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Research

Pest Management

Chronology of Gloomy Scale (Hemiptera: Diaspididae) Infestations on Urban Trees

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Abstract

Pest abundance on urban trees often increases with surrounding impervious surface. Gloomy scale (*Melanaspis tenebricosa* Comstock; Hemiptera: Diaspididae), a pest of red maples (*Acer rubrum* L.; Sapindales: Sapindaceae) in the southeast United States, reaches injurious levels in cities and reduces tree condition. Here, we use a chronosequence field study in Raleigh, NC, to investigate patterns in gloomy scale densities over time from the nursery to 13 yr after tree planting, with a goal of informing more efficient management of gloomy scale on urban trees. We examine how impervious surfaces affect the progression of infestations and how infestations affect tree condition. We find that gloomy scale densities remain low on trees until at least seven seasons after tree planting, providing a key timepoint for starting scouting efforts. Scouting should focus on tree branches, not tree trunks. Scale density on tree branches increases with impervious surface across the entire studied tree age range and increases faster on individual trees that are planted in areas with high impervious surface cover. There is a lag between the onset of pest infestations and a decline in tree condition, indicating that gloomy scale management should begin prior to a visible decline in tree condition. Our results inform management of gloomy scale in cities.

Key words: scale insect, urban tree, pest management, maple (*Acer*), herbivory

Impervious surface cover can benefit pests by increasing the local temperature and by causing tree stress (Raupp et al. 2012, Meineke et al. 2013, Dale and Frank 2017). Thus, as the area of impervious surface around a tree increases, pest abundance, and damage often increase too (Speight et al. 1998, Sperry et al. 2001, Dale et al. 2016, Just et al. 2018). Impervious surface predicted nearly 50% of the variation in abundance of the invasive Asian citrus psyllid in urban landscapes, five times more than any other environmental variables (Thomas et al. 2017). Likewise, infestations of horse chestnut scale, mimosa webworm, and honey locust spider mite become more severe as the amount of impervious surface around trees increases (Speight et al. 1998, Sperry et al. 2001). The relationship between pest density and impervious surface is typically evaluated on established trees that already have pest infestations (e.g., Sperry et al. 2001; Dale et al. 2016). Thus, little is known about the progression of pest density on trees from the time of tree planting to maturity. Pest density may gradually increase over time in relation to variables such as impervious surface, or pest populations may erupt at particular periods in tree development. Understanding the progression of pest density on urban trees will identify times when scouting or other integrated pest management (IPM) tactics will be most effective to identify or prevent infestations.

Gloomy scale (*Melanaspis tenebricosa* Comstock; Hemiptera: Diaspididae) is the most important pest of urban red maples (*Acer rubrum* L.; Sapindales: Sapindaceae) in the southeast United States (Frank 2019; Metcalf 1912, 1922; Frank et al. 2013). Gloomy scale densities are up to six times higher on street trees than on forest trees and increase exponentially as impervious area around trees increases (Youngsteadt et al. 2015, Dale et al. 2016, Long *et al.* 2019). This is due in part to temperature and tree water stress that increase gloomy scale fecundity, survival, and population growth rate (Dale and Frank 2014a,b, 2017). At high densities, gloomy scale and other scales cause branch dieback and canopy thinning that reduce tree condition (Metcalf 1922, Frank et al. 2013, Dale and Frank 2014a, Just et al. 2018). Infested trees have a very low chance of recovery after their condition has declined, and managing gloomy scale with insecticides is difficult and yields inconsistent results (Metcalf 1922; Sinclair and Hudler 1988; Dale and Frank 2014a, 2017). Thus, IPM of gloomy scale depends on forecasting and preventing heavy infestations.

In this study, we examine patterns in gloomy scale density over time and in relation to impervious surface cover to identify when gloomy scale monitoring and management may be necessary. First, we determine whether gloomy scales colonize trees in nurseries or after they are planted. Then we use a chronosequence (trees of different ages that represent a temporal sequence) to measure gloomy scale density on street trees from the first year after tree planting to 13 yr after planting to determine how infestations develop over time and in relation to impervious surface. We count scales on tree trunks and at several locations on the branches to determine which locations provide accurate assessment of gloomy scale density when scouting. Finally, we evaluate how red maple condition changes after planting in relation to scale density and impervious cover. We predict that trees surrounded by impervious surface will have higher scale densities at younger ages. Knowledge about the temporal development of gloomy scale infestations, in particular the amount of time it takes for populations to reach damaging levels after a tree is planted, will facilitate more efficient and targeted monitoring of trees in the landscape.

