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Factors affecting long-term mortality of residential shade trees: Evidence from Sacramento, California

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ABSTRACT

Urban tree survival is essential to sustain the ecosystem services of urban forests and monitoring is needed to accurately assess benefits. While some urban forestry studies have reported street tree survival, little is known about the factors influencing residential yard tree survival, especially over the long-term. We assessed residential shade tree survival in Sacramento, California over 22 years. Tree survival data were collected through field surveys and aerial photointerpretation. Survival analysis was used to evaluate longitudinal tree survivorship. Multivariate logistic regression was used to identify factors associated with mortality at the property- and tree-level. Our results showed that 22-year survivorship was 42.4% with 96.2% annual survival rate and 3.82% annual mortality rate. Our observed mortality was substantially higher than initial projections that were used to estimate long-term energy saving performance of the Sacramento Shade program. We found that higher mortality during the establishment phase was associated with greater number of trees delivered and with planting in low and high net property value properties (compared to those with medium net property value). For the post-establishment phase, trees with small mature size those planted in backyards and those in properties with very unstable homeownership were more likely to die. This study has implications for the development of data-driven urban forestry programs and provides more realistic assumptions to accurately estimate the long-term benefits of tree planting initiatives.

Introduction

Urban forests play a key role in providing environmental, social and economic benefits and enhancing human health and quality of life in cities (Young and McPherson, 2013). A large number of tree planting initiatives have been launched over the past decade, many purported to produce ecosystem services with substantial monetary value (McPherson et al., 2005; Roy et al., 2012; Young and McPherson, 2013). Tree survival, growth and long-term management are essential for these initiatives to reach their goals (Roman, 2014). Longitudinal monitoring provides actual data on tree loss rates that underpin realistic mortality assumptions for population projections (McPherson et al., 2011; Morani et al., 2011; Roman et al., 2014a). Uncertainly regarding mortality rates is an acknowledged limitation of urban tree population projections (Hildebrandt and Sarkovich, 1998; McPherson et al., 2008, 1998; McPherson and Simpson, 2001; Morani et al., 2011). Little is known about the factors that influence urban tree survival, especially over the long-term.

Previous studies reported that various biophysical and human factors are associated with urban tree survival, with site types such as streets trees (most common), park landscapes and residential yards (Table 1). Most studies spanned 2–8 years, with the exception of 25 years of monitoring in Milwaukee, WI (Koeser et al., 2013). Biophysical factors included tree size, age, species, condition, land cover, soil compaction, water stress and natural disturbances such as storms and pests. Human and socioeconomic factors included land use, unemployment rate, construction damage, vandalism, and stewardship. While trees along streets and in other public spaces are typically the focus of mortality studies, residential yard trees are also important for cities to achieve their canopy cover goals (Turner and Mitchell, 2013). Residential land uses are a ubiquitous component of urban ecosystems (Cook et al., 2012). Street tree and yard tree environments have noticeable differences in site characteristics (yard trees typically in lawns vs. street trees often in

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Table 1
Factors associated with urban tree survival, limited to studies that tracked cohorts of planted trees. "+" indicated association with higher tree survival and "−" indicated association with lower survival. Time period is years since planting.

Reference	Location	Time period	Samples	Cumulative survivorship (annual mortality)	Statistical analysis	Significant factors
Nowak et al. (1990)	Berkeley and Oakland, CA	2 yrs	Street trees (n = 480)	66% (19%)	Chi-square test	*Socio-economic status*: Unemployment rate (−) *Land use*: Apartments (−), public green spaces (−), single family residential (+), subway station (+)
Lu et al. (2010)	New York City, NY	3–9 yrs	Street trees (n = 1891 for 2–3 yrs; 3690 for 6–8 yrs; 4381 for 8–9 yrs)	78.2% for 2–3 yrs; 73.0% for 6–8 yrs; 73.8% for 8–9 yrs (not reported[a])	Chi-square test	Fewer years since planting (−) *Land use*: Industrial (−), open space (−), vacant land (−), one- and two-family residential (+) *Species*: *Pyrus calleryana* (+) Tree pit enhancement (+) Stewardship index (+) Low traffic area (+)
Koeser et al. (2013)	Milwaukee, WI	25 yrs	Street trees (n = 793 for first 10 yrs; 895 for 11–25 yrs post planting)	77.9–83.6% for 0–10 yrs; 81.1–82.6% for 11–25 yrs (not reported[a])	Multivariate logistic regression	*Species*: *Gleditsia triacanthos* (+) *Acer saccharum* (−) Trunk diameter (−) Planting space width (+) Tree condition (+) Adjacent to construction (−)
Roman et al. (2014a)	Sacramento, CA	5 yrs	Single-family residential yard trees (n = 370 trees planted)	70.9% (6.6%)	Conditional inference trees; Logrank tests	Species water use demand (−) Homeownership stability (+) *Tree care*: Front yard (+) Maintenance rating (+)
Koeser et al. (2014)	Various FL towns	2–5 yrs	Parking lots, highways, street trees, lawns, parks (n = 2354)	93.6% (not reported[a])	prop.test in R	In-ground irrigation (+) Irrigated container-grown trees (+)

