and McBride, 2003). Conversely, the majority of studies reviewed by Roman and Scatena (75%) showed annual survivorship rates above 91%. This analysis did not investigate causes of mortality.

In contrast to street trees, Roman et al. (2014b) focused on trees planted in single-family residential areas in Sacramento, CA, distributed during a tree give-away program. The study found that 85% of the trees were planted, with ~70% survivorship after five years post-planting. This study area was prone to unstable housing ownership during the study period, leading to high housing turnover and thus increasing the potential for lack of tree maintenance, particularly irrigation. As a consequence, home ownership stability, a proxy for tree stewardship, was found to be the most important variable for predicting survivorship within the first five years of tree planting. Other important variables were yard side (front yard, back yard), species water demand, season planted, days since planting, and mature tree size. For these variables, survival was increased for: front versus back yard location, decreasing species water demand, planting during the wet season, less time since planting, and smaller mature size. Neighborhood income was shown to have inconsistent impacts on survival. The authors concluded that tree care and climate-appropriate species selection were the most important determinants of tree survivorship.

Koeser et al. (2014) calculated mortality rate and mortality factors within the first two to five years for trees in public locations across 26 sites in Florida. Logistic regression was used to determine significant factors of mortality, including irrigation status and species.

While there is a growing body of research concerning predictors of mortality for urban forests, many of these studies have focused on trees planted in publicly owned locations, such as parks, other green spaces, and particularly street trees in planting strips, medians, or sidewalk cutouts. Knowledge from this research is very important, but it has typically excluded trees planted on private property, such as residential yards, which constitute a substantial portion of the urban forest. For example, Nowak et al. (1996) found that approximately 43–72% of urban tree cover is located on residential land-use, with considerable variation across forested, grassland, and desert ecoregions. These residential landscapes form an important and complex element of the broader urban ecosystem (Cook et al., 2012). Because of this important contribution to overall canopy coverage, and due to the potential energy savings seen by individual residents, it is important to extend knowledge of the urban forest ecosystem to include yard trees.

This research examines the predictors of juvenile tree mortality among a newly planted cohort of yard trees in Worcester, MA, using data from three field campaigns, and a combination of Conditional Inference Trees (CIT) and logistic regression modeling. The goal is to determine the most relevant biophysical and socioeconomic variables for predicting tree mortality, and to then quantify the changes to mortality likelihood based on these variables. This information contributes to the growing body of knowledge regarding juvenile tree mortality in a wide range of urban ecosystems.

1.1. Study area

The study area centers on Worcester, MA, USA, and includes parts of six adjacent towns. Worcester has a humid continental climate, with an average daily high of 26 °C in July and 0 °C in January. Average annual precipitation is 1220 mm, as well as 163 cm of snow per season (www.nws.noaa.gov 2015). The Worcester area is highly susceptible to 'Noreaster' storm events, which often produce strong winds and high amounts of precipitation, thus contributing to the natural vegetation disturbance regime. Worcester's population of 183,000 makes it the second largest city in New England after Boston, MA (US Census, 2010). Of this population, approximately 55% lives in renter-occupied housing. The city has a diverse industrial history, and is currently home to prominent healthcare and biotechnical industries (Herwitz, 2001). Worcester's median household income is $45,932, which is substantially lower than the MA median of $66,866 (US Census, 2010). The spatial distribution of wealth shows distinct clustering, with a low-income cluster in the central business district. The five towns surrounding Worcester have broadly similar sociodemographic characteristics, but in general contain lower population densities and higher proportion of rural land-uses. Worcester's population density is 1947 persons/km^2, while the surrounding towns have only 547 persons/km^2. These five towns have a median household income of approximately $80,000. As of 2008, Worcester had 17,113 street trees, providing roughly $2.4 million dollars of gross ecosystem service benefits, or $980,000 of net benefits after subtracting maintenance and management (Freilicher et al., 2008).

The study area was a regulation zone designated by the United States Department of Agriculture (USDA) to control the spread of Asian Longhorned Beetle (ALB; *Anoplophora glabripennis*) (Fig. 1). This regulation zone was established to prohibit unsanctioned movement of wood or wood products originating within the area, and also served to define the extent of the subsequent tree planting initiative. ALB is an

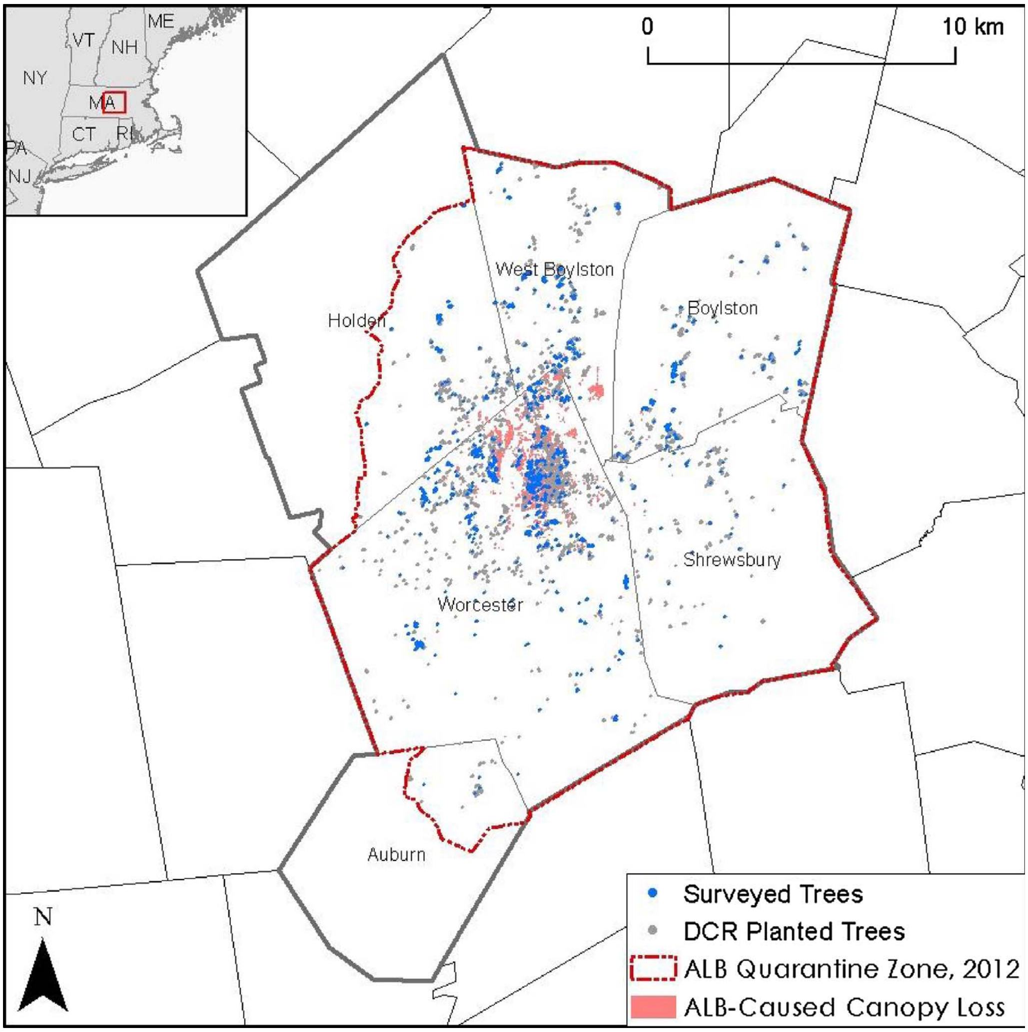

Fig. 1. Study area, showing recent tree plantings by the Massachusetts Department of Conservation and Recreation. The map also shows recent tree canopy loss caused by the Asian Longhorned Beetle eradication program.

invasive insect pest native to mainland China and the Korean Peninsula, where it is considered a pest species, and has caused large economic losses (Haack et al., 2010; Hu et al., 2009; Williams et al., 2004). ALB has spread to port cities in North America and Europe via infested wooden shipping pallets, and has subsequently become established in several surrounding rural, peri-urban, and urban areas (Haack, 2006). The pest is polyphagous and infests hardwood genera, including maple (*Acer*), horse chestnut/buckeye (*Aesculus*), birch (*Betula*), willow (*Salix*), and elm (Ulmus) with *Acer* spp. particularly vulnerable (Haack et al., 2010; Hu et al., 2009; Santos and Bond, 2015). An established ALB population was detected in Brooklyn, New York City, NY in 1996, and other infestations have since been identified in Chicago, IL (1998), Jersey City, NJ (2002), Toronto, Ontario (2003), Worcester, MA (2008), Boston, MA (2010) (Dodds and Orwig, 2011), and most recently Bethel, OH. Due to its wide host tolerance and its use of containerized shipping as a dispersal vector, ALB has been listed as one of the 100 worst alien invasive species (ISSG, 2013).

