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Redevelopment and the urban forest: A study of tree removal and retention during demolition activities

Justin Morgenroth [a,*], Jarlath O'Neil-Dunne [b], Luis A. Apiolaza [a]

[a] New Zealand School of Forestry, University of Canterbury, Christchurch, New Zealand
[b] Spatial Analysis Laboratory, University of Vermont, United States

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ABSTRACT

Though relationships between urbanization and tree cover are generally well studied, the effect of redevelopment on urban trees, at the scale of the individual property, is not well understood. Developing knowledge in this area is important in order to limit tree loss during redevelopment and thus, ensure sustained ecosystem services. Here, we explore the removal or retention of trees adjacent to building demolition in Christchurch, New Zealand. We mapped the presence or absence of individual trees on 123 properties prior to, and following, building demolition. Using a classification tree (CT) analysis, the presence or absence of 1209 trees was modelled as a function of: tree-related variables, property-related variables, and economic variables. The CT model estimated tree presence/absence with overall accuracy of 80.4%. Results show that 21.6% of all trees were removed as a consequence of building demolition, resulting in a tree canopy cover reduction of 19.7% across all 123 properties. The CT showed that tree crown area was the most important variable for predicting the presence/absence of trees, whereby trees with small crown areas ($<$7.9 m^2) were most frequently removed, especially if they were within 0.7 m of a demolished building. Land value was also an important determinant of tree presence/absence, such that tree removal was more prevalent on properties with higher land value ($/$m^2$). The results provide important new insights into some of the reasons for tree removal or retention during redevelopment at the scale of the individual property where most tree-related decisions are made.

1. Introduction

More people currently live in cities than ever before, with more than half the world's population (54% in 2014) living in cities (UN DESA, 2014). To satisfy rural to urban migration, city morphologies respond through urbanization (conversion from undeveloped to developed land cover), redevelopment (replacement of structures on site, amalgamation or subdivision of existing property boundaries), and densification (also known as intensification or compaction; (Williams, 2000)). Together urbanization, redevelopment, and densification put pressure on the growth and survival of trees in urban ecosystems (McKinney, 2002).

Tree cover response to urbanization has previously been studied via conceptually simple urban-rural gradient models (Berland, 2012), but these fail to consider development density, which is rarely linear from the urban core outwards (Tratalos, Fuller, Warren, Davies, & Gaston, 2007). Nonetheless, development of land at the urban-rural interface is generally believed to cause initial tree cover decline (Sharpe, Stearns, Leitner, & Dorney, 1986), then rapid increase following development (Berland, 2012). But the impact of property redevelopment on trees within the urban boundary remains understudied.

Redevelopment and densification's impact on urban greenspace was recently reviewed (Haaland & Konijnendijk van den Bosch, 2015) and the specific impact on urban trees has previously been reported at the scale of the city block, neighbourhood, city and metropolitan area. Koeser, Hauer, Norris, and Krouse (2013) found that city block redevelopment activities nearly doubled the probability that street trees would die in Milwaukee, while densification reduced tree canopy cover in neighbourhoods in Toronto (Steenberg, Millward, Duinker, Nowak, & Robinson, 2015), the city of Sheffield (Davies et al., 2008) and Minnesota's Twin Cities Metropolitan Area (Berland, 2012). While these studies provide valuable insights, property-scale research is rare, which is

* Corresponding author.
E-mail addresses: justin.morgenroth@canterbury.ac.nz (J. Morgenroth), Jarlath.ONeil-Dunne@uvm.edu (J. O'Neil-Dunne), luis.apiolaza@canterbury.ac.nz (L.A. Apiolaza).

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problematic as tree-related decisions are generally made by individual property owners (Shakeel & Conway, 2014). In the absence of property level research, fundamental questions about the relationship between redevelopment and city trees remain (Haaland & Konijnendijk van den Bosch, 2015). What happens to trees on a property when it is redeveloped – are they removed or retained? Further to that, why are trees retained or removed during redevelopment? Answers to these questions are necessary given the ecosystem services provided by urban forests (Dwyer, McPherson, Schroeder, & Rowntree, 1992), many of which are relevant at the scale of the individual property (e.g. fruit production, aesthetic value, mental health amelioration).

In this study we explore the relationship between trees and redevelopment at the scale of the individual property. We specifically investigate whether trees are retained or removed during building demolition, the first stage of property redevelopment. We begin by quantifying the impact of demolitions on tree cover and then explore the reasons for individual tree removal during demolition, inclusive of tree-related (e.g. tree size), property-related (e.g. building cover), and economic (e.g. land value) explanatory factors.

2. Methods

Opportunities to collect data to study the dynamics of property-level redevelopment and tree cover are rare, perhaps because data collection would need to occur over long time periods in order to generate a sufficiently large dataset. In this study, an opportunity to collect the necessary data within a short duration was presented by the wide-scale demolition occurring in Christchurch, New Zealand following earthquakes in 2010–2011 (Bray, Cubrinovski, Zupan, & Taylor, 2014; Moon et al., 2014).

2.1. Study site

The study was conducted in Christchurch, located on the east coast of the South Island of New Zealand (Lat: −43.53, Long: 172.62). Buildings were identified for demolition by the Canterbury Earthquake Recovery Authority (CERA, 2012), with an evident concentration in Christchurch's city centre (Fig. 1). At the time of field data collection for this study, buildings on 854 properties were listed to be demolished; this represents a small proportion (0.005%) of Christchurch's approximately 165,300 properties (LINZ, 2013). All 854 properties were visited during July and August 2012 and a subset of 123 properties was selected for inclusion in this study. Conditions for inclusion in the subset included: 1) all structures on the property were fully demolished (and rubble cleared off site) at the time field-based tree inventory was undertaken; and 2) properties were residential, commercial, or industrial. The first condition was instated to ensure that the field work accurately detected tree presence or absence after demolition was completed, rather than part-way through, while the second condition was designed to include only privately-owned properties. The vast majority ($n = 95$) of properties studied here were within the ‘4 Aves’. This area is considered Christchurch's central city and is bounded by Bealey Avenue, Fitzgerald Avenue, Moorhouse Avenue, and Deans Avenue. The remaining properties studied were scattered throughout the surrounding suburbs (Fig. 1).