[a] Cumulative survivorship, sometimes broken down by age class, is reported for studies that did not report annual mortality.

restricted sidewalk spaces) and ownership (private yards vs. public right-of-way). The shortage of residential yard tree survival studies may be explained by difficulties accessing private properties and by the relatively recent emphasis on increasing residential tree cover through giveaway programs (Turner and Mitchell, 2013); municipal forestry programs have more traditionally focused on street and park trees.

Although some studies have found that street trees in single family residential areas are more likely to survive than those in other land uses (Lu et al., 2010; Nowak et al., 1990), Roman et al. (2014a) found that the annual mortality of young yard trees (5 years post-planting) in Sacramento, CA was 6.6%, which is higher than young street tree mortality reported in many other studies (Lu et al., 2010; Roman and Scatena, 2011). This 6.6% rate was in addition to tree loss from failure to plant, and was higher than mortality assumptions in comparable studies across California (McPherson and Simpson, 2001) and reported for the early years of the Million Trees Los Angeles (MTLA, now known as City Plants) program (McPherson, 2014). Tree giveaway programs such as MTLA and Sacramento Shade often rely on residents to plant and maintain residential yard trees, whereas public trees are commonly planted by contractors or through supervised neighborhood events. Failure to plant, low post-planting survival, and slow growth may contribute to low performance of residential giveaway programs in the long-term, such as lower energy savings in the case of shade tree programs.

The Sacramento Shade program is the largest and longest-operating, utility-sponsored tree giveaway program in the United States, and specifically targets building energy savings (Sarkovich, 2009). An internal program report found that survivability – the percentage of trees alive out of the total distributed (instead of trees planted) – was considerably below the initial projections. Shade trees in Sacramento had 54% survivability 5 years after tree distribution and 43% after 10 years (M. Sarkovich, pers. commun.). These survivability rates are comparable to the 59% rate after 5 years from the more recent study by Roman et al. (2014a). It is imperative to identify the drivers of long-term survival to improve the performance of trees in existing programs and guide practices used in new programs.

Our study investigated the long-term survival of residential yard trees. We monitored trees distributed by the Sacramento Shade program in 1991–1993 over 22 years through field surveys and aerial image interpretation. Using survival analysis and multivariate logistic regression, we report: (1) 22-year post-planting survival curve and (2) factors associated with the long-term mortality of the residential shade trees. To the best of our knowledge, this study is the first to present survival outcomes for residential trees over multiple decades, and the first to utilize aerial images in monitoring urban trees on private lands. The results of the study provide important information for data-driven urban forest management, especially for tree giveaway programs. This study can lead to more accurate quantification of the projected performance of tree planting initiatives.

Methods

We used field surveys and visual interpretation of aerial images to monitor survival of residential yard trees over 22 years. The field surveys were conducted in 1994 and 2013 to check the initial and mature status of program trees. To observe the survival of

Table 2
Numeric and categorical variables included in a multivariate logistic regression for testing effects on tree mortality for Sacramento Shade trees from 1991–1993 to 2013. For categorical variables, the reference variable is given in parentheses.

Variable	Description	Type	Level	Source
Response variables				
dead1994	Trees dead in 1994	Binary	Tree	Field survey in 1994
dead2013	Trees dead in 2013	Binary	Tree	Field survey in 2013
Explanatory variables				
Hwater (mwater) lwater	Species water use demand (high, medium, low)	Categorical	Tree	Costello and Jones (2014)
highnvp (mednvp) lownpv	Net property value in 2013 (high, medium, low)	Categorical	Property	Sacramento Tax Assessor parcel map (2014)
largetree (medtree) smalltree	Mature tree size (large, medium, small)	Categorical	Tree	SMUD/STF classification in 1994
rainyseason (dryseason)	Trees planted during rainy vs. dry season	Categorical	Tree	SMUD/STF distribution record
(stable13) modunstab13 vryunstab13	Homeownership stability from 1994 to 2013 (stable, moderately unstable, very unstable)	Categorical	Property	Multiple Listing Service
(stable94) Unstab94	Homeownership stability from planting through 1994 (stable vs. unstable)	Categorical	Property	Multiple Listing Service
backyard (frtyrd)	Trees planted in back yards vs. front yards	Categorical	Tree	Field survey in 1994
(pt91) pt92 pt93	Planting year (1991, 1992, 1993)	Categorical	Tree	Field survey data in 1994

the program trees between field surveys we analyzed aerial images obtained at approximately 2–4-year intervals. We conducted survival analysis to construct the overall survivorship curve for all shade trees over the study period. Using two-level multivariate logistic regression, we assessed the biophysical and socioeconomic determinants that are associated with the long-term mortality (see Table 2). In this paper we define mortality as tree loss that includes standing dead or removed since planting (following Lu et al., 2010; Nowak et al., 2004; Roman et al., 2014a). Establishment mortality was observed during the 1994 field survey, 1–3 years after planting. Post-establishment mortality was observed in 2013 and encompassed any standing dead or removed trees that survived the establishment phase.