ALB was first detected in Worcester in 2008 near an industrial and shipping district, suggesting transportation in infested shipping materials. Due to the large number of infested trees found during the initial inspection, it has been estimated that the pest began infesting the area at least a decade earlier (Danko et al., 2016). In an effort to curtail the spread of ALB in Worcester, the United States Department of Agriculture Animal and Plant Health Inspection Service (USDA-APHIS) inspected over nine million trees in the greater Worcester area since 2008, and enacted a regulation zone in Worcester and the surrounding towns, covering 166 km^2 as of August 2009 (Haack et al., 2010; Santos and Cole, 2012), and expanded to 285 km^2 as of 2015 (Santos and Bond, 2015). Within the regulation zone, unauthorized transport of wood or wood products is not permitted (USDA-APHIS, 2008), due to the potential unintentional transportation of ALB in firewood and other wood products. Individual beetles tend to disperse less than 300 m per year by flying or walking, and typically infest new hosts in the immediate vicinity of their natal tree, or else re-infest their natal tree (Meng et al., 2015; Zhou et al., 1984). The beetles are capable of moving up to 2000 m per season when in search of suitable host trees, with the vast majority of individuals moving less than 1000 m (Haack et al., 2010; Hu et al., 2009; Junbao et al., 1998; Smith et al., 2004). The USDA quarantine area reflects this potential for movement, extending a buffer distance of at least 1.5 mi (2.4 km) from any known ALB presence location (USDA-APHIS, 2008). In order to eradicate the established ALB population, USDA-APHIS initiated a host tree removal program in the Worcester ALB regulation zone, encompassing parts of six towns: Auburn, Boylston, Holden, Shrewsbury, West Boylston, and Worcester (Fig. 1). This program has focused on the removal of infested trees and high-risk host trees, with 20,400 infested and 10,250 high-risk trees removed between 2008 and 2012 (Santos and Cole, 2012).

A large-scale tree replanting program was initiated in spring 2010 to aid the recovery from the ALB-related tree removals in the Worcester area. This program consisted of a public/private partnership between the City of Worcester, the MA Department of Conservation and Recreation (DCR), and non-profit Worcester Tree Initiative. The DCR program, funded by a grant from the *American Recovery and Reinvestment Act* of 2009, has emphasized replanting in private residences via a tree giveaway program (Santos and Bond, 2009), while the City of Worcester has focused on replanting on public lands (i.e., street trees). To date, roughly 30,000 non-host trees have been replanted by these organizations combined (Danko et al., 2016; WTI, 2015). This paper analyzes trees planted by the DCR, which constitute the majority of the full planting effort. These trees were planted by DCR staff, professionally trained in arboriculture. This is in contrast to previously described tree giveaway programs, where residents were responsible for tree planting. Additionally, a large majority of plantings (89%) occurred on private residential property, as opposed to city-managed street trees. Selection of each tree and specific planting location was determined by the arborists, in consultation with the home/land-owner. While residents were able to select from a broad planting list, the ultimate decision to plant was at the discretion of the arborist, with considerations for site conditions and species. The number of trees given to each resident was limited only by expert arborist opinion, based on the property size and other site-specific considerations. The average number of DCR-planted trees per property was 3.6, with a maximum of 32 trees planted.

The most commonly planted species were *Abies concolor* (white fir), *Thuja occidentalis* (American arborvitae), *Cornus* spp. (dogwood), *Picea pungens* (Colorado spruce), and *Prunus* spp. (cherry). The number of planted trees is roughly commensurate with the number removed due to ALB eradication; however, the newly planted trees do not yet replace the lost ecosystem services provided by those removed, as they are juvenile individuals with much smaller diameter at breast height (DBH) and stature. The replanting effort continues to date (as of August 2017), with a strong emphasis on planting in residential areas, coupled with homeowner education on tree maintenance best practices.

2. Data

2.1. Tree data

The core dataset for this study consisted of a sample of juvenile trees, recently planted by staff of the MA DCR as part of the post-ALB reforestation program. Data on each tree was recorded during planting, yielding a geodatabase containing geographical coordinates, species, homeowner/property manager address, date of planting, irrigation status, nominal caliper-measured diameter, specific tree location notes, and a unique identification number. Our study focused on trees planted between 2010 and 2012: 15,743 trees in total. Of these, we collected a simple random sample of 1895 unique trees. For this sample, each tree was individually assessed for mortality status (alive, dead), overall condition (excellent, good, fair, poor, critical, dead), yard side (front, back, other), and land-use (residential, institutional, other). A principal motivation of the DCR tree planting program was to recover lost canopy over private residential properties, and therefore 89% of the trees in our sample were planted in residential land-use areas.

2.2. Candidate mortality predictive variables

Twenty-one potential predictor variables were investigated for their influence on mortality (Table 1), including both sociodemographic and biophysical factors that have been proposed as drivers of mortality in previous literature (Ko et al., 2015b; Lu et al., 2010; Roman et al., 2014b). Some candidate variables were taken from the DCR tree database described above, which contained basic tree properties and planting site descriptions, including tree species, status of irrigation at time of planting, and date of planting. Tree species were also grouped into stature categories, captured by the Tree Type variable, which includes three categories: deciduous shade, ornamental shade, and coniferous. The Tree Type definitions were provided by the MA DCR, with the differentiation between ornamental and shade based on average mature tree height. This variable was included specifically due to interest from the DCR, based on institutional conjecture that Tree Type may relate to mortality outcomes (Mat Cahill, personal communication). The distinction between shade and ornamental was based partially on average mature tree size, with the ‘shade’ designation typically reserved for species with a mature height above 35 feet. However, the shade/ornamental distinction also took into consideration the perceived tree value or use from the perspective of the residents, who often preferred ‘ornamental’ species for their aesthetic appearance as opposed to their capacity to provide shade (Mat Cahill, personal communication; Nguyen et al., 2017). Previous research has found that residents value tree aesthetics highly, and some residential planting programs have shifted their species palette accordingly (Almas and Conway, 2017; Locke and Baine, 2015; Nguyen et al., 2017). Therefore, the Tree Type variable can be considered a hybrid of average biological characteristics and also resident perceptions of tree utility.

Additional variables were selected from the MA Office of Geographic Information archive (MassGIS, www.mass.gov), MA town tax assessors, the U.S. Census, a high spatial resolution landcover map of the area, and from the field sampling campaigns. This range of variables was intended to capture a wide range of possible influences on tree mortality, with particular emphasis on anthropogenic predictors of mortality. Trees inherited attributes from polygon- and raster-based data layers based on spatial intersection, yielding a dataset in which individual trees were the units of analysis, rather than properties, tax parcels, or land cover pixels.

Candidate variable selection was partially informed by previous studies that have investigated drivers and predictors of urban tree mortality (Table 1), and partially from site-specific knowledge and communications from MA DCR staff. The variables measured by tax parcel data – date of building construction, last property sale price and date, and parcel size and value – were not found to have been commonly analyzed in the available literature, and therefore represent a novel suite of useful information. The variable Years Since Built may capture several unmeasured social/urban-environmental variables, of which the most important for tree mortality is recent soil disturbance from construction-induced soil compaction and soil quality, which could negatively affect tree health and thus influence mortality (Hauer et al., 1994). The study area contains a wide range of building construction dates, and the geographic pattern of this variable is linked to neighborhoods and housing developments (Fig. 2).

A summary of all numerical explanatory variables is shown in Table 2. This table indicates the mean and standard deviation of each variable, grouped by mortality status, which provides an initial quantitative description of the dataset, and also indicates statistical separability of the mean values between the live and dead groups.