2.2. Data

In order to determine the effect of demolition on tree canopy cover, we compared the presence and absence of individual trees on properties before and after demolition had occurred. We used a hybrid approach to data collection including remote sensing and field surveys. Remote sensing was used to map individual trees prior to building demolition, while field surveys were used to confirm tree removal or retention following building demolition. It was not possible to use a remote sensing approach following demolition as no remote sensing imagery of sufficiently high spatial resolution was available.

2.2.1. Remote sensing data acquisition

Individual tree crowns were mapped to establish baseline values for tree canopy cover, as well as the location and size of individual trees on properties prior to demolition. The data used included high-resolution aerial photography and aerial LiDAR data. The true-colour aerial photographs were acquired by New Zealand Aerial Mapping (NZAM) on 24 February 2011, two days after the 22 February Christchurch Earthquake and before any of the demolitions had occurred. NZAM used an UltraCamXp sensor (Microsoft Corporation, Photogrammetry Divison, Graz, Austria) at 1700 m above ground level to produce very-high resolution (10 cm) true colour photographs. The aerial photography was obtained for this study from NZAM in orthorectified form and projected into the New Zealand Transverse Mercator projection based on the NZGD2000 spheroid.

The LiDAR data were also supplied by NZAM. The LiDAR acquisition flights occurred between 8–10 March 2011, prior to any demolitions occurring. Data were captured from 900 m above ground level using an Optech Gemini sensor (model # 07SEN211) with settings of 100 KHz PRF, 48 Hz scan frequency, and 40° field of view. Average point spacing for all returns was 0.57 m. LiDAR data were supplied as classified LAS files, with points classified into three classes: ground, non-ground, water.

2.2.2. Analysis of remote sensing data

2.2.2.1. Data pre-processing. The raw LiDAR data were used to produce two layers for subsequent use. First, the LiDAR data were imported and processed to yield a Digital Elevation Model (DEM) from the ground returns, a Digital Surface Model (DSM) from the first returns, and finally a normalized digital surface model (nDSM) by subtracting the DEM from the DSM. Processing was carried out using the ArcGIS 10.1 software package (ESRI, 2012). The surface models were created using natural neighbours interpolation with a cell size of 10 cm to match the resolution of available RGB aerial photography. To minimize the existence of spurious cells in the nDSM, the dataset was smoothed with a 3×3 moving window focal analysis. Next, a slope dataset (degrees) was derived from the smoothed nDSM dataset.

2.2.2.2. Tree cover mapping. Mapping of individual trees prior to building demolitions at each studied property was undertaken via a combination of object-based image analysis (OBIA) (see review in Blaschke, 2010) and manual crown delineation. OBIA on RGB photography has successfully been used for classifying vegetation (Li & Shao, 2012; Walker & Briggs, 2007) and classification accuracy of vegetation in urban areas is improved with OBIA compared to pixel-based image analysis (Cleve, Kelly, Kearns, & Moritz, 2008).

An OBIA routine, built using eCognition Developer 8.7 (Trimble Navigation, Ltd., Sunnyvale, CA), was used to segment then classify landscape features into ‘woody vegetation’, ‘buildings’, and ‘other’ based on spectral, structural, textural, and neighbourhood characteristics. For segmentation, a multiresolution segmentation (scale = 15, shape = 0.1, compactness = 0.5) algorithm was applied to group objects based on the red, green, and blue bands, as well as the median nDSM and slope.

Objects were classified based on feature values: a) spectral; b) structural; c) textural; and d) neighbourhood characteristics. The feature values of sample image objects were used to build a user-