Materials and Methods

Study System

Red maple is native to eastern North America and is commonly planted in urban areas (McPherson 2010, USDA NRCS 2019). Gloomy scale is a univoltine armored scale insect with a range extending from Florida to New York (Metcalf 1922, Nakahara 1982, Miller and Davidson 2005), with highest abundance at midlatitudes (e.g., North Carolina) (Just et al. 2019). First instar scales, called crawlers, emerge in June and July and walk short distances or are transported by wind (Beardsley and Gonzalez 1975, Miller and Davidson 2005, Frank et al. 2013). The crawlers settle on the bark and insert their mouthparts into the tree to feed on parenchyma cells. They develop through two additional nymphal instars during summer and overwinter as mated adult females (Metcalf 1922). The scales feed and cause tree dieback and canopy thinning and reduce tree condition when abundance is high (Metcalf 1922, Frank et al. 2013, Dale and Frank 2014a).

Gloomy Scale Colonization on Nursery Trees

In September 2016, we visited three nurseries in North Carolina that supplied red maple trees for Neighborwoods, the Raleigh, North Carolina, municipal tree planting program (Panther Creek Nursery, Willow Springs, NC; Taylor's Nursery, Louisburg, NC; Worthington Farms, Greenville, NC). At each nursery, we randomly selected 12 red maple trees in each of two different areas of the nursery separated by at least 100 m. Tree calipers ranged from 3 to 6.5 cm. We used an OptiVISOR magnifier (Donegan Optical Company, Inc., Lenexa, KS) to visually inspect trees for gloomy scale. We inspected the trunk and the five lowest branches on the tree, excluding any branches that joined the trunk lower than 1 m above the root flare.

Gloomy Scale Infestation Development on Street Trees

The Parks, Recreation and Cultural Resources Department in Raleigh, North Carolina (35.8° N, 78.6° W; humid subtropical climate), provided us with an inventory of planting dates and locations for 700 red maples planted along city streets between 2003 and 2014. We grouped the trees into 'planting groups' by the number of opportunities they had to be colonized by gloomy scales (Supp Table S1 [online only]). Since gloomy scale crawlers are active in early summer, generally late May through July (Miller and Davidson 2005, Frank et al. 2013), trees planted before the end of July could have been colonized by gloomy scale in the year of planting. Trees planted after July could not have been colonized until the following year. Therefore, we assigned trees planted before July 31 to the calendar year of planting and trees planted after July 31 to the next calendar year. We identified five planting groups with adequate sample sizes and geographic spread to use in the study (trees planted in 2004, 2006, 2010, 2013, and 2014). These planting groups do not correspond to tree age per se, but for simplicity, we refer to trees with their first growing season in 2014 as the 'youngest' planting group and trees planted in 2004 as the 'oldest' planting group.

In ArcMap 10.3 (ESRI 2011), we randomly selected 11 trees in each planting group, all separated by at least 150 m. Dale and Frank (2014b) previously found that gloomy scale abundance is related to the amount of impervious surface within a 100 m radius around a tree, so we used a 1 m resolution map of Raleigh's impervious surface cover, prepared as described in Bigsby et al. (2014), to calculate the percent impervious surface within a 100 m buffer around each tree.

Gloomy scale density on branches

Gloomy scale has one generation per year. Live scales on trees in winter and spring developed during the previous growing season. We counted scales that developed during 2014 (counted April/early May 2015), 2015 (counted December 2015), and 2016 (counted December 2016) (Supp Table S1 [online only]). At the start of the study, we used Miller and Davidson (2005) to verify that gloomy scale identifications done in the field using an OptiVISOR matched identifications done in the lab with a dissecting microscope. Scales in the family Diaspididae develop tests (waxy covers) over their bodies that remain on the plant after the insects die. It is not possible to distinguish between live and dead scales without killing the insects. We did not want to kill scales and thus affect population growth, so we only counted scales between the tip of a branch and the most recent bud scar, which marks the branch growth from the latest growing season ('new growth'). All scales on the new growth developed during the previous year. We used a random number assignment system to select the branches for counting. On each tree, we counted scales on 30 cm of new growth on four cardinal sides of the tree using an OptiVISOR binocular headband magnifier. Some trees did not have 120 cm of new growth. We recorded the total length inspected to adjust counts during analyses. Except where otherwise noted, we report all counts of gloomy scale on branches as the number of insects per 15 cm of branch per tree.