To ensure that species type were not associated with geographical or statistical clusters of any variable, the mean value of each variable was calculated for each species, and was used to calculate the z-score relative to the entire dataset. For example, the mean value of days since sale for Colorado spruce was 5278, compared to the overall mean of 5503, yielding a z-score of -0.06 for this species and variable. This process showed that only 1% of species/variable combinations had mean values outside of the 95% confidence level, indicating a lack of statistical clustering of the variables by species. The implication of this is that species were planted across a representative range of all variables. Additionally, spatial overlay analysis did not detect spatial clustering of any given species.

3. Methods

Predictors of juvenile tree mortality were determined using a three-step process. First, mortality rates for the age cohorts and species were calculated. This step was used to contextualize the exploratory and

Table 1
Candidate variables for determining tree mortality.

Variable Name	Description	Units	Source	Rationale	Rationale/Supporting Literature
Season Year	Season and year of tree planting, e.g. Spring 2011	Nominal	MA DCR	Impact of each season's planting campaign, involving potentially different planting crews, training, and/or tree nursery stock	Lu et al. (Lu et al., 2010); Ko et al. (Ko et al., 2015a)
Species	Tree species	Nominal	MA DCR	Species-level mortality risk	Lu et al. (Lu et al., 2010); Koeser et al. (Koeser et al., 2013)
Genus	Tree genus	Nominal	MA DCR	Genus-level mortality risk	Lu et al. (Lu et al., 2010); Koeser et al. (Koeser et al., 2013)
Tree Type	Tree group, either conifer, deciduous shade, or ornamental shade	Nominal	MA DCR	Tree functional-level mortality risk	Roman et al. (Roman et al., 2014b)
Irrigation	Presence of irrigation during time of planting	Binary	MA DCR	Water availability	Koeser et al. (Koeser et al., 2014)
Days Since Planting	Number of days between planting date and 7/1/2016 (final observation season)	Days (integer)	MA DCR	Tree age	Sherman et al. (Shermana et al., 2016)
Total Parcel Value	Total value of land and building for tax parcel containing tree	Dollars (integer)	MassGIS/Town Tax Assessors	Property value, homeowner socioeconomic status	Grove et al. (Grove et al., 2014); Roman et al. (Roman et al., 2014b)
Total Parcel Size	Total area in acres of tax parcel containing tree	Acres (decimal)	MassGIS/Town Tax Assessors	Property value, homeowner socioeconomic status	
Days Since Sale	Days since last sale of property containing tree	Days (integer)	MassGIS/Town Tax Assessors	Homeowner stability/tenure	Roman et al. (Roman et al., 2014b)
Years Since Built	Years since building built on tax parcel containing tree	Years (integer)	MassGIS/Town Tax Assessors	Parcel and neighborhood age, indication of age of initial (pre-ALB) urban forest age. Could also relate potentially to soil/site conditions.	Hauer et al. (Hauer et al., 1994)
Last Sale Price	Dollar amount of last property sale for tax parcel continuing tree	Dollars (integer)	MassGIS/Town Tax Assessors	Property value, homeowner socioeconomic status	Roman et al. (Roman et al., 2014b)
Total Population	Total population of census block group containing tree	Persons	USCensus/American Community Survey	Population/housing density/pressure	Nowak et al. Crane (Nowak et al., 2004);
Total Households	Count of households in census block group containing tree	Households	USCensus/American Community Survey	Population/housing density/pressure	Nowak et al. Crane (Nowak et al., 2004);
Median Household Income	Median household income of census block group containing tree	Dollars (integer)	USCensus/American Community Survey	Homeowner socioeconomic status	Roman et al. (Roman et al., 2014b)
Median Home Value	Median home value of census block group containing tree	Dollars (integer)	USCensus/American Community Survey	Homeowner/property socioeconomic status	Grove et al. (Grove et al., 2014); Roman et al. (Roman et al., 2014b)
Population Density	Population per square km of census block group containing tree	Persons/km^2	USCensus/American Community Survey	Population/housing density/pressure	Nowak and Crane (Nowak et al., 2004); Nguyen et al. (Nguyen et al., 2017)
Renter Proportion	Proportion of population renting vs owning home for census block group containing tree	Proportion	USCensus/American Community Survey	Homeowner stability/tenure, socioeconomic status	Roman et al. (Roman et al., 2014b); Nguyen et al. (Nguyen et al., 2017)
Impervious Surface	Proportion of surface covered by ground-level concrete, asphalt, or other impervious cover, within 10 m of tree	Proportion	WorldView-2 imagery landcover classification	Proximal tree planting environment	Hauer et al. (Hauer et al., 1994); Nielsen et al. (Nielsen et al., 2007); Sherman et al. (Shermana et al., 2016)
Yard Side	Side of house tree planted on, either front or back	Binary	Field Survey	Tree siting/visibility	Larson et al. (Larson et al., 2009)
Land-Use	Type of residential, commercial, or other land-use	Nominal	Field Survey	Tree siting/visibility; home/land owner type	Nowak et al (Nowak et al., 1990); Nowak and Crane (Nowak et al., 2004); Lu et al. (Lu et al., 2010); Grove et al. (Grove et al., 2014); Locke and Baine (Locke and Baine, 2015)
Number of Trees on Property	Total number of trees planted at address as part of current planting program	Count	MA DCR	Tree siting/visibility/resource availability	Roman et al. (Roman et al., 2014b)

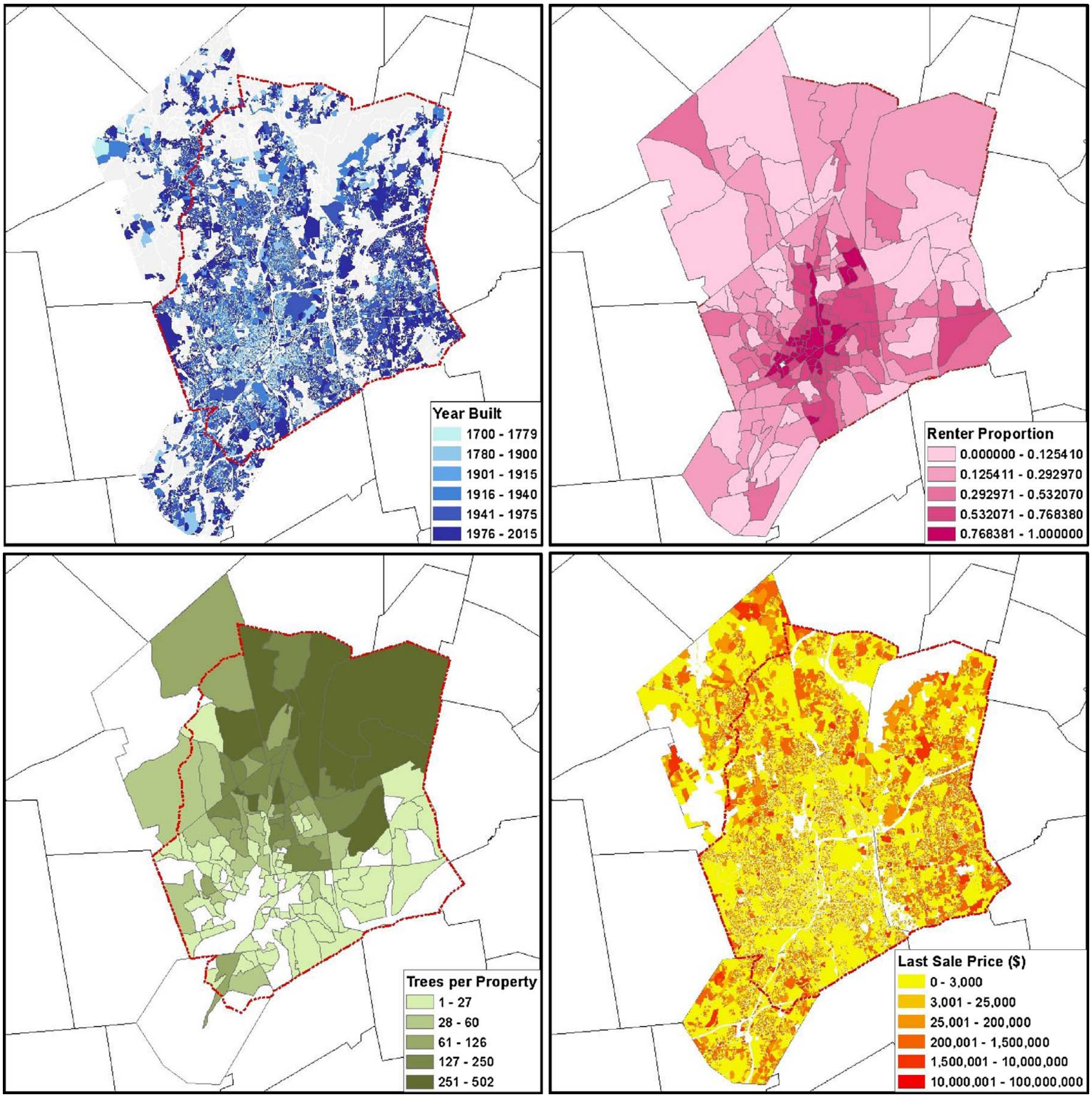

Fig. 2. Map series showing spatial distribution of four of the candidate predictor variables. This figure is provided to contextualize the study area.