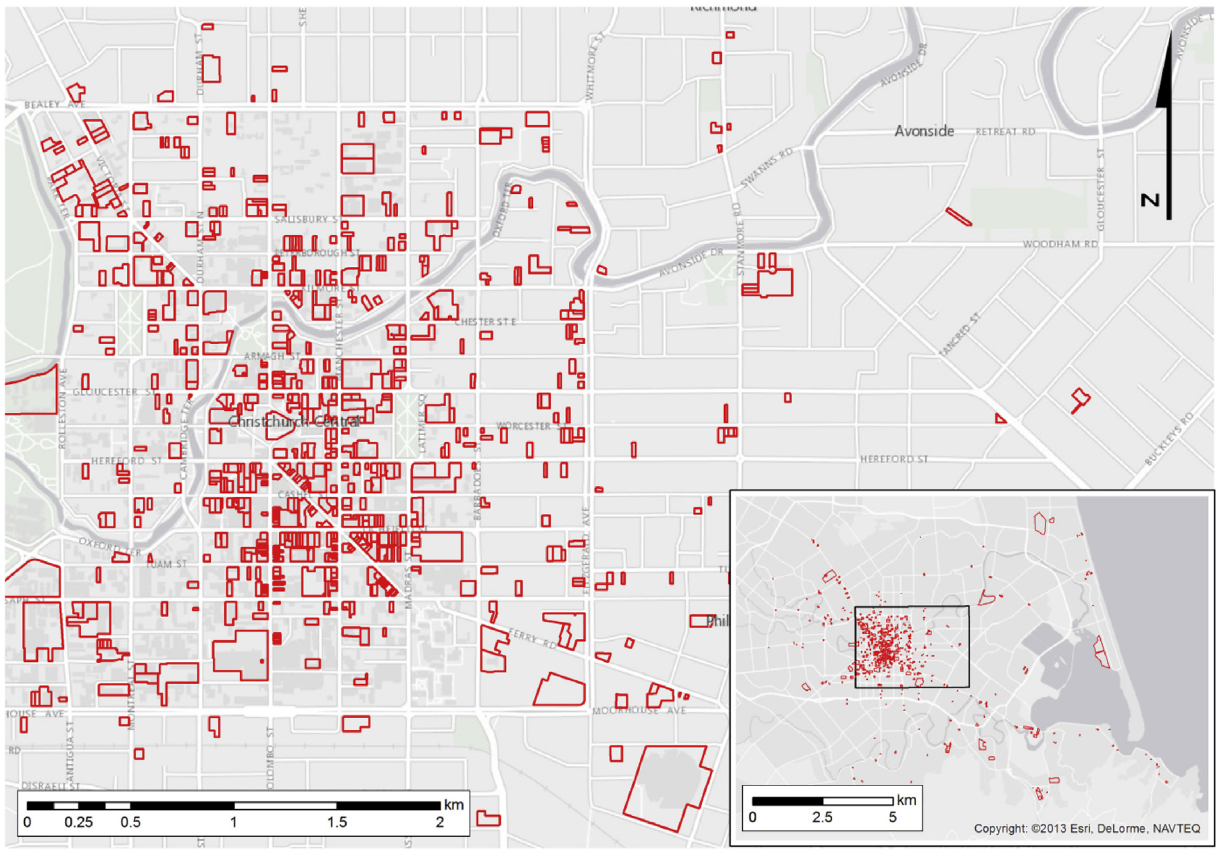

Fig. 1. Property boundaries of buildings identified for demolition. Main map shows Christchurch's city centre, where demolition density is highest. Inset map shows range of property demolitions across Christchurch, with extent rectangle representative of area shown on main map. NOTE: based on official Christchurch Earthquake Recovery Authority demolitions list (CERA, 2012).

defined profile of characteristic thresholds used to discriminate between 'woody vegetation', 'buildings', and 'other' land cover classes. The nDSM was used to exclude short woody vegetation (<2.5 m), so that the resulting 'woody vegetation' class contained only trees and not shrubs. The 'woody vegetation' and 'buildings' features were exported into a GIS where 1209 individual trees were manually delineated from the area determined to be 'woody vegetation' (Fig. 2). The external boundaries of woody vegetation objects resulting from the OBIA classification were kept as is, however internal boundaries were manually added to separate individual crowns within a given woody vegetation object. This was done visually on the basis of differences in colour and nDSM values. As a final step, tree-related variables were derived for use in the classification tree model described below. The variables, including how they were derived, are described in Table 1.

2.2.3. Field survey

During July and August 2012, all 123 demolition sites included in this study were visited to assess tree presence/absence following demolition. Printed aerial photographs showing trees that existed prior to demolition (e.g., Fig. 2) were used as a reference at each property to identify every tree that had existed prior to demolition. A visual inspection was used to systematically classify each tree feature identified in the pre-demolition aerial photographs as 'present' or 'absent'. No other assessments of tree health or damage were undertaken. The presence/absence status for all trees was used to update the pre-demolition tree canopy cover layer in the GIS and create a post-demolition tree canopy cover layer.

2.2.4. Property data

In order to investigate potential causal mechanisms for tree removal during demolition of buildings, property-related variables and economic data were determined for each property and were included in analyses as explanatory factors (Table 1). The official government-managed property titles (boundaries) were downloaded as a shapefile from Land Information New Zealand (LINZ, 2013) and were used to determine property area, perimeter, and perimeter:area ratio. We also measured the length of the shared boundary between each property and the adjacent street, which we termed street frontage. This explanatory factor was deemed important because it was indicative of ease of access onto the property for large demolition equipment. Property values were based on a valuation made by the Christchurch City Council for rates purposes; these values were current as at 1 August 2007. Property values were normalized by area, such that data units were NZ$ m^{-2}. In addition, we measured the linear distance between the edge of the crown for each tree and the nearest demolished building, the driveway, and the public road. These data allowed us to test the hypothesis that proximity to a building, driveway, or road would result in a higher probability of tree removal.

2.3. Statistical analysis

2.3.1. Canopy cover analysis

For each property boundary, the pre- and post-demolition tree canopy cover layers were used to determine the percentage tree canopy cover lost as a result of demolition. The percentage tree canopy cover lost ($CC_{loss\_\%}$) was calculated as:

Fig. 2. Tree cover classification for an individual property in central Christchurch. Results of the eCognition OBIA classification of woody vegetation (left) and the manually delineated individual trees (right). In the image at right, green represents woody vegetation present after demolition, while red represents woody vegetation absent after demolition. Note the bricks surrounding the house; the brick cladding has fallen off the house during the earthquake. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
– A summary of tree, property, and economic variables used in modelling the presence or absence of trees following demolition of a building. * A Pearson correlation analysis showed these explanatory variables to be redundant ($|r| > 0.6$), so they were not included in further analysis.