Gloomy scale density could be considerably higher on older branch growth where scales have accumulated for multiple years. To get more robust scale density estimates, similar to previous research, for analyzing relationships between scale density, impervious surface, and tree condition, we revisited trees from the three oldest planting groups at the end of the study in February 2017 to count live scales on branch growth from the 2016, 2015, and 2014 growing seasons on four branches per tree, using bud scars to distinguish between years. In some cases where gloomy scale density was very high, we only counted scales on a portion of the growth for each growing season, and we standardize results down to the number of scales per 15 cm. Hereafter, we refer to these counts on multiple years of branch growth as 'cumulative' scale insect counts to distinguish them from the yearly scale insect counts on new branch growth that we previously described.

Analysis: Yearly samples.

We conducted all analyses in RStudio 1.1.463 (RStudio Team 2015). Four trees, three planted in 2014 and one planted in 2013, died during the study. Two trees, both planted in 2013, were heavily pruned by residents, making scale insect counts unreliable. These six trees are excluded from all analyses.

To determine whether the density of scale insects increases with impervious surface and the number of years since tree planting, we used generalized linear mixed effects models with negative binomial distributions in *lme4* (Bates et al. 2015), with the number of scales on new growth, counted yearly from 2014 to 2016, as the response variable. The initial model included the number of years since tree planting, mean-centered impervious surface within a 100 m buffer, and their interaction as fixed effects and tree ID as a random intercept to account for repeated measures. We include an offset term to account for different branch lengths and used *DHARMa 0.2.0* (Hartig 2018) to check model diagnostics. Based on a likelihood ratio test comparing models with and without an interaction term, we removed the interaction ($\chi^2 = 1.649$, df = 1, $P = 0.199$).

We also calculated per-tree rates of change in gloomy scale density. During all sampling years, trees in the three youngest planting groups had on average less than one scale per 15 cm. We therefore focus on per-tree rates of change for trees in the two oldest planting groups. For each of these trees, we calculated the absolute rate of change in scale density by subtracting 2014 density per 15 cm from 2016 density per 15 cm, giving the change in scale density over the 2-yr period. We did not use a relative rate of change (2016 density/2014 density) because some sites had abundance equal to zero in 2014, making division impossible. The rates of change are nonintegers, and some are negative. Data violated the assumptions of linear models, so we used a Wilcoxon rank-sum test in *stats 3.5.1* (R Core Team 2018) to compare them in 'low' and 'high' impervious surface sites. We used the amount of impervious surface within a 100 m buffer to classify trees into the two groups. The mean impervious surface in a 100 m buffer in our study was 30.84%, and we used 30% impervious surface as a threshold to divide the trees into two groups. To test the sensitivity of the results to the selected threshold, we also tested two higher and two lower thresholds: 26% impervious surface, 28%, 32% (which had the same groups of 'high' and 'low' impervious sites as when we used 34%), and 36%.

Analysis: Cumulative samples.

For the cumulative samples on multiple years of branch growth, we used generalized linear models to test whether scale density on 2014 branch growth and, separately, 2015 branch growth changed with impervious surface and years since tree planting. We treated years since tree planting as a categorical predictor because we only had three values. We mean-centered impervious surface to improve model convergence and added an offset term to account for branch lengths. Models included an interaction between impervious surface and years since tree planting. For counts on 2014 branch growth, we used a likelihood ratio test to compare models with and without the interaction term. The model for counts on 2015 branch growth would converge only if the interaction term was included.

Gloomy scale density on trunks

We counted gloomy scales on tree trunks on the same days that we counted scales on branches. On the east and west sides of each tree, we marked a 1 cm wide by 10 cm tall rectangle, with the bottom of the rectangle at a randomly assigned height of 30, 45, 60, or 75 cm above the soil. In April/early May 2015, we counted live scales by removing every scale and all empty tests, leaving the patches empty. In December 2015, we counted the number of adult scales in each patch without removing tests. We counted each new scale in the patch as alive since it had colonized the patch during the 2015 growing season. In December 2016, we again destructively counted the scales in each patch by removing tests to distinguish live insects. All trunk counts are reported as the number of live adult scales per 20 cm^2.