Table 2
Explanatory variable summary, grouped by tree mortality status. The right-most column indicates statistical separability, based on a two-tailed *t*-test between the live and dead means.

	Live (n = 1363)		Dead (n = 505)		
Explanatory Variable	Mean	SD	Mean	SD	Significant Difference? (90% CL[a])
Days Since Planted	1990.51	167.39	1981.36	147.29	No
Days Since Sale	5584.2	3588.72	5353.61	3436.58	No
Impervious Cover within 10 m diameter	23.6	37.7	16.56	32.22	Yes
Last Sale Price	135040.32	194887.88	151891.62	294273.95	No
Medan Home Value	272146.22	64926.41	277720	78760.48	No
Median House Income	68842.81	19121.04	70238.45	20719.06	No
Number of Trees Planted	14.63	19.07	16.73	19.68	Yes
Parcel Size	3.53	30.21	1.86	5.93	Yes
Parcel Value	1046434.9	11389495	336406.93	560090.54	Yes
Population Density	1305.44	1090.68	1181.04	1074.3	Yes
Renter Proportion	0.25	0.2	0.23	0.2	No
Total Households	529.64	245.58	511.47	234.05	No
Total Population	1363.99	675.33	1343.52	664.63	No
Years Since Built	57.19	40.65	55.77	46.43	No

[a] Confidence Level.

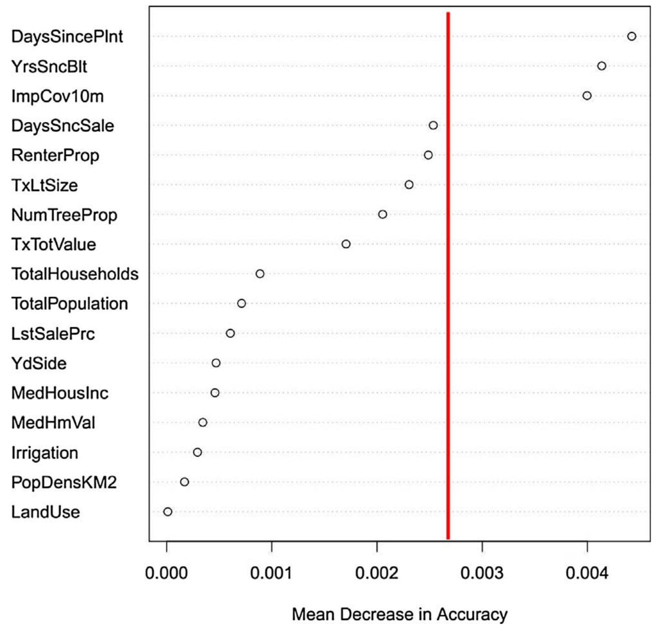

Fig. 3. Example scree plot generated from CIT conditional variable importance. The red line defines the inflection point, at which the mean decreases in accuracy become distinctly smaller with each variable. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

modeling steps. After basic data description, the next step was to narrow the suite of candidate predictor variables down to a manageable subset by estimating relative variable importance. This exploratory step provided a small subset of predictor variables for use in modeling mortality likelihood.

3.1. Mortality

We use the term 'raw mortality' to refer to the simple ratio between the number of dead and total trees from a given planting season year. Raw mortality rates for the study time period were calculated over the entire dataset, and also for subsets of each species and each planting season year. We also calculated annual mortality, defined by:

$$m_{annual} = 1 - (N_t/N_0)^{1/t} \tag{1}$$

where N_0 and N_t are population numbers at the beginning and end of time interval t (Roman et al., 2016). In this study, N_0 was the number of trees planted during each season, and N_t was the number of trees alive at the time of observation interval t. Note that mortality in the context of urban forests includes both trees observed standing dead and those that were removed (Roman et al., 2016). An overall annual mortality rate was calculated by the average of annual mortality rates from each planting season year.

3.2. Determining variable importance

For initial data exploration and description, and to contextualize further analysis, Chi-squared tests for association and *t*-tests for separability of means were performed between candidate predictor variables and mortality status. Chi-squared tests were used to determine the statistical significance of individual categorical variables on tree mortality, using a 90% confidence level. Mortality was tested against tree placement (front/back yard), tree functional type, and planting season year (Table 4). Additionally, *t*-tests were used to indicate significant difference between numerical variable means, based on mortality status (alive/dead), using a 90% confidence level (Table 2). Based on the initial importance of planting season year and tree type, further investigations of mortality were conducted on twenty overlapping subsets of the dataset, defined by unique combinations of these two categorical variables. Therefore, twenty subsets of the overall dataset were created using each combination of three 'Tree Type' values for all planting seasons (all trees, conifer, deciduous shade, ornamental shade), and each 'Planting Season Year' (fall 2010, spring 2011, fall 2011, spring 2012). This provided mortality information relevant to the overall dataset, as well as for age cohorts and tree stature groups.

The main analysis relied on a two-step approach. First, Conditional Inference Trees (CIT) (Hothorn et al., 2006; Strobl et al., 2009, 2008) were used to systematically explore each candidate variables' influence on mortality for various subsets of the population. CIT analysis is an ensemble method for recursively partitioning predictor variables to non-parametrically predict a response variable (Hothorn et al., 2006; Strobl et al., 2009, 2008, 2007), similar to Random Forests (Breiman, 1999). This step provided lists of relevant variables to be used in the second step: logistic regression to quantify the effects of each variable on the probability of mortality. This two-step approach was used to distill the large quantity of candidate variables into an appropriate subset of variables to be used in logistic modeling, which provides information regarding specific changes in probabilities of mortality based on changes in the explanatory variables. This process was also helpful given that multiple subsets of the tree dataset were analyzed, based on tree type and date of planting; the systematic exploration of the large dataset with CIT facilitated rigorous logistic modeling for these subsets.

CIT analysis is capable of incorporating highly correlated and interacting predictor variables (Strobl et al., 2007), producing robust class predictions by randomizing both the observations and predictor variables at each node. This method differs from 'traditional' Random Forests in that it produces unbiased partition trees, which do not favor continuous variables or categorical variables with many factor levels (Hothorn et al., 2006; Strobl et al., 2007). The R 'party' package (Strobl et al., 2009) was used to conduct CIT analysis. To ensure robust variable importance rank, 10,000 conditional inference trees were generated for each model, and three variables were used for each split node.

The CIT output of primary interest was the rank of conditional variable importance, which is a measure of the predictive power of each variable that adjusts for correlations between predictor variables, and is conditional in the sense of beta coefficients in regression models (Strobl et al., 2008). The resulting variable importance scores were ranked and displayed on dot charts such as Fig. 3, facilitating isolation of the most important variables for inclusion in logistic regression modeling. For almost all models, clear break points were found separating the important and unimportant variables, as shown in Fig. 3, indicated by the red vertical line. For models without a clear break point, all variables with mean decrease in accuracy scores above zero were used for logistic modeling. CIT was conducted on the twenty subsets of the dataset described above, yielding twenty CIT models, each with a ranking of conditional variable importance.

Preliminary modeling determined that Genus and Species were overwhelmingly the strongest predictors of tree mortality. Based on this dominance in the mortality signal, and the fact that these variables have a large number of factor levels, both were excluded in subsequent CIT and logistic regression modeling. However, Species were grouped by tree stature/functional group, represented by the Tree Type variable, as described above.