Study area

The Sacramento Shade program is operated by a partnership between the Sacramento Tree Foundation and Sacramento Municipal Utility District (SMUD) since 1990. The program has distributed approximately 500,000 deciduous trees to homes, businesses, and public spaces for free (Sacramento Tree Foundation, 2014). Our study was limited to single-family residential (SFR) properties. When the trees in our study were distributed, participating residents were required to attend a 40-min educational session that focused on planting and maintenance techniques, as well as the benefits of trees. This was followed by a community forester site visit to each residential property several weeks later, and shade tree distribution at a centralized neighborhood location after another several weeks (R. Tretheway and L. Leineke, pers. commun.). Notably, these operations differ from more recent program procedures, in which residents and community foresters primarily interact through a brief home visit followed by delivery directly to the property (Roman et al., 2014a); the educational workshops and neighborhood distribution events are no longer used.

Shade trees (#5 container, 1.5-m tall, 1.0-m crown diameter) were distributed throughout the SMUD service area, which includes nearly all of Sacramento County and a part of Placer County (SMUD, 2014). Sacramento County is located in Northern California, and has a Mediterranean climate characterized by wet, mild winters and hot, dry summers. In the city of Sacramento, on average, there are 74 days a year with maximum temperature equal to or above 32.2 °C, mostly distributed from June to September (National Oceanic and Atmospheric Administration, 2014).

Study sample

Our sample followed-up on residential shade trees initially surveyed by Simpson and McPherson (1998). That study involved 254 properties randomly selected from the 20,123 program participants who received trees from 1991 to 1993. We randomly sampled 92 properties from these original 254 to best represent the initial sample with minimal bias. Four of these properties were excluded due to missing information on property ownership, a key predictor of residential tree survival (Roman et al., 2014a). Thus, our final sample consisted of 88 properties and 317 trees. Our sample included 18 species: five species with small mature size (*Lagerstroemia hybrid*, *Cercis canadensis*, *Acer palmatum*, *Magnolia* × *soulangeana*, and *Acer buergerianum*), four species with medium mature size (*Triadica sebifera*, *Carpinus betulus*, *Nyssa sylvatica*, and *Pistacia chinensis*), and nine species with large mature size (*Tilia americana*, *Quercus macrocarpa*, *Celtis sinensis*, *Ginkgo biloba*, *Platanus* × *acerifolia*, *Acer rubrum*, *Quercus rubra*, *Quercus coccinea*, and *Quercus lobata*).

Data collection

Tree survival data

During summer 1994 US Forest Service staff reported status as alive, dead, missing, or in container. Trees in container were clearly not planted, while those observed missing may have either been removed after planting, or never planted. This first survey also included location information in terms of distance and orientation to the house, as well as tree species. The second field survey was conducted during summer 2013 to monitor the survival and growth of program Trees 20–22 years after planting. We recorded survival status as alive, replaced, dead, or missing, based on the location data from the 1994 survey. Prior to the 2013 site visits, we sent post-cards to describe the purpose and background of the study, and request permission to access the back yard when relevant.

In addition to these field surveys, we performed visual interpretation of high resolution aerial images (DOQ NAPP for 1998 and Urban Image for 2002, 2006, 2009, and 2011) to monitor longitudinal survival of program trees between the two field surveys. Most images had high resolution (15–30 cm pixel size), which made identifying tree survival possible. The 1998 images were an exception (1 m resolution). Sometimes it was difficult to recognize objects clearly; however, knowledge of exact tree locations allowed us to identify survival status.

Other tree-level data

Tree-level factors that could potentially influence survival were selected based on previous research (Roman et al., 2014a) and data availability. The field data and tree distribution records from 1994 included mature tree size, property address, and delivery date. There were three mature tree sizes: large for tree height 13.7–16.7 m and crown width 12.2–13.7 m, medium for tree height 10.6 m and crown width 6.1–10.6 m, and small for tree height 7.6 m and crown width 7.6 m. Previous findings show somewhat conflicting results with regards to the effect of mature tree size on survival. SMUD's recent projections for shade tree benefits assumed lower survival rates for small stature trees (M. Sarkovich, pers. commun.). Roman et al. (2014a) found that survival rates of small size trees were higher during the establishment phase.