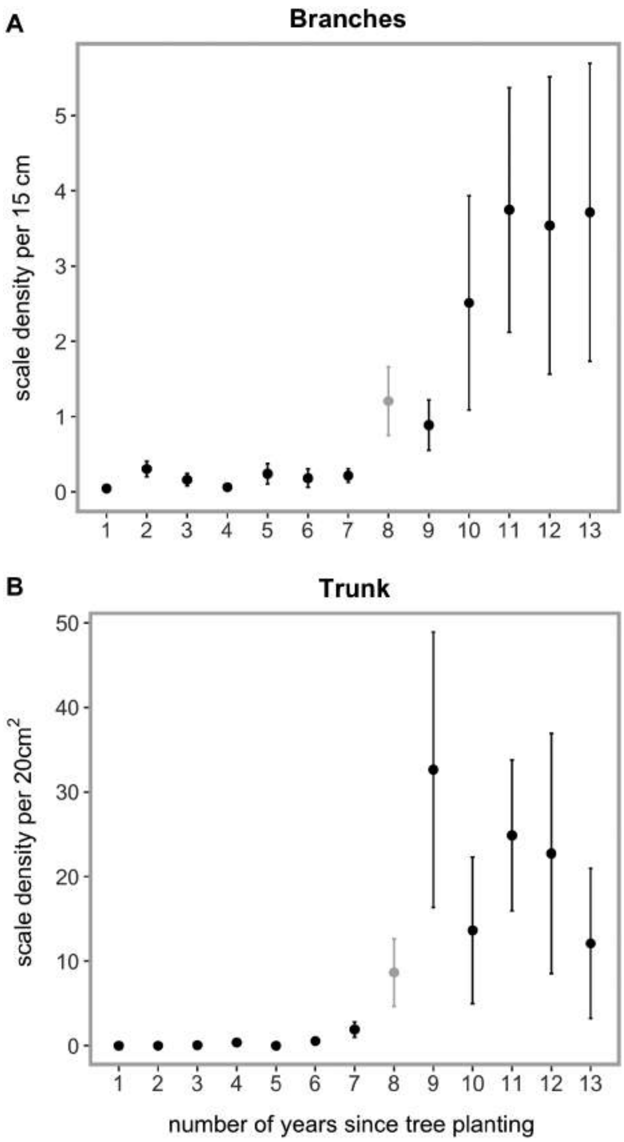

Fig. 1. Scale insect density with years since tree planting on (A) tree branches and (B) tree trunk. Black points are from yearly counts on new growth (total number of observations $N = 147$; Supp Table S1 [online only]), and gray points are from a supplemental sample of trees in their eighth growing season ($n = 17$). Points are means ± the standard error of the mean, calculated using all available trees for each year since tree planting.

Analysis.

To test for an increase in trunk scale density with impervious surface and the number of years since tree planting, we used the same generalized linear model as for yearly branch counts, with the exception that an offset term was not necessary because scales were counted on 20 cm^2 on all trees. Based on a likelihood ratio test comparing models with and without an interaction term, we removed the interaction term from the model ($\chi^2 = 1.807$, df = 1, $P = 0.179$).

The number of scales in the trunk patches in 2016 represents a recolonization rate following clearing of the patches in 2014. Trees in the youngest two planting groups had a maximum of one scale in 20 cm^2. Therefore, we focus on per-tree changes in scale density on trees from the oldest three planting groups. We fit a linear model with the number of live adults in 2016 as a response and impervious surface, the number of live adults in the patch in 2014, and their interaction as predictors. We $\log_{10}(x+1)$ transformed the 2014 and 2016 counts.

Table 1. Generalized linear mixed effects model predicting scale insect density using counts from 3 yr of sampling for all tree planting groups

	Estimate	SE	z value	*P* value
Branch				
Intercept	−5.744	0.485	−11.843	**<0.001**
Impervious surface	0.0465	0.0219	2.126	**0.0335**
Number of years since tree planting	0.221	0.0565	3.919	**<0.001**
Trunk				
Intercept	−5.264	1.141	−4.615	**<0.0001**
Impervious surface	−0.0144	0.0396	−0.364	0.716
Number of years since tree planting	0.557	0.123	4.524	**<0.0001**

Models include a random effect (not shown) to account for repeated measures per tree (n = 49) and an offset term in the branch model to account for branch length. Impervious surface is the amount of impervious surface within a 100 m buffer and is mean-centered. Significant *P* values (< 0.05) are bolded.