	Variable	Description
Tree Variables	Crown area (m^2)	Crown area for each tree
	Height (m)*	The maximum height within the polygon delineating each tree crown. Measured from LiDAR-derived nDSM.
	Volume (m^3)*	A simplified approximation of total tree volume derived by multiplying crown area by height
	Canopy cover (%)	Total area of each property covered in tree canopy prior to building demolition
	Area-normalized tree volume (m)	An area-normalized tree volume metric calculated as the sum of the volume of all trees for each property divided by the property area
	Total tree count*	A count of the number of trees for each property
	Tree density (trees/m^2)	An area-normalized metric describing the number of trees per square meter.
Property Variables	Distance to building (m)	The linear distance between the edge of each tree's crown and the edge of the demolished building.
	Distance to driveway (m)	The linear distance between the edge of each tree's crown and the nearest edge of the property's driveway
	Distance to street (m)*	The linear distance between the edge of each tree's crown and the nearest edge of the public road.
	Property area (m^2)*	Total area of the property defined in the official government cadastre.
	Property area:perimeter ratio*	The ratio of property area to perimeter, both of which are defined in official government cadastre.
	Street frontage (m)	The length of the boundary between the property and the adjacent public road. This metric describes how narrow the property is.
	Building cover (%)*	Total area of each property covered by the demolished building
Economic Variables	Area-normalized land value (NZ $/$m^2$)	Derived from a Christchurch City Council valuation, current as at 1 August 2007.

$$CC_{loss\_\%} = (CC_{before} - CC_{after}) \times CC_{before}^{-1} \quad (1)$$

where, CC_{before} is the canopy cover prior to demolition and CC_{after} is the canopy cover after demolition has taken place. A paired *t*-test was conducted to determine whether canopy cover following demolition differed significantly from canopy cover before demolition.

2.3.2. Classification tree analysis

Classification trees (CT) are a specific instance of classification and regression trees (CART) used for categorical response variables. CARTs are used frequently in forestry-related studies (Fan, Kabrick, & Shifley, 2006). Here we use a CT approach for an urban forestry application, namely to estimate the probability of a tree's removal during the demolition process. CTs use a binary partitioning algorithm to recursively split a dataset into mutually exclusive subgroups with minimized heterogeneity (De'Ath & Fabricius, 2000). Explanatory variables were selected one at a time from all available variables with the aim of maximizing homogeneity in the subgroups. CTs are a flexible analysis technique, allowing for nonlinear data, missing values, and combinations of categorical and continuous explanatory variables (De'Ath & Fabricius, 2000). Furthermore, their output, in the form of a decision tree, is sufficiently simple to be used for decision support and communication (Ambelu et al., 2014). CTs were well suited to this study for all these reasons and also due to their ability to predict presence/absence (e.g. Coops, Waring, & Schroeder, 2009).

Prior to developing a CT model, a Pearson correlation analysis showed that some explanatory variables (Table 1) were highly associated with each other (Appendix A.1), meaning that they were redundant for further modelling and were not included in the CT model. A Pearson correlation coefficient (|r|) threshold of 0.6 was used to determine correlation between explanatory variables. We modelled the presence or absence of 1209 trees as a function of the following explanatory variables: tree-related variables (crown area, canopy cover, area-normalized tree volume, tree density); property-related variables (distance to building, distance to driveway, street frontage), and economic variables (land value).

Data were randomly split into two subsets: two-thirds of the data (800 trees) comprised the training subset which was used to build the classification tree; one-third of the observations (409 trees) were used as the testing subset to test the model. The CT was grown to a maximum depth of five nodes with a minimum of ten observations at any terminal node, then pruned to avoid over-fitting. Pruning was done by setting the complexity parameter to the minimum cross-validation error of the model. All statistical analyses were conducted in the R programming environment (R Core Team, 2014) and packages rpart (Therneau, Atkinson, & Ripley, 2014) and rpart.plot (Milborrow, 2011) were used to develop and plot the classification tree.

3. Results

3.1. Canopy cover changes and loss of trees on demolition sites

For the 123 properties surveyed, a paired *t*-test showed that mean canopy cover decreased significantly ($p < 0.001$, $t(122) = 6.68$) from 17.8% (*s.e.* = 1.15%) to 14.3% (*s.e.* = 1.09%), which represents a relative decrease of 19.7%. Canopy cover loss (Equation (1)) was not evenly distributed (Fig. 3); 46 properties lost no canopy cover, while 9 lost 100%. There was an observed shift in the canopy cover distribution with a greater proportion of properties having lower canopy cover following demolitions. Of the 1209 trees in the initial survey, 948 remained present (78.4%), while 261 were absent (21.6%).

3.2. Classification tree analysis for presence/absence of trees following demolition

The classification tree model derived from the training dataset was used to predict the presence or absence of a tree following building demolition. The CT is summarized in Fig. 4. An accuracy assessment of the CT model was undertaken using a confusion matrix (Fielding & Bell, 1997). Using the testing data subset, the CT model predicted presence and absence with overall accuracy of 80.4%, though the CT predicted tree presence (User's Accuracy = 90.7%, Producer's Accuracy = 85.4%) better than tree absence (User's Accuracy = 42.5%, Producer's Accuracy = 55.2%).

Of the nine terminal nodes in the CT, five predicted tree presence. Trees whose crown area exceeded 7.9 m^2 and that were further than 20 m from a driveway comprised the largest percentage of present trees (38%). Meanwhile, four of the terminal nodes in the CT predicted tree absence, whereby the greatest predicted absence (7%) was for trees with crown area less than 7.9 m^2 that were within 0.7 m of the demolished building on properties with a street frontage exceeding 16 m (Fig. 4).