The irrigation water use requirements for different species are important to consider because of Sacramento's seasonal summer drought. Species were classified into three water use categories (low, medium and high) appropriate to the Central Valley of CA (Costello and Jones, 2014). Tree delivery date was used in two ways: to determine the number of days and years between planting and the 1994 field observation, and to classify trees by planting season. Date of planting was assumed to be at or very close to delivery date. Lastly, we also included planting location (front or back yard) based on previous research that suggests higher survival for front yard trees because front yards tend to receive more intensive care than back yards (Larsen and Harlan, 2006; Larson et al., 2009; Roman et al., 2014a).

Although tree maintenance rating appears to be an important predictor for shade tree mortality in this program (Roman et al., 2014a), we did not include it in our study because of the limited data availability and reliability. Although we recorded general conditions of trees and sites during field surveys, they hardly represent the maintenance efforts for the entire study period. Therefore, we included number of trees delivered and homeownership stability as indirect measures of maintenance and stewardship.

Property-level data

Program trees in the same property are influenced by property-specific conditions. We collected property-level data – number of trees delivered, assessed net property value, and homeownership stability – that indicate socioeconomic status and stewardship of the residents. The field data from 1994 includes how many trees were delivered to each property. Roman et al. (2014a) suggested that residents receiving more trees may provide less care for each tree based on speculation of the program staff (J. Caditz, pers. commun.); they found that number of trees delivered was negatively associated with tree survival 2–5 years after planting (Roman et al., 2014a).

For an indirect measure of the residents' socioeconomic status, we included the net property value (NPV) as determined by the Sacramento County Assessor for 2013. Although we used the NPVs from 2013, we assumed that the relative housing value of a property tends not to change radically over time; it still provides reasonable estimation of socio-economic status relative to their neighbors (Coffee et al., 2013; Shavers, 2007). The average NPV of our sample properties was US $192,341 and the median value was US $176,110 in 2013. For easier interpretation, we classified NPV into three categories: properties with the assessed NPV less than $150,000 were classified as low NPV; those with the NPV equal or greater than $150,000 but less than $250,000 as medium NPV; those with the NPV greater than $250,000 as high NPV.

As a proxy to consistent tree stewardship, we included homeownership stability, which was found to be the most important predictor for young tree survival in Roman et al. (2014a) and was also associated with field-observed maintenance. The influence of homeownership stability was assessed for the establishment and post-establishment phases. Two categories were created for the establishment phase: (1) stable – person who ordered the tree had the same name as the owner that year, with no home sales or foreclosures through summer 1994, which was interpreted to mean that the same person or family that ordered the tree stewarded it until summer 1994; (2) unstable – home was sold and/or foreclosed between distribution date and summer 1994. Three categories were created for the post-establishment phase: (1) stable – no home sales or foreclosures from summer 1994 through summer 2013, which was interpreted to mean that the same person or family was responsible for stewarding this tree over that 19 year period; (2) moderately unstable – home sales and/or foreclosure events in 1 or 2 years out of the 19 year period; (3) very unstable – home sales and/or foreclosure events in more than 2 years out of the 19 year period. Our definition of foreclosures and sales follows Roman et al. (2014a), and ownership information was obtained through the Multiple Listing Service, a proprietary service for realtors.

Data analysis

Survival curve

We performed survival analysis of our sample trees using records obtained from two field visits and interpretation of five aerial images over the study period. To calculate the survival curve, we used Turnbull's (1976) procedure for the Kaplan–Meier curve, also known as the product limit estimator (Kaplan and Meier, 1958), via the 'interval' package in R (Fay and Shaw, 2010; R CoreTeam, 2013). This method allows computing a survival curve with interval censored data, for which the death occurred between two observation dates and the exact date of death is unknown (Gómez et al., 2009). In this study, the interval of observation was approximately 2–4 years, which made it difficult to determine the exact date of death. For example, if a tree was found to be alive in the 2011 image but was observed to be dead when visiting the site July 15, 2013, the date of death should be between April 9 2011 (when the image was taken) and July 15 2013 (when we surveyed the site).

The Kaplan–Meier estimator curves show a set of piecewise horizontal steps of declining magnitude with breakpoints at the event times t_j. The curves show the nonparametric maximum likelihood estimate of $S(t)$, the probability that a sample tree from a given population will have a lifespan exceeding time, t. When n_j is the number of subjects at risk just prior to time t_j, and d_j, is the number of deaths at time t_j, the Kaplan–Meier estimate is (for more details on survival analysis and censoring, see Fay and Shaw, 2010; Kaplan and Meier, 1958; Klein and Moeschberger, 2010):

$$\hat{S}(t) = \prod_{j|t_j^* \le t}^{n} \left(\frac{n_j - d_j}{n_j} \right)$$

Tree delivery date was considered time zero. Our survival analysis included 278 program trees that were distributed and planted in 1991–1993. For examples, the trees recorded as "dead" in the first field visit in 1994 were included; however, trees found to be "missing" in 1994 were not included in this survival analysis.