3.3. Logistic regression of mortality

Logistic regressions were run for each subset of the data described above, using the most important variables as determined by CIT for each subset. This yields estimates of change in mortality odds ratio based on changes in the predictor variables, which is an easily interpreted quantity. A 90% confidence level was used to determine statistical significance of variables in the logistic regression models. Reference level coding was used for categorical variables, meaning that categorical variable values (i.e. factor levels) were compared against

Table 3
Summary of mortality by species.

Species Name – Latin	Species Name – Common	Tree Type	Total Observations	Overall Mortality Rate (%)
Styrax japonicus	Japanese Snowbell	O	1	100.00
Crataegus	Hawthorn	O	1	100.00
Styphnolobium japonicum	Japanese Pagoda	O	1	100.00
Pinus nigra	Austrian Pine	C	3	100.00
Abies balsamea	Balsam Fir	C	17	64.71
Quercus coccinea	Scarlet Oak	SD	13	53.85
Quercus alba	White Oak	SD	6	50.00
Nyssa sylvatica	Blackgum	SD	57	49.12
Liquidambar styraciflua	Sweetgum	SD	57	45.61
Quercus rubra	Red Oak	SD	58	43.10
Gingko biloba	Gingko	SD	21	42.86
Abies concolor	White Fir	C	266	42.48
Larix spp.	Larch	C	10	40.00
Abies fraseri	Fraser Fir	C	21	38.10
Fagus spp.	Beech	SD	38	34.21
Genus	Hophornbeam	O	28	32.14
Picea pungens	Colorado Spruce	C	121	31.40
Carpinus caroliniana	Hornbeam	SD	34	29.41
Amelanchier spp.	Serviceberry	O	111	28.83
Chionanthus virginicus	Fringe Tree	O	28	28.57
Quercus bicolor	Swamp White Oak	SD	25	28.00
Metasequoia spp.	Dawn Redwood	C	65	27.69
Picea omorika	Serbian Spruce	C	15	26.67
Stewartia pseudocamellia	Japanese Stewartia	O	20	25.00
Ostrya spp.	Tulip	SD	42	23.81
Cornus spp.	Dogwood	O	132	21.21
Juniperus spp.	Juniper	C	38	21.05
Picea abies	Norway Spruce	C	21	19.05
Gleditsia triacanthos	Honey Locust	SD	85	16.47
Halesia tetraptera	Carolina Silverbell	O	7	14.29
Malus spp.	Crabapple	O	52	13.46
Prunus spp.	Cherry	O	130	11.54
Thuja occidentalis	American Arborvitae	C	136	11.03
Tilia cordata	Littleleaf Linden	SD	59	10.17
Zelkova spp.	Zelkova	SD	20	10.00
Syringa reticulata	Japanese Tree Lilac	O	87	9.20
Quercus palustris	Pin Oak	SD	27	7.41
Pinus strobus	White Pine	C	33	3.03
Cladrastis kentukea	Yellowwood	SD	3	0.00
Oxydendrum arboreum	Sourwood	SD	1	0.00
Magnolia acuminata	Cucumber Magnolia	O	1	0.00
Pyrus calleryana	Bradford Pear	O	1	0.00

one another using the first value as a reference. Therefore, the number of coefficients reported is one less than the number of distinct values (factor levels). Odds ratios were calculated from the coefficients for meaningful interpretations. In many cases the variables had a large range in terms of their inherent units (e.g. Median Home Value is reported in dollars), and so the results section below describes some of the odds ratios in terms of a 1 unit change in the predictor.

4. Results

4.1. Tree mortality

The overall mortality of the most frequently planted species of trees is presented in Table 3, which shows the number of observations and the overall mortality rate for each. Several species showed extremely high or low mortality rates; however, this is due to very small sample sizes for less frequently planted species, and therefore should be interpreted with caution. Notable highlights from Table 3 include low mortality for *Pinus strobus* (3.03%, n = 33), while the very frequently planted *Abies concolor* showed a much higher 42.48% mortality (n = 266). Also, while *Quercus palustris* showed low mortality (7.41%), other *Quercus* species fared much worse, with *Quercus bicolor, rubra, alba,* and *coccinea* at 28.0%, 43.1%, 50.0%, and 53.85%, respectively. The cumulative mortality rate for the entire dataset was 26.7%, and the average annual mortality rate was 6.11% (Table 4). These two metrics were calculated for each planting season year. Chi-squared analysis revealed that trees planted in front yards had significantly lower mortality than those planted in back yards, and that ornamental trees had significantly lower mortality than shade and conifer trees (Table 4). Also, this analysis indicated a significant difference in the mortality rates by Planting Season Year.

Table 4
Summary of mortality by planting season and tree type. Note that the total number of trees used for mortality calculations was smaller than the total sample size (n = 1895) due to several trees that could not be located.

Tree Type	Alive	Dead		Overall Mortality Rate	Chi^2 P-value
Conifer	501	223		30.8	< 0.01
Ornamental	481	120		19.97	
Shade	381	162		29.83	
Yard Side	**Alive**	**Dead**			
Back Yard	788	317		1105	< 0.01
Front Yard	468	139		607	
Other	107	49		156	
Planting Season	**Alive**	**Dead**	**Annual Mortality**	**Overall Mortality**	
Fall 2010	241	60	4.35	19.93	< 0.01
Spring 2011	589	210	5.92	26.28	
Fall 2011	305	175	8.67	36.46	
Spring 2012	228	60	4.56	20.83	
Grand Total	1363	505	6.11	27.03	

4.2. Conditional inference tree variable importance

The candidate variables for mortality (Table 1) were selected with CIT variable importance for each of the twenty data subsets defined above and spanning 5 planting season by 4 tree type conditions. The summary of variable importance for each of these subsets, representing combinations of planting season and tree type, is shown in Table 5. For the overall dataset, including all tree types and planting seasons, six variables were selected based on the variable importance: Days Since Tree Planted, Years Since Built, Number of Trees Planted, Proportion Renter Occupancy, Tree Type, and, Median Household Income. Splitting the dataset up by tree type produced notably different groups of important variables, as shown reading left to right in Table 5. For all shade trees, six variables were selected, with some overlap: Days Since Tree Planted, Impervious Cover within 10 m, Yard Side, Last Sale Price, Tax Parcel Size, and Median Home Value. Similarly, the subsets of all conifer and all ornamental trees produced eight important variables each, with some amount of overlap between variables, but with each subset representing a unique suite of variables which best predicted mortality.

Due to the large number of subsets analyzed, and the unique suite of predictor variables determined with CIT for each, a summary table was created in order to determine the most frequently selected variables (Table 6). This table indicates the number of times each variable was selected as important in any of the planting season/tree type subsets. The most commonly selected variable was Years Since Built, referring to the age of the structure whose property contains the tree in question;

Table 5

Variable importance as defined by CIT, calculated by mean decrease in accuracy. Results are shown for different planting seasons and for different tree type groups, as well as for all conditions lumped together. Grey shading indicates that the variable was important, relative to other candidate variables, and was therefore included in logistic regression modeling. Significance codes are as follows: ^ = 0.1, * = 0.05, ** = 0.001, and *** = less than 0.000. The sign of each coefficient indicates whether the variable increased (+) or decreased (−) the probability of tree mortality, provided a one-unit increase in the given variable. For categorical explanatory variables, the significant category is indicated in parentheses. The coefficients were converted into Odds Ratios (OR) to facilitate interpretation, since the odds ratios can be directly compared.