Because explanatory variables in the CT are selected in order of declining deviance of the dependent variable (Crawley, 2007), we

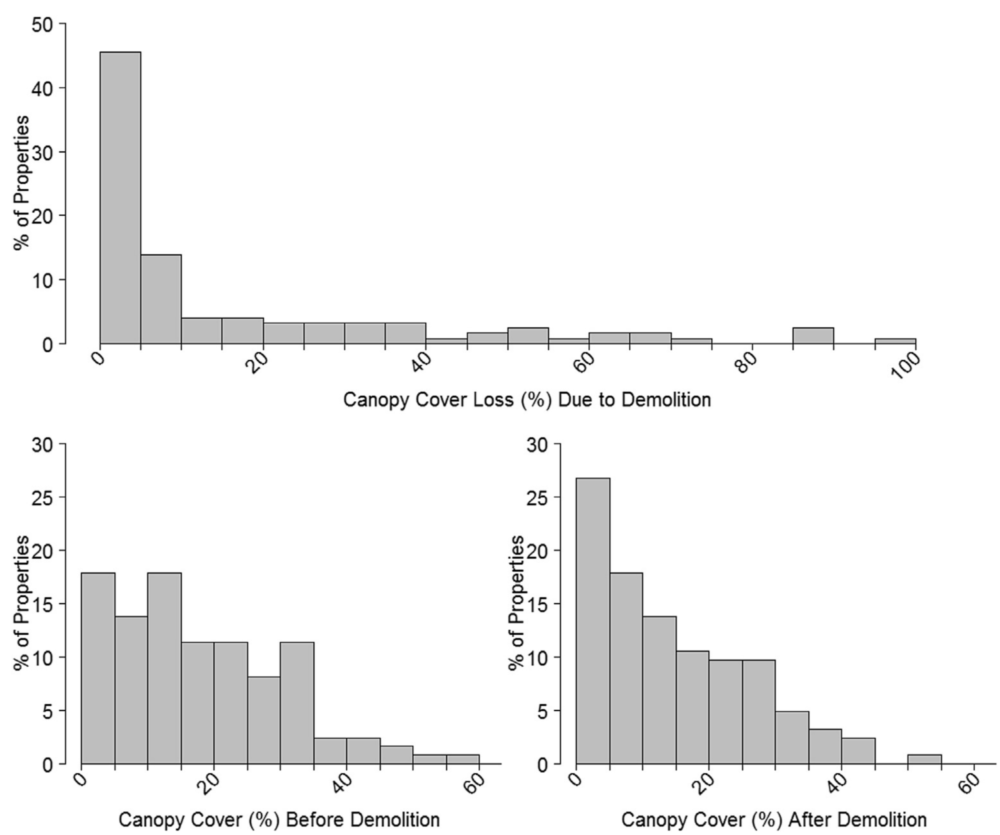

Fig. 3. A frequency distribution for percentage canopy cover loss as a consequence of demolition reveals an uneven distribution (*top*). Frequency distributions for canopy cover before (*bottom left*) and after (*bottom right*) demolition show a shift towards properties with less canopy cover as a consequence of building demolition.