We also calculated overall survivorship, annual survival rate, and annual mortality rate over the study period (Roman and Scatena, 2011; Sheil et al., 1995). The overall survivorship (l_x) at 22 years post planting was obtained from the output value of the survival curve at day 8036 (365.25 days per year multiplied by 22 years). This survivorship is cumulative from the time of planting to year *x*. Assuming that annual mortality is constant, annual survival rate (p_x) and annual mortality rate (q_x) were calculated using:

$$p_x = (lx)^{1/x}$$
$$q_x = 1 - p$$

Factors associated with mortality

Multivariate logistic regression was used to investigate factors associated with the mortality of residential shade trees over 22 years. We developed three sets of mortality models: (1) establishment phase (1991–1994), (2) post-establishment phase (1994–2013), and (3) overall tree mortality (1991–2013). The later included both (1) and (2). In many cases, multiple trees were delivered to a property. The average number of trees delivered per property was 3.62, and numbers ranged from 1 to 14. Because sample trees were clustered by property a multilevel mixed logistic regression was used to model binary response variables (alive or dead), in which the log odds of the response variable are predicted as a linear combination of the predictors. This model includes a property-specific random intercept in the linear predictor, thus relaxing the assumption of conditional independence among the trees for the same property given the predictors (Rabe-Hesketh and Skrondal, 2008). We used the xtlogit function in Stata 11 (StataCorp, 2009). Odds ratios for each predictor were calculated to report the increased likelihood of tree mortality (including natural death and removal) given each predictor. Our approach to assessing the determinants of urban tree mortality using multilevel logistic regression is aligned with the methods used by Koeser et al. (2013), Koeser et al. (2014), Lawrence et al. (2012), Staudhammer et al. (2011), and Roman et al. (2014b). Urban forest researchers are increasingly using multivariate models to study mortality outcomes, rather than univariate chi-squared analyses (Table 1).

Models with various sets of predictors were compared using the error estimate (α) and the goodness of fit of the model. We used the Akaike Information Criterion (AIC), a measure of the relative goodness of fit, to select a model that minimizes the Kullback–Leibler distance between the model and the true probability distribution (Burnham and Anderson, 2002). More specifically, we calculated the corrected AIC (AIC_C), which considers sample size by increasing the relative penalty for complex models with small data sets (Burnham and Anderson, 2002). Different sets of models are presented in Table 3 with their AIC_C value and ΔAIC_C, a difference in AIC_C relative to the best model. The final model showed the lowest AIC_C value and ΔAIC_C of zero.

Results

Tree survival

Fig. 1 shows the survival status based on the 1994 and 2013 field surveys. Out of 317 trees that were distributed in 1991–1993, 40 trees (12.6%) were found missing or not planted at the first field visit in 1994. Five of these trees were found in containers and 35 were missing. Because the 1994 field crews did not distinguish between missing trees that were never planted and missing trees that were removed shortly after planting, we must be cautious in interpreting standing dead trees from 1994 as representing the entirety of post-planting mortality. Only trees observed alive or standing dead in 1994 were confirmed planted. Out of 277 trees confirmed planted, 243 trees (87.7%) were found to be alive in 1994. Among the 1994 survivors, 112 trees (46.1%) were found to be alive in 2013. To compare to SMUD's 30-year survivability projections (57.5%) (Hildebrandt and Sarkovich, 1998), the proportion of trees surviving to 2013 ($n = 112$) out of those delivered 1991–1993 ($n = 317$) was 35.3%.

The survival curve showed a steady decline over the study period after an initial steep drop during the first year (Fig. 2). The 22-year post-planting survivorship was 42.4% (the value at day 8036); annual survival was 96.2% and annual mortality was 3.82% when assuming constant annual mortality. The overall survivorship obtained from this curve is different from the monitoring diagram (Fig. 1) because the survival curve considers variation in planting

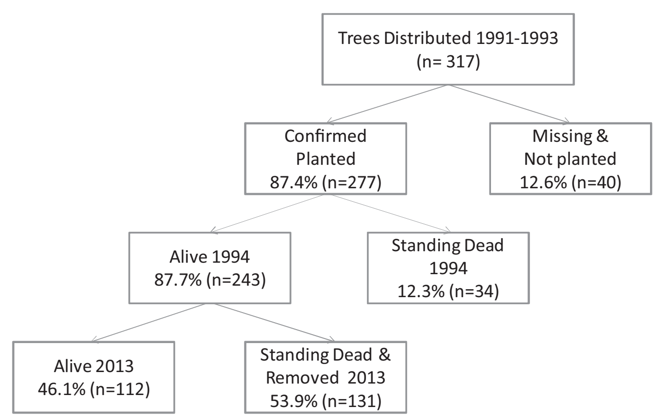

Fig. 1. Field monitoring results of Sacramento Shade program trees distributed in 1991–1993, modifying Roman et al.'s (2014a) monitoring outcome diagram.