All Seasons

Var. Importance Rank	All	Coef.	Odds Ratio	Shade	Coef.	Odds Ratio	Conifer	Coef.	Odds Ratio	Ornamental	Coef.	Odds Ratio
	Intercept			**(Intercept)****	-4.64E+00	9.71E-03	**(Intercept)****	3.84E+00	4.63E+01	**(Intercept)*****	-8.68E+00	1.70E-04
	Days Since Tree Planted			Days Since Tree Planted*	1.82E-03	1.00E+00	Days Since Tree Planted**	-1.90E-03	9.98E-01	Population Density		
	Years Since Built			Impervious Cover within 10m*	2.00E-02	1.02E+00	Years Since Built			Days Since Tree Planted**	3.14E-03	1.00E+00
	Number of Trees Planted			Yard Side			Impervious Cover within 10m**	-1.09E-02	9.89E-01	MedHmVal**	6.94E-06	1.00E+00
	Proportion Renter Occupancy			Last Sale Price			Days Since Parcel Sale			Tax Parcel Value*	7.55E-07	1.00E+00
	TreeType (Ornamental)***	-6.71E-01	5.11E-01	Tax Parcel Size			Proportion Renter Occupancy*	-1.06E+00	3.46E-01	Number of Trees Planted*	2.71E-02	1.03E+00
	Median Household Income			MedHmVal*	4.47E-06	1.00E+00	Tax Parcel Size			Tax Parcel Size		
							Number of Trees Planted			Last Sale Price*	-2.32E-06	1.00E+00
							Tax Parcel Value			Days Since Parcel Sale		

Fall 2010

	All	Coef.	Odds Ratio	Shade	Coef.	Odds Ratio	Conifer	Coef.	Odds Ratio	Ornamental	Coef.	Odds Ratio
	(Intercept)***	7.89E+00	2.68E+03	**(Intercept)**			**(Intercept)** ^	1.89E+00	6.61E+00	**(Intercept)** ^	7.50E+00	1.80E+03
	Proportion Renter Occupancy***	-9.27E+00	9.46E-05	Proportion Renter Occupancy			Proportion Renter Occupancy **	-5.45E+00	4.30E-03	Proportion Renter Occupancy		
	Tax Parcel Size			Tax Parcel Value			Tax Parcel Size			Median Home Value.	-2.87E-05	1.00E+00
	Median Household Income**	-1.00E-04	1.00E+00	Days Since Tree Planted			Tax Parcel Value			Impervious Cover within 10m		
	Tax Parcel Value			Tax Parcel Size			Years Since Built *	-1.83E-02	9.82E-01			
	Years Since Built			Last Sale Price			Days Since Parcel Sale					

Spring 2011

	All	Coef.	Odds Ratio	Shade	Coef.	Odds Ratio	Conifer	Coef.	Odds Ratio	Ornamental	Coef.	Odds Ratio
	(Intercept) **	-6.33E-01	5.31E-01	**(Intercept)** ^	-1.16E+00	3.13E-01	**(Intercept)**			**Intercept**		
	Years Since Built ^	4.46E-03	1.00E+00	Years Since Built			Years Since Built			Years Since Built		
	Number of Trees Planted***	2.16E-02	1.02E+00	Total Population			Days Since Parcel Sale			Yard Side		
							Number of Trees Planted					
							Days Since Tree Planted					

Fall 2011

	All	Coef.	Odds Ratio	Shade	Coef.	Odds Ratio	Conifer	Coef.	Odds Ratio	Ornamental	Coef.	Odds Ratio
	Intercept			**(Intercept)****	1.76E+00	5.82E+00	**(Intercept)**			**(Intercept)***	-4.81E+01	1.30E-21
	TreeType (Ornamental)*	-7.26E-01	4.84E-01	Years Since Built ^	-7.37E-03	9.93E-01	Years Since Built			MedHmVal		
	Proportion Renter Occupancy**	1.80E+00	6.03E+00	Impervious Cover within 10m			Number of Trees Planted			Years Since Built		
	Years Since Built			Total Households*	-2.55E-03	9.97E-01	Population Density			Days Since Tree Planted*	2.40E-02	1.02E+00
	Days Since Tree Planted			Proportion Renter Occupancy			Total Households*	1.94E-03	1.00E+00	Tax Parcel Size		
							Median Household Income ^	-3.54E-05	1.00E+00	Tax Parcel Value		
							Proportion Renter Occupancy					

Spring 2012

	All	Coef.	Odds Ratio	Shade	Coef.	Odds Ratio	Conifer	Coef.	Odds Ratio	Ornamental	Coef.	Odds Ratio
	Intercept	-7.77E-01		**Intercept**			**(Intercept)***	4.63E+00	1.03E+02	**Intercept**		
	TreeType (Ornamental)**	-1.92E+00	1.46E-01	Irrigation			Total Population					
	TreeType (Shade)**	-1.35E+00	2.58E-01	Yard Side			MedHmVal**	-1.63E-05	1.00E+00			
	Years Since Built						Years Since Built					

Table 6
Summary of most commonly important candidate variables, based on CIT conditional variable importance. The first column indicates the number of times the given variable was found to be important by the CIT modeling. The subsequent three columns indicate the number of times that variable was significant in subsequent logistic modeling, and indicate the sign/direction of the association with mortality.

Variable	Count of Variable in all Models	Count of Variable Significant in Logit	Count of Negative Logistic Regression Coefficient	Count of Positive Logistic Regression Coefficient
Years Since Built	14	3	2	1
Proportion Renter Occupancy	9	4	3	1
Days Since Tree Planted	8	4	1	3
Tax Parcel Size	7	0	0	0
Number of Trees Planted	6	2	0	2
Tax Parcel Value	6	1	0	1
Impervious Cover within 10m	4	2	1	1
Days Since Parcel Sale	4	0	0	0
Last Sale Price	3	1	1	0
Median Household Income	3	2	2	0
Population Density	2	0	0	0
Total Households	2	2	1	1
Total Population	2	0	0	0
Median Home Value	1	1	1	0
Irrigation	1	0	0	0
Yard Side	0	0	0	0
Land Use	0	0	0	0
Tree Type (Ornamental)	3	3	2	1
Tree Type (Shade)	1	1	1	0

this variable was selected in fourteen of the twenty CIT models. The subsequent five most frequently selected variables predominantly reflected the characteristics of the property on which the tree was planted, with only a single purely biophysical variable: Days Since Tree Planted. In descending order, they were: Proportion Renter Occupancy, Days Since Tree Planted, and Tax Parcel Size, Number of Trees Planted, and Tax Parcel Value. This summary of variable selection contextualizes the following stage of the analysis, in which the selected variables were used for logistic regression.

4.3. *Logistic regression modeling of mortality*

The variables deemed most important by CIT analysis of each data subset were used as predictor variables in logistic regression models for the same subset. The overall results of this process are shown in Table 5 and Table 6. In Table 5, grey cells indicate statistically significant variables found from the CIT-determined important variables. For each significant variable, the coefficient estimate and corresponding odds ratio are reported.

The sign of each coefficient indicates whether the variable increased (+) or decreased (−) the probability of tree mortality, provided a one-unit increase in the given variable. For categorical explanatory variables, the significant category is indicated in parentheses. For the entire dataset of all three tree types and all planting periods, the only significant variable was Tree Type, with Ornamental trees significantly less likely to die than shade or coniferous trees (p-value < .000). This implies that, for the entire population of replanted trees, the odds of an ornamental tree dying were approximately 50% less than the reference group, which in this case is conifer by default.

Narrowing the data by Tree Type and planting date (represented by seasons in the table) changed the group of CIT-selected variables found to be important, and therefore led to different significant predictors of mortality. However, the conifer subsets tended to retain the most important variables, as reflected by the larger number of rows under the conifer heading in Table 5. For all deciduous shade trees, days since planting, quantity of impervious cover surrounding the tree, and median home value were all significant and positive, indicating that these trees had increasing chances of mortality as they aged, were more likely to die when planted beside higher quantities of impervious surfaces (e.g. sidewalks, driveways, buildings), and had higher mortality when planted beside more expensive homes. Conifer trees showed reverse signs for the significant variables Days Since Tree Planted and Imperious Cover within 10 m^2, and also showed a significant reduction in mortality associated with higher proportion of renter occupancy. With each additional 10 m^2 of impervious cover, conifer trees showed a roughly 1% reduction in mortality odds, whereas shade trees showed a roughly 2% increase.

Finally, ornamental trees showed five significant variables: Days Since Tree Planted (+), Median Home Value (+), Tax Parcel Value (+), Number of Trees Planted (+), and Last Sale Price (−). As with deciduous shade trees, ornamental shade trees experienced a higher probability of mortality as time since planting increased, unlike with conifers, which saw the opposite tendency. Also like the shade category, ornamental trees showed increased mortality risk with increasing median home value. However, these trees showed lower probability of mortality for higher values of Last Sale Price, indicating a potentially more complex relationship. The other significant variables, Tax Parcel Value, Number of Trees Planted, and Last Sale Price, were unique to ornamental trees. The number of trees planted on the property was also an important and significant variable predicting ornamental trees mortality, with an approximately 2.7% increase in odds of mortality for each additional tree planted.