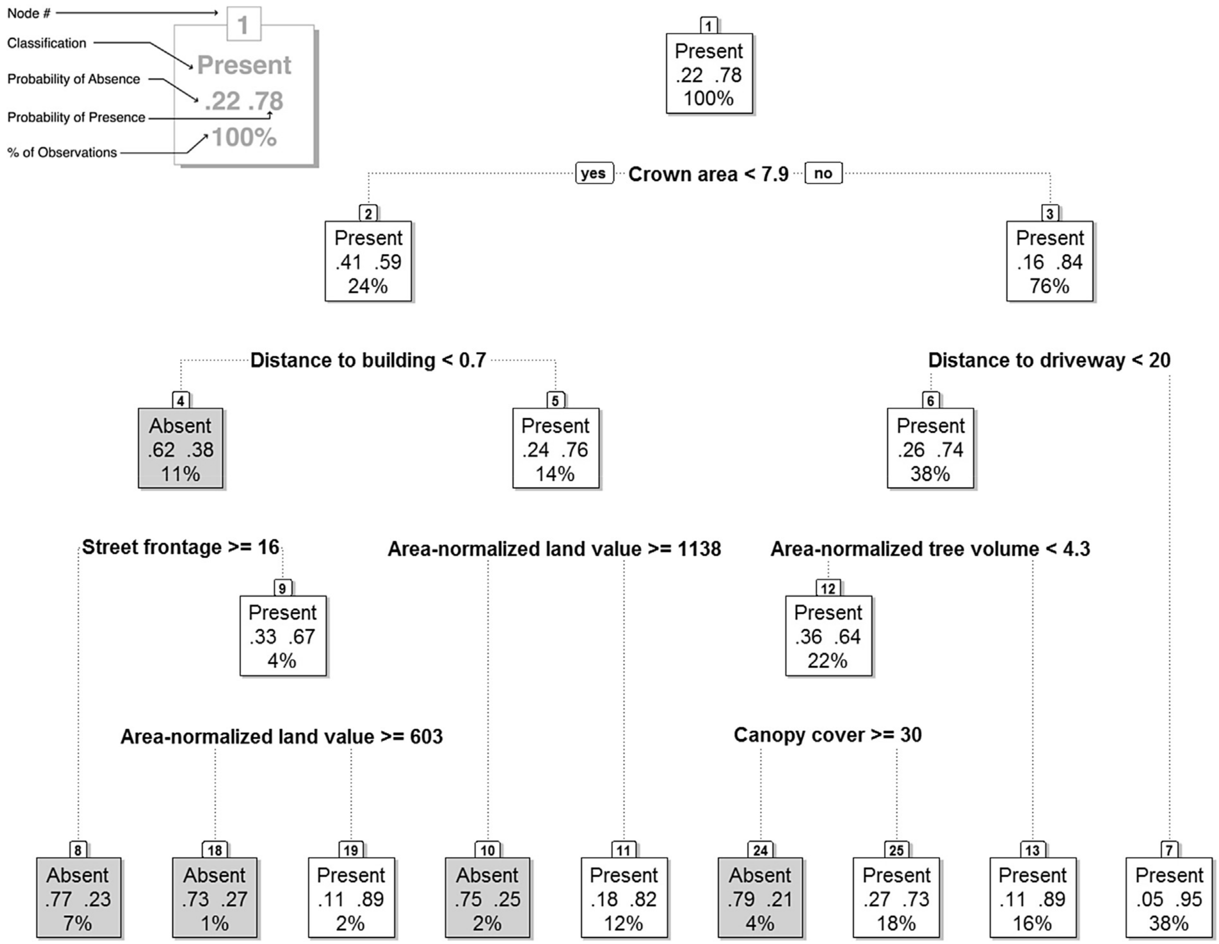

Fig. 4. Classification tree (CT) model of the presence/absence of trees following demolition of an adjacent building. The path of trees moving downward through the CT is determined by the condition at each node. A tree follows the leftward path if it meets the condition and the rightward path if it does not meet the condition. Nodes are labelled either Present (white) or Absent (grey) based on probability of each tree's presence or absence at that node. Probabilities and the percentage of total trees are included for each node. Descriptions of variables used in nodes, including units of measurement, are in Table 1. A legend is provided (top left) to describe values in each node.

can infer the relative importance of the explanatory variables (Coops et al., 2009). Variables higher in the CT influence presence/absence more than those lower in the CT. For example, crown area (Fig. 4, node 1) is more important than distance to driveway (Fig. 4, node 3) for determining presence/absence of trees following demolition.

Crown area (Fig. 4, node 1) was the most important predictor of a tree's presence or absence. Trees were 2.6 times more likely to be absent if their crown area was less than 7.9 m^2 (small trees) than if their crown area exceeded 7.9 m^2 (large trees) ($probability_{absence}$(small trees) = 0.41), $probability_{absence}$(large trees) = 0.16) (Table 2). Over 50% of removed trees had crown area smaller than 10 m^2 and approximately 75% of removed trees had a crown area smaller than 20 m^2 (Fig. 5). Assuming that small crown area implies small trees, tree removal data confirm that small trees were disproportionally represented.

The second most important discriminating factor was a tree's distance to the demolished building (Fig. 4, node 2). Small trees closer than 0.7 m to demolished buildings were 2.6 times more likely to be absent following demolition than trees further than 0.7 m to the demolished building ($probability_{absence}$(<0.7 m) = 0.62, $probability_{absence}$(>= 0.7 m) = 0.24) (Table 2).

The third most important explanatory variable was distance to driveway (Fig. 4, node 3). Large trees closer than 20 m to a driveway were 5.2 times more likely to be absent than those further than 20 m to the driveway ($probability_{absence}$(<20 m) = 0.26, $probability_{absence}$(>20 m) = 0.05) (Table 2).

Other explanatory factors, including street frontage, area-normalized land value, area-normalized tree volume, and canopy cover all contributed to the presence or absence for trees following demolition, but were less influential. The probabilities of tree absence are summarized in Table 2 and provide an alternative way of interpreting the importance of the explanatory variables. Two of the three highest absence probability factors were economic factors, and suggest that a tree is 4.2 times more likely to be absent after demolition if the land value exceeds \$1138/m^2 and 6.6 times more likely to be absent above land values of \$603/m^2.

4. Discussion

4.1. Demolitions and tree removal

While redevelopment and densification's negative impact on canopy cover has been reported at the scale of the neighbourhood (Byrne, Sipe, & Searle, 2010; Searle, 2010), property-level tree research is sparse. This is surprising and problematic, since the property is the scale at which most tree-related decisions are made (Shakeel & Conway, 2014).

The canopy cover reduction of 19.7% on properties where building demolition had occurred is noteworthy as it provides

Table 2
Summary of CT probability results for tree absence following building demolition. For each explanatory variable, the probabilities of absence based on the given threshold are provided. The absence probability factor is calculated as c/d if c > d or d/c if c < d. The absence probability factor can be used to interpret the importance of explanatory variables, e.g. the probability of a tree being absent is 2.6 times greater if its crown area is < 7.9 m^2.

Node	(a) Explanatory Variable	(b) Threshold	(c) Probability of absence when a ≥ b	(d) Probability of absence when a < b	Absence probability factor
1	Crown area	7.9 m^2	0.16	0.41	2.6
2	Distance to building	0.7 m	0.24	0.62	2.6
3	Distance to driveway	20 m	0.05	0.26	5.2
4	Street frontage	16 m	0.77	0.33	2.3
5	Area-normalized land value	$1138/$m^2$	0.75	0.18	4.2
6	Area-normalized tree volume	4.3 m^3/m^2	0.11	0.36	3.3
9	Area-normalized land value	$603/$m^2$	0.73	0.11	6.6
12	Canopy cover	30%	0.79	0.27	2.9

quantitative evidence of the negative impact of demolition on urban tree cover that had previously only been described anecdotally (Jim, 1998). The explanations for tree removal, explored via the classification tree analysis, are the most significant contribution of this research. The analysis suggests that property-level tree loss was a consequence of tree, property, and economic explanatory variables.

4.2. Tree-related effects as predictors of tree removal during demolition

CT analysis showed that tree crown area was the most important predictor of whether a tree was removed during demolition of a house on the same property. Crown area is not always correlated with tree size, but in Christchurch where the vast majority of trees are broadleaf species, it is reasonable to assume that crown area is a good proxy for tree size. The correlation analysis undertaken showed crown area to be highly correlated with tree volume ($r = 0.948$) and moderately correlated with tree height ($r = 0.626$), thereby generally supporting crown area as a reasonable proxy for tree size. We had assumed trees with large crown area (i.e. large trees) would have been removed to facilitate demolition, or provide a 'blank canvas' for future property redevelopment, but it was trees with small crown area that were disproportionately removed during demolition (Figs. 4 and 5). This may be because small trees are relatively easy to remove. Conversely, large trees would typically require specialized equipment and arborists to remove safely, so it may have been easier to leave them standing during demolition work.