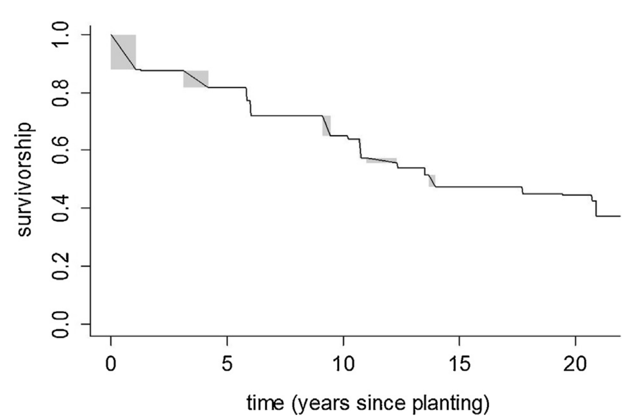

Fig. 2. Survival curve for all confirmed planted shade trees ($n = 277$) over 22 years. Survivorship was assessed from Kaplan–Meier survival analysis with Turnbull (1976) estimator for censored observations (Fay and Shaw, 2010). Gray rectangles indicate the range of possible values given censoring.

Table 3
Model selection using the corrected Akaike Information Criterion (AIC_C). Significant predictors are bolded.

	M#	Models	AIC_C	ΔAIC^C
Early mortality status 1991–1994	1	hwater lwater **lownpv*** **highnpv**** unstable94 largetree smalltree **rainyseason*** pt92 pt93 **ntreesdlvd****	336.07	8.44
	2	hwater lwater **lownpv*** **highnpv**** unstable94 **rainyseason*** pt92 pt93 **ntreesdlvd****	332.76	5.14
	3	hwater lwater **lownpv*** **highnpv**** unstable94 **rainyseason**† **ntreesdlvd****	330.14	2.51
	4	**lownpv*** **highnpv**** **ntreesdlvd****	328.93	1.31
	5	**lownpv*** **highnpv**** **rainyseason**† **ntreesdlvd**** **(BEST MODEL)**	327.63	0.00
Post-establishment mortality 1994–2013	1	hwater lwater lownpv highnpv modunstab13 **vryunstab13**† largetree **smalltree*** rainyseason bckyrd ntreesdlvd pt92 pt93	337.17	8.84
	2	lownpv highnpv modunstab13 vryunstab13 largetree **smalltree*** rainyseason bckyrd ntreesdlvd pt92 pt93	339.25	10.92
	3	lownpv highnpv modunstab13 vryunstab13 largetree **smalltree*** rainyseason bckyrd ntreesdlvd	336.96	8.63
	4	modunstab13 vryunstab13 largetree **smalltree*** rainyseason bckyrd ntreesdlvd	333.48	5.15
	5	modunstab13 vryunstab13 largetree **smalltree**†	331.53	3.20
	6	modunstab13 vryunstab13 largetree **smalltree*** rainyseason bckyrd	331.55	3.22
	7	largetree **smalltree***	329.99	1.66
	8	largetree **smalltree*** rainyseason **bckyrd**†	328.95	0.62
	9	largetree **smalltree*** **bckyrd**† **(BEST MODEL)**	328.33	0.00
Overall tree survival 1991–2013	1	hwater lwater lownpv highnpv unstable94 modunstab13 **vryunstab13**† largetree **smalltree*** rainyseason ntreesdlvd pt92 pt93	407.93	6.40
	2	hwater lwater lownpv highnpv unstable94 modunstab13 **vryunstab13**† largetree **smalltree*** rainyseason ntreesdlvd	404.22	2.68
	3	lownpv highnpv unstable94 modunstab13 vryunstab13 largetree **smalltree*** rainyseason ntreesdlvd	407.30	5.77
	4	lownpv highnpv unstable94 modunstab13 vryunstab13 largetree **smalltree*** ntreesdlvd	405.46	3.93
	5	unstable94 modunstab13 vryunstab13 largetree **smalltree*** **ntreesdlvd**†	402.82	1.28
	6	modunstab13 vryunstab13 largetree **smalltree*** ntreesdlvd	403.43	1.89
	7	largetree **smalltree***	401.57	0.03
	8	largetree **smalltree*** ntreesdlvd **(BEST MODEL)**	401.54	0.00

† $p < .10$.
* $p < .05$.
** $p < .01$.

dates in 1991–1993 and observation dates in 2013 for each sample tree.