The remaining models shown in Table 5 represent smaller subsets of the data, as defined by the subheadings. Overall, the most frequently significant variables were Proportion of Renter Occupancy and Days Since Tree Planted, which were each significant in four models (Table 6). Years Since Built and Tree Type (Ornamental) were the second most frequently significant variables, appearing in three models each, followed by Number of Trees Planted, Impervious Cover within 10 m^2, Median Household Income, and Total Households, each of which appeared twice. The twenty data subsets varied substantially in variables associated with mortality, but using the summary tables it is possible to identify the variables most important, overall, for predicting juvenile tree mortality from this population.

5. Discussion

The overall annual mortality rate of 6.11% (Table 4) was slightly higher than the range of 3.5–5.1% reported in a recent meta-analysis of street tree mortality rates (Roman and Scatena, 2011). However, this reported range is not directly comparable, since the populations studied in the meta-analysis were specifically street trees, whereas the bulk of trees studied here were planted in residential yards, often far from the nearest street. Also, the Roman et al. analysis was not limited to juvenile trees, which are known to have higher mortality rates than mature trees (Miller and Miller, 1991; Roman et al., 2014a; Shermana et al., 2016). Therefore, the annual mortality rates presented here can be viewed as roughly commensurate with previous findings and expectations, such as Roman et al. (Roman et al., 2014b), who showed a 6.6% annual mortality rate at five years after planting. Mortality was higher for younger tree cohorts. While these data represent a relatively short time period, the trend of decreasing annual mortality rate with increased tree age conforms to the expectation that mortality falls as juvenile trees become established (Roman et al., 2016). The fact that the Days Since Planted variable was *positively* associated with mortality risk seems contradictory to this finding,

Initial CIT models for the overall dataset including all trees and all planting time periods indicated that the most important predictor of mortality was tree species, a finding that is strengthened by the widely varying mortality rates presented in Table 3. The dominance of tree species on mortality was initially determined using Species and Genus variables in CIT models, which gave overwhelming importance to these two variables. The fact that species and genus are strong predictors of mortality could be attributed to species-specific tolerances for various environmental stressors (e.g., water, salt, heat), but it should be noted that each tree was sited and planted by experienced arborists, so it is unlikely that improper species site selection caused this large mortality signal.

The strong prediction of mortality based on tree species was the rationale for subdividing the data into structural/perceived-value groups with the Tree Type variable. These broad groups based on tree stature and resident perception were necessary because forty-nine species were represented in the dataset, resulting in forty-nine factor levels to incorporate as dummy variables in logistic regression, which was deemed inappropriate. The Chi-squared analysis performed on Tree Type versus mortality confirmed the statistical separability of the tree stature groups.

An important finding from the overall dataset is that even when species data are aggregated to the tree stature type (Tree Type), ornamental trees were shown to have significantly lower overall mortality rate than shade and conifer trees, with rates of 21%, 29%, and 30%, respectively. Ornamental trees also showed reduced mortality odds in the overall logistic regression model, relative to conifer and shade trees. This indicates that either the species in this group are hardier or better suited to the study area environment and climate, or alternatively that these trees received additional stewardship and care from homeowners. Such stewardship has been shown to be the most important predictor of juvenile tree mortality by previous studies (Koeser et al., 2014; Roman et al., 2014b; Vogt et al., 2015). Additionally, a separate but related study of homeowner maintenance practices in the Worcester tree planting program is ongoing, and to date has found initial evidence that homeowner irrigation and maintenance practices are variable and may affect mortality (Rogan and Martin, 2017). This parallel study has also confirmed that homeowner tree selection is biased towards ornamental trees, which are valued for their appearance (Locke and Baine, 2015). This value is demonstrated by the fact that ornamental trees are statistically more likely to be planted in the front yard, relative to the back yard of residences, based on homeowner preferences (Martin and Rogan, personal communication). Other residential yard tree programs have similarly reported that participants favor ornamental trees (Nguyen et al., 2017). While resident preferences are important in attaining active tree stewardship, the goal of the DCR reforestation program is to regain as much canopy as possible, so as to offset the loss of 30,000+ mature shade trees. Therefore, the role of smaller ornamental trees must be limited, as such trees do not have smaller potential for ecosystem services provision. The DCR program's planting lists have been formulated to provide residents with a variety of options while also attaining a biodiverse urban tree canopy, but nevertheless a concerted effort has been made at the individual level to encourage the planting of shade trees rather than ornamental trees. Although the planting list itself is not biased to smaller stature trees, it has become evident that resident choices are (Mat Cahill, personal communication).

The mortality differences between tree stature classes are particularly relevant in the context of long-term ecosystem services. Ornamental may provide better initial resident satisfaction based on aesthetic value, but their smaller mature stature implies lower overall provision of evaporative cooling, air and water filtration, and water runoff control than larger stature trees, represented by the 'deciduous shade' and 'conifer' classes (McPherson, 1992; McPherson et al., 2011; Nowak et al., 2008). The finding that shade trees died at a higher rate implies either that larger numbers of such trees must be planted in order to attain the same mature cohort size, or that additional stewardship be given to shade trees to correct this imbalance. Findings from yard tree survival studies in Sacramento have had mixed results with regards to tree stature (Ko et al., 2015b; Roman et al., 2014b). This suggests the need for more research into the relationship between tree stature classes and functional groupings and mortality outcomes, particularly with respect to potential intersections with resident perceptions and values regarding different tree forms.

The age of homes (or other buildings) associated with newly planted trees was found to be an important variable for the majority of the twenty data subsets, indicating that this variable (Years Since Built) likely contains valuable information for understanding tree mortality. This variable showed no strong correlations with any other explanatory variable ($r < 0.3$). Mortality was more often higher for trees located in properties with more recently built homes.[1] However, the variable was only found to be significant in three of the subsequent logistic models, so its overall contribution is unclear. The relevance of this variable to tree health could be related to construction or landscaping-related soil compaction and quality, both of which may be poorer in more recently built housing stock (Coder, 2000; Kozlowski, 1999). The map of this variable presented in Fig. 2 provides some geographic context. The city-center, located in the southwestern portion of the map, shows predominantly older building/housing stock, while Burncoat and Greendale neighborhoods located towards the center of the map show more intermediate building ages. Moving away from the city center towards the edges of the map, building ages decrease, representing the expansion of urban and residential zones. This figure also shows tree plantings as red points, and clusters of plantings are apparent in neighborhoods of different building ages. While the immediate interpretation of Years Since Built may be unclear or indirect, it is likely to be an important consideration for future research, since it was empirically found to be an important variable by the majority of models.

The importance of Number of Trees Planted (important six times, significant two times; Table 6) is another interesting finding, and is potentially linked to tree stewardship. For both models in which this variable was found to be significant, it had a positive relationship with mortality odds, meaning that the more trees a residence received, the more likely a given tree was to die. This potentially implies a competition issue for either light and nutrients or a resident's resources for tree care. This is consistent with findings from a yard tree program in Sacramento (Roman et al., 2014b), which similarly found that number of trees planted per property was connected to higher mortality. Program staff there suspected that the difficult physical work of taking care of many trees was not feasible for some residents.

Including Years Since Built, four of the six most frequently CIT-selected variables related to the resident property characteristics: Proportion Renter Occupancy, Tax Parcel Size, and Tax Parcel Value. These variables were included in the candidate list as proxies for socioeconomic conditions and the built environment in which each tree

[1] Many variables reported small increases in odds of mortality per unit change, but note that this is an artifact of the large ranges of most variables relative to their unit size (e.g., Median Home Value is reported in dollars), and so small changes in predicted odds form a one-unit change in the variable should be considered meaningful when they are significant at a given confidence level.