4.3. Property-related effects as predictors of tree removal during demolition

The finding that property-related variables (e.g. distance to driveway and distance to building) influenced tree removal or retention supports previous research that has demonstrated the influence of the built environment on tree condition and structure (Pham, Apparicio, Landry, Séguin, & Gagnon, 2013; Shakeel & Conway, 2014). For small trees (i.e. crown area <7.9 m^2), distance to the demolished building was the strongest predictor of presence/absence. Small trees close to buildings (<0.7 m) were removed 2.6 times more than small trees further than 0.7 m from a demolished

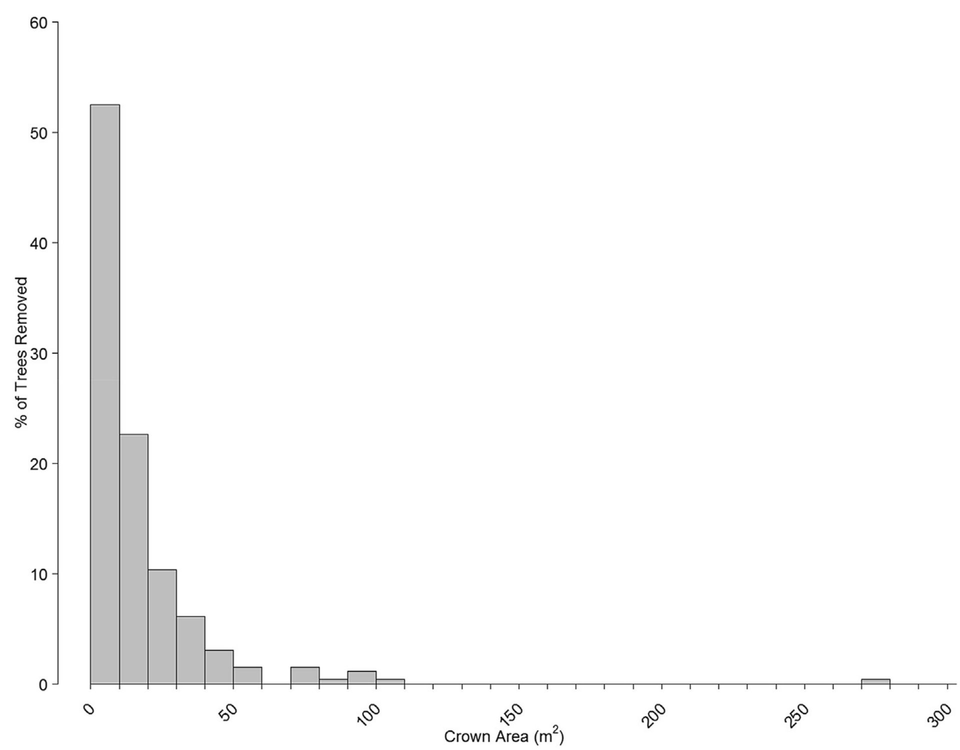

Fig. 5. Trees removed from properties during demolition typically had small crown areas, suggesting that they were small trees.

building. It could be inferred that trees nearer than 0.7 m to buildings were collateral damage during the demolition process. For large trees (i.e. crown area >7.9 m^2), the most important criterion for presence/absence was the distance to a driveway. If large trees were near the driveway (<20.5 m) they were more likely to be removed; otherwise they were left on the property. If large trees near a driveway had the potential to increase demolition costs by impeding access and restricting machinery (e.g. Brunner & Cozens, 2013), it could have resulted in their removal. In contrast, larger trees further than 20.5 m from a driveway would be unlikely to inhibit access, and so they would have been retained on properties. This inference is supported by previous research that shows that tree removal on construction sites is primarily related to site constraints (Despot & Gerhold, 2003).

There are some important implications related to tree removal or retention being dependent upon their spatial relationship to property infrastructure. Perhaps there is an argument to be made for positioning slow-growing, high-value, large-stature trees away from buildings and driveways in order to ensure a greater chance of surviving redevelopment.

4.4. Economic effects as predictors of tree removal during demolition

Previous studies have suggested the importance of considering economic factors as influencers of urban forest dynamics (Conway & Bourne, 2013; Conway, Shakeel, & Atallah, 2011; Grove et al., 2006) and also property redevelopment (Brueckner, 1980; Dye & McMillen, 2007; Rosenthal & Helsley, 1994; Wheaton, 1982). A case study in Australia that reported tree removal to maximize land value (Brunner & Cozens, 2013). Likewise, anecdotal evidence from Hong Kong suggests high land values nurture the mentality that buildings have a precedence over trees (Jim, 2001). Redevelopment occurs when the income resulting from redeveloped land exceeds the income from the sum of its existing use and the costs of redevelopment (Brueckner, 1980). When redevelopment occurs in markets with high land prices (proportional to the total value of a property), as is the case in Christchurch's city centre, developers generally build denser forms of housing to economize on the land value and increase income (Wheaton, 1982). Building density can manifest itself as replacing existing buildings with larger ones (Dye & McMillen, 2007; Rosenthal & Helsley, 1994), thereby intensifying the land use following redevelopment (Siodla, 2015). Unfortunately, high building density reducing the proportion of land within a property available for planting trees (Shakeel & Conway, 2014).