Determinants for tree mortality

For early-establishment mortality, assessed net property values (NPV) and number of trees delivered were primary determinants, which were statistically significant in all models including the final one (Table 3). The odds of tree mortality for a tree planted in a low NPV property were 2.4 higher than trees in a medium NPV property, which was the base level (Table 4). Trees in the high NPV property were 3.1 times more likely to die or be removed than the base level. Adding a tree for delivery increased the likelihood of tree death and removal by 1.1 times. Planting season – whether a tree was planted during the rainy season or dry season – showed a weak significance in the final model. The final model reports that a tree planted during the rainy season was more likely to die or be removed than one planted during the dry season, and was statistically significant at the alpha 0.1 level.

Mature tree size was a key determinant of post-establishment mortality in 2013. A tree with small mature size was 2.7 times more likely to die or be removed than one with medium mature size (Table 4). Planting location – whether planted in front yard or back yard – was statistically significant at the alpha 0.1 level. A tree planted in the backyard was twice as likely to die or be removed as one planted in the front yard. Although not included in the final

Table 4
Results from the final mortality models for Sacramento Shade trees (selected using the lowest AIC_C value).

Parameter	OR estimate	95% CI	p-value	Baseline
Early establishment mortality in 1994 ($n = 317$, trees planted in 1991–1993)				
Low net property value	2.363	1.224, 4.559	0.010	Medium net property value
High net property value	3.051	1.495, 6.226	0.002	
Planted in rainy season	1.681	0.959, 2.946	0.070	Dry season
# of trees delivered	1.134	1.043, 1.234	0.003	
Post-establishment mortality in 2013 ($n = 243$, trees survived in 1994)				
Large sized trees	1.284	0.589, 2.800	0.530	Medium sized trees
Small sized trees	2.732	1.089, 6.853	0.032	
Planted in backyards	1.967	0.955, 4.051	0.066	Front yards
Overall tree mortality from planting to 2013 field Survey ($n = 317$, trees planted in 1991–1993)				
Large sized trees	1.106	0.568, 2.154	0.767	Medium sized trees
Small sized trees	2.638	1.183, 5.882	0.018	
# of trees delivered	1.101	0.968, 1.253	0.144	

model, a very unstable homeownership was associated with higher mortality in the full model at the alpha 0.1 level.

Mature tree size was the single most important factor for overall 22-year tree mortality (Table 4). The odds of death/removal for a tree with small mature size were 2.6 times higher than for one with medium mature size. Large sized trees did not show a statistically significant difference from medium sized trees for death/removal.

Discussion

We found that the 22-year post planting survivorship of Sacramento shade trees was 42.4% with 96.2% annual survival rate and 3.82% annual mortality rate. This rate compares favorable with the 4.6% average annual mortality rate reported for young yard trees in the MTLA program (McPherson, 2014) and is similar to the average annual mortality rate of street trees planted across various geographic areas, land uses, and time periods (3.5–5.1%) (Roman and Scatena, 2011). Whether yard trees typically have higher or lower mortality than street trees is unknown, but out results suggest that this particular shade tree program's losses are on par with street tree losses. Although residential yard trees might receive different care than street trees, due to residential stewardship investments and growing environments, yard trees are vulnerable to changing landscape design and tree care predilections of residents (Larsen and Harlan, 2006; Lawrence et al., 2012), especially over many decades with changing owners.

Our five-year post planting annual mortality rate (4.0% from our survival curve) was lower than Roman et al.'s (2014a) rate for Sacramento Shade tree's five-year establishment phase (6.6%). We propose three potential causes for this difference. First, the Roman et al. (2014a) study was conducted 2007–2012, when the economic recession and foreclosure crisis which have led to inconsistent tree care from abnormally high levels of unstable homeownership. Second, mortality in our study did not include "missing" trees that were planted and subsequently removed by the time of the 1994 field visit. Therefore, young tree mortality was undervalued by an unknown amount. Third, Sacramento Shade Tree's operations have changed. In the early 1990s, residents were required to have more contact time with program staff through educational sessions and neighborhood events. Currently, contact time is limited to a 30 min site visit (R. Tretheway and L. Leineke, pers. commun.).

Our observed mortality was substantially higher than initial mortality projections that were used to estimate long-term energy saving effects of the Sacramento Shade program. Simpson and McPherson (1998) optimistically assumed that residents would replace all dead and removed trees with new trees. In our 2013 field survey, we found that 30 trees out of 131 dead or removed trees (23.0%) were suspected to have been replaced in the location of original program trees. Hildebrandt and Sarkovich (1998) used 57.5% tree survivability at 30 years, the portion of trees that survived out of those delivered. When using SMUD's term survivability, we found 35.3% survivability at 22 years.