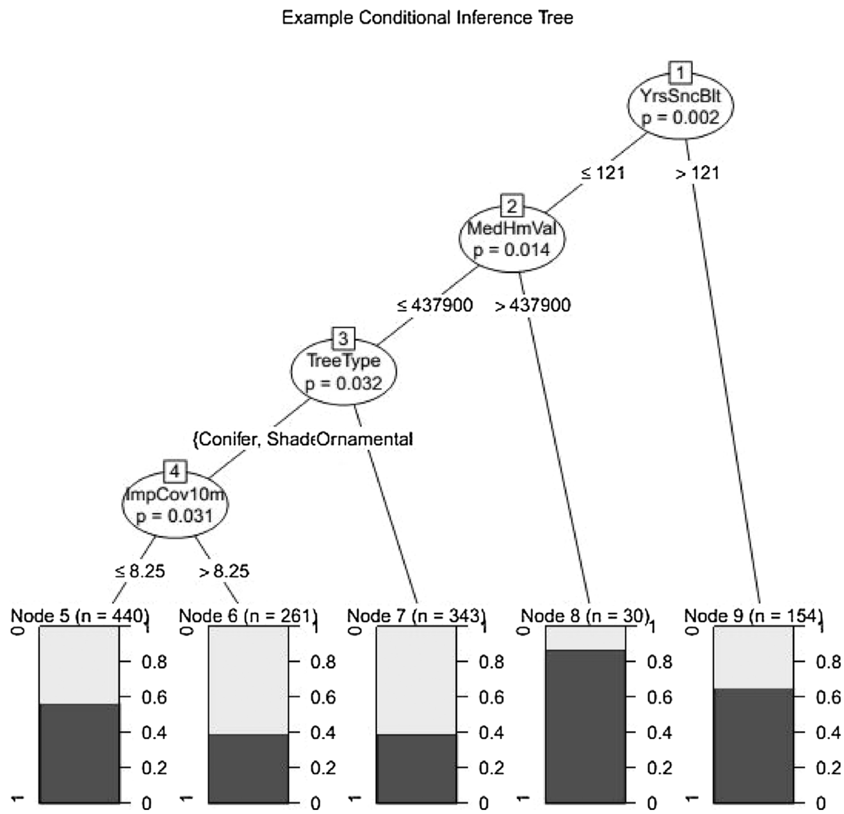

Fig. 4. Example of an individual conditional inference tree. Note that a single tree cannot be used to interpret the ensemble of trees used in the entire model. In this tree, the terminal nodes at the bottom indicate the node purity by proportion alive (coded as 0) and dead (coded as 1).

was planted. Increases in the proportion of renter occupancy tended to result in higher mortality odds, with three logistic models having negative coefficients and one having a positive coefficient for this variable. This finding is not surprising given that irrigation and other stewardship activities are very important for tree survivorship during the establishment phase (Boyce, 2010; Roman et al., 2015), and renters are less likely to contribute to active stewardship of the trees near their dwelling. Tax Parcel Size was not significant in any logistic models, despite being found important by seven CIT models. However, other tax parcel variables, value and last sale price, were both significant in the same model: ornamental trees, all planting seasons. For this subset, higher parcel value was associated with increased mortality, but higher last sale price associated with decreased mortality. This implies that the most valuable parcels in the study area saw slightly higher than average ornamental mortality, while simultaneously mortality odds decreased from increased recent sale price. This may relate to the use of ornamental trees as a means of increasing property value due to aesthetics, which would be more important for properties being bought and sold (last sale price), as opposed to those under stable ownership (parcel value). Further research is needed to fully contextualize these interpretations, and to understand the tree selection and placement from a homeowner perspective

Impervious surface had a similarly nuanced relationship with mortality, showing positive and negative associations with mortality odds for all shade trees and conifer trees, respectively. In this study, impervious surfaces included all paved surfaces. For shade trees, each additional 10 m^2 of impervious cover within a 10 m radius of a given tree was associated with a 2% increase in mortality odds. This finding supports the conventional understanding that urban trees close to sidewalks and other impervious surfaces suffer from reduced soil volume and constrained root growth space (Grabosky and Gilman, 2004; Hauer et al., 1994; Sanders et al., 2013; Sanders and Grabosky, 2014; Scharenbroch et al., 2017). Conversely for conifers, mortality likelihood was higher with reduced impervious surface. While this appears to be an unexpected result, it is likely that this relationship results from the use of conifers planted as privacy screens towards the extreme edges of properties, particularly in back yards with little or no impervious surface within 10 m. These locations tended to be as far as possible away from the home, often behind fences, shrubbery, or other existing trees, making them less visible to the homeowner. In addition to the reduced visibility of such trees, it is likely that their physical distance made regular irrigation and care more difficult. It is possible that these less accessible, less visible trees suffered from reduced stewardship, and therefore increased mortality.

CIT was found to be an effective means of reducing a large number of candidate variables for use in logistic regression modeling, based on its ability to handle a large number of potentially collinear predictor variables. While conventional Random Forests potentially give undue variable importance to categorical variables, CIT did not show this problem, with three of the four categorical variables ranked last in terms of frequency of use in the models. Although CIT can itself be used for classification of mortality status (alive vs dead), the fact that it is an ensemble method means that determining the specific relationships between each predictor variable and mortality is unclear. A single constituent classification tree, as shown in Fig. 4, is very effective for understanding subsets of mortality, but lacks the analytical power of CIT. The variable importance derived from CIT provided unbiased, conditional rankings of predictor variables, and in itself is a useful information product. The summary of variable importance and significance frequency in all models (Table 6) provides a perspective on predictor variables from a range of tree ages (i.e. planting season) and structural types (i.e. Tree Type), which is important because of the widely differing suite of variables used for each data subset. However, important and statistically significant differences were found in the best predictor variables and also the direction of variable influence on mortality probability. This indicates that it is appropriate and useful to analyze age and type cohorts of young trees separately, which can provide more specific information than when using undifferentiated datasets.

Based on the results, it is evident that in this planting effort, species was an important variable in determining mortality. This is shown by the raw mortality rates in Table 3 and extremely high variable importance of species in the CIT models, relative to all other variables (not shown). In addition to species-specific water, heat, and other stress tolerances, it is worth noting that the nursery sourcing of trees for planting may have influenced mortality. In particular, *Abies concolor* (white fir) were noted by planting crews to have poor soil quality upon delivery, which may have contributed to the high mortality rate of this species, which coincidentally was the most frequently planted tree to be surveyed (M. Cahill, personal communication). It is also important to note that *Thuja occidentalis* (American arborvitae) posed a challenge for measurement and assessment, as these trees tended to be planted in closely spaced lines, making individual tree identification difficult.

Future research could incorporate additional field data and potential explanatory variables to further nuance and characterize juvenile tree mortality. An extended time series of tree characteristics, including condition and mortality status, will allow for supplemental age/cohort-based mortality analysis, exploring whether predictors of mortality change over time or are constant for particular planting seasons. Also, further investigation could incorporate additional variables, such as household-level vegetation diversity, homeowner stability, household vacancy, and individual sociodemographic information, all of which are potentially important in determining resident attitudes towards and interactions with trees (Lin et al., 2017; Meléndez-Ackerman et al., 2014; Roman et al., 2014b).

6. Conclusions

This study investigated a tree planting program somewhat different from many others previously studied and reported on in the literature. While many studies (Nowak et al., 2004; Roman and Scatena, 2011) report on urban street tree mortality, few were found to report on drivers or predictors of mortality for juvenile trees professionally planted in private yards. Other studies of residential tree giveaway programs (Ko et al., 2015a; Nguyen et al., 2017; Roman et al., 2014b) involved trees that were distributed for residents to plant, rather than professionally planted, and so the mortality signal was potentially strongly influenced by the planting practices, rather than solely by environment and post-planting stewardship. Nonetheless, our findings concur with conclusions from those and other studies (Koeser et al., 2013; Vogt et al., 2015) about the critical role of stewardship for juvenile tree survival. Mortality increased with an increasing number of trees planted on a given property, implying that homeowner care and resources are easily exhaustible. Additionally, tree type was found to be an important predictor of mortality, with ornamental trees showing lower occurrence of mortality than shade deciduous and coniferous trees. Trees planted adjacent to more recently constructed buildings showed increased mortality rates, suggesting that construction soil disturbance may be an important consideration. The findings presented here provide insights regarding predictors of juvenile tree mortality on residential lands for land managers, non-profit tree giveaway programs, local and state government planting initiatives, and private residents.

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