Here, we found that the proportion of tree removals due to demolition increased with increasing land value. Taken together with previous research, this result implies that the possibility of economic gains from redevelopment of high value land may provide incentive for tree removal. If Christchurch follows models of redevelopment previously proposed (e.g. Wheaton, 1982), redevelopment will be undertaken in such a way as to increase building size and density on a property, thereby providing greater income for developers. Tree removal is a simple way of maximizing the land necessary for larger buildings. If this is what has occurred in Christchurch, it may be ill-informed as previous research generally supports increased property values when mature trees are present (Laverne & Winson-Geideman, 2003; Sander, Polasky, & Haight, 2010).

4.5. Consequences of tree removal during redevelopment

Damage to, or removal of, trees on construction sites is common, such that some cities protect trees with bylaws or ordinances during land development (Cooper, 1996; Dunster, 1994; Jim & Liu, 2000; Landry & Pu, 2010; Sung, 2012; Wyse, Beggs, Burns, & Stanley, 2015). But such deterrents are limited in Christchurch where only a small number of trees on private land, designated significant trees, are protected by the district plan; currently, approximately 1200 trees on private property hold this status. Significant trees are designated according to exception botanical value, historic heritage value, amenity value, landscape value, cultural value, and ecological value. Of the 1209 trees included in this study, 11 of them were designated significant trees. All 11 remained present following demolition, suggesting that their status as significant trees may have played a role in their retention. The vast majority of trees on private land are not protected by any bylaws or ordnances. Given the limited regulatory barriers to tree removal on private land, the impediment to tree removal during demolition was low.

The impact of demolition-related tree removal on ecosystem service provision by Christchurch's urban forest is debatable. A large proportion of removed trees had small crowns, so are relatively minor contributors to ecosystem services, in particular regulating services. Many regulating ecosystem services (e.g. carbon sequestration, stormwater attenuation, micro-climate amelioration) are dependent upon a tree's total leaf area (Nowak et al., 2008; Nowak, Hoehn, Bodine, Greenfield, & O'Neil-Dunne, 2013) and thus small trees contribute low levels of regulating ecosystem service relative to large trees. From this perspective, the effect of removing small trees on regulating ecosystem services, at the scale of the individual property, is negligible. But in aggregate, the loss of numerous small trees during redevelopment activities may have negative effects on regulating services at the neighbourhood or city scale. With respect to provisioning services (e.g. fruit/nut production), cultural services (e.g. mental health), and supporting services (e.g. biodiversity), the loss of even small trees at the individual property scale has the potential to be significant.

The effect of the loss of small trees during demolition in Christchurch could be alleviated if tree planting has been stipulated as a condition of resource consent; resource consent is required for redevelopment under NZ's Resource Management Act 1991. While possible, it is not likely that resource consents would have required tree replanting for the vast majority of properties in this study as tree planting stipulations are usually reserved for large, commercial properties (e.g. shopping centre). Nevertheless, previous studies have reported rapid increases in tree cover following development at the urban-rural interface (Berland, 2012). While this development type is not analogous to Christchurch's redevelopment, perhaps the same will hold true. The need for tree planting following Christchurch's redevelopment will almost certainly exist for aesthetic and functional purposes (Smith, Clayden, & Dunnett, 2009).

4.6. Limitations of the research

It was assumed that demolitions were the sole cause of tree removals. But, it is possible that trees had to be removed from properties due to earthquake-related damage (Morgenroth & Armstrong, 2012; Quigley et al., 2016) or changes in soil conditions (Morgenroth, Almond, Scharenbroch, Wilson, & Sharp-Heward, 2014) that rendered the trees unsafe. As such, the reported tree canopy cover reduction and total tree loss should be considered upper limits.

Furthermore, some potentially useful explanatory variables were not measured in this study. We know nothing about the influence of ‘human’ factors, including property owner or developer intentions for each property. Likewise, we know nothing about the person or company who undertook the demolition.

Despite these limitations, explanations for the loss of trees as a consequence of demolition can confidently be inferred from the classification tree model given its overall accuracy of 80.4%, which is roughly in line with previous studies that used CT analysis to predict the presence or absence of trees (Coops et al., 2009). However, reliance on the model for decision support should be tempered by the uneven classification of presence (87.1%) and absence (54.2%).

5. Conclusion

Redevelopment is a global phenomenon, occurring in cities at widely varying rates; cities like Glasgow redevelopment slowly (1.5 buildings per annum from 1946 to 1969 (Whitehand, 1987)), while cities like Hong Kong redevelop rapidly (1.5 buildings per day from 1987 to 1996 (Susnik & Ganesan, 1997)). Despite its ubiquity, surprisingly little was known about the impact of redevelopment on urban trees at the property level. This gap in knowledge has been partially addressed by this study.

Building demolition resulted in 21.6% of the trees on the 123 surveyed properties to be removed. This reduced tree canopy cover on all properties by 19.7%. A tree's crown area and its distance to a demolished building were the most important predictor variables for determining their removal or retention during demolition. Small trees immediately adjacent to a demolished building were most frequently removed. Land value was also an important determinant of tree removal/retention, whereby tree removal was more prevalent on properties with higher land value ($/m^2).

The results provide new insights into some of the reasons for tree removal or retention during redevelopment, but fall short of a complete elucidation. Critically, only tree, property, and economic variables were included as explanatory factors in this study. Human factors are absent and thus opportunity exists to expand upon this work. Future research will include property owner surveys and tree cover monitoring through the rest of the redevelopment process, including construction of new buildings and subsequent landscaping. Combined with the present research, this will allow a more robust understanding of the effects of the complete redevelopment cycle on tree cover at the scale of the individual property.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.apgeog.2017.02.011.

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