Regarding the biophysical factors influencing tree loss, we found that mature tree size was the most important determinant that affected overall and post-establishment long-term tree mortality. Trees with small mature size were about 2.7 times more likely to die over 22 years compared with those of medium mature size. There was no statistically significant difference found between medium and large trees. Our result on mature tree size was consistent with SMUD's recent mortality projections (M. Sarkovich, pers. commun.). Another biophysical factor in our model was planting season; we found that trees planted in rainy season were more likely to die than those in the dry season, the opposite of what Roman et al. (2014a) found. The reason for this conflicting result is unclear. Additionally, the 95% confidence value of our result for planting season crossed 1.0 (Table 4), therefore evidence for an effect of planting season was not strong. Further investigation is necessary to evaluate the effect of planting season. Previous studies also explored survival differences across various species or tree size classes (e.g., Koeser et al., 2013; Lawrence et al., 2012); our study could not do so because of insufficient and uneven sample size per species and tree size classes. Future research is needed to determine how mortality rates vary by species and habitat characteristics.

Tree care also appeared to be an important factor for long-term survivorship of residential yard trees. Several predictors that indirectly reflect the intensity and consistency of residents' tree care showed statistically significant relationships with tree mortality. Number of trees delivered, an indirect indicator of care intensity per tree, was a significant predictor in the final model for early establishment mortality and in one of the partial models for the overall tree mortality with relatively low AIC_C (Table 3). Additionally, we found that a tree's location on the property – front yard or back yard, another indirect indicator of tree care intensity – was significantly associated with post-establishment mortality. This supports Roman et al.'s (2014a) interpretation that trees planted in front yards are more likely to survive than those planted in backyards, perhaps because front yards are considered as a showcase to neighbors (Larsen and Harlan, 2006; Larson et al., 2009). Lastly, very unstable homeownership status, another indirect measure of tree care consistency, was as a significant variable in the full model (not the final model selected) for post-establishment mortality. Our study showed a weaker relationship between homeownership stability and mortality compared to Roman et al.'s (2014a) study, possibly because our metrics for homeownership stability only incorporated ownership changes and foreclosures, but could not take into account rental status due limited data availability over many decades. Overall, based on several proxies for tree care, we support the assertion that consistent stewardship is critical for tree performance on residential properties (Roman et al., 2014a).

Socioeconomic status, represented by assessed net property value in our study, had a significant effect on mortality in the early establishment phase. Interestingly, we found that properties with medium net property value were associated with low mortality; properties with both low and high net property value had relatively higher mortality. We suspect that different classes of net property values could have affected the amount of tree care in different ways. Although high income residents are more likely to pay contractors for tree care than those in lower income groups, homeowners with higher income are also more prone to alter their landscapes to incorporate new landscape trends (e.g., converting lawns to desert or oasis landscapes with low irrigation needs (Larsen and Harlan, 2006)). These kinds of alterations can affect tree survival. Roman et al. (2014a) also reported that neighborhood-level income was important to 5-year survival, but showed an inconsistent pattern. Their observation is somewhat comparable with our finding. For more accurate analysis of tree losses, it would be helpful to distinguish declines-in-place from removal of healthy trees. Our study could not track the difference between natural death and elective removal; further research could explore how socioeconomic status affects tree death and removal in different manners. Also, future research could explore relationships between resident actions and tree outcomes by including more property-level characteristics such as education attainment, opinions on environmental issues, and cultural norms and values through surveys and interviews.

Conclusions

We found that mature tree size, tree care, and socioeconomic status affected long-term survival of residential shade trees in

Sacramento, CA. This study has important implications for urban tree planting and giveaway programs, especially long-term management. Residential yards are an important component of the urban landscape (Cook et al., 2012), and harbor the majority of trees in the urban forest (Seto et al., 2011). Tree giveaway programs will continue to impact canopy in residential yards (Turner and Mitchell, 2013). To maximize the effectiveness of such programs, our results suggest that survival could be enhanced by distributing trees with medium and large mature sizes, limiting the number of trees ordered per property, and developing targeted outreach strategies for residents with different socioeconomic characteristics and different planting locations. Realistic expectations for tree loss, emphasis on consistent stewardship, and awareness that homeownership may change over time are also essential for constructive ongoing communications between the program and residents. Survival studies of yard trees are still scarce, compared to trees in streets and open spaces, and urban tree data sets over several decades are rare in general (Table 1). Our 22-year study is therefore a unique contribution to the growing body of research on urban tree survival.

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