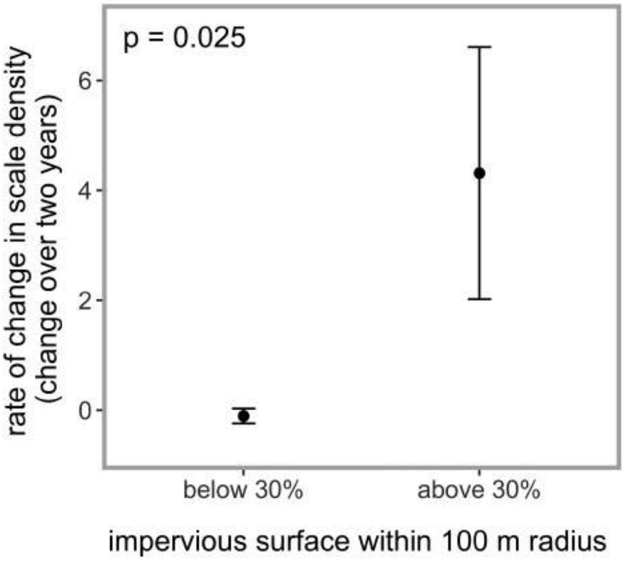

Fig. 2. Per-tree absolute rate of change in scale insect density per 15 cm of branch from 2014 to 2016. The absolute rate of change is the difference in 2014 scale density per 15 cm and 2016 scale density per 15 cm on the same tree. A positive rate indicates higher density in 2016. The point shows the mean ± the standard error of the mean. Results are limited to trees planted in 2004 and 2006 (the two oldest planting groups), pooled. Trees are divided into those surrounded by less than 30% impervious surface (n = 10) and those surrounded by more than 30% impervious surface (n = 12).

Gloomy scale scouting locations

Proper scouting for gloomy scale depends on searching in the right locations on a tree. To inform recommendations, we used linear models to test for a correlation between the trunk counts on each tree and the yearly and cumulative branch counts, with all abundances $\log_{10}(x+1)$ transformed. We also used the cumulative scale counts to compare gloomy scale density on new branch growth with the density on growth from earlier years to determine if scouting sparsely infested new growth is a reliable indicator of scale density on previous growth. We again $\log_{10}(x + 1)$-transformed data to meet the assumptions of linear models.

Supplemental trees in their eighth growing season

After observing a large jump in scale counts between trees in the three youngest versus the two oldest planting groups, we visited 17 additional red maples that were in their eighth growing season in 2015. All of the trees were within a single 2 km^2 neighborhood in Raleigh that did not contain any other study trees. From December 2015 to January 2016, we counted gloomy scales on the branches and trunks of these 17 trees using the same methods described for our original yearly counts.

Analysis.

Separately for branches and trunks, we used Wilcoxon rank-sum tests to compare scale density (per 10 cm for branches, per 20 cm^2 for trunks) on trees in their eighth growing season with trees from their seventh growing season. We then repeated the procedure to compare trees in their eighth growing season to trees in their ninth growing season.

Tree Condition

We rated the condition of each tree using a qualitative protocol employed by the Raleigh Department of Parks, Recreation and Cultural Resources, which ranks trees as dead, poor, fair, good, or excellent, as described in Dale and Frank (2014a). We excluded dead trees during site selection but marked a tree as 'dead' in subsequent years if it had dry, brittle branches and no live foliage. 'Excellent' trees had full canopies, healthy foliage, and no visible damage. 'Good' trees had thinner canopies or minor damage but no dieback. 'Fair' trees had sparse canopies, dieback, and/or other damage. 'Poor' trees had major dieback, crispy leaves, excessive canopy thinning, and/or major damage. In July 2015, three observers assigned condition ratings to each tree, and we retained the rating assigned by at least two of the three observers. In May 2017, two researchers rerated the tree conditions.

We used binomial logistic regression in *stats* (R Core Team 2018) to model the probability that a tree was in good condition. Almost all trees (45 of 49 in 2015 and 43 of 49 in 2017) were rated as Fair or Good condition (Supp Figs. S1 and S2 [online only]), so we classified them into two groups (Fair/Poor => 0, Excellent/Good => 1). We were most interested in whether condition is affected by scale density, so we excluded the three youngest planting groups, which had 2014 and 2016 mean scale densities less than one per 15 cm on branches or two per 20 cm^2 on trunks. Separately for branches and trunks, we fit models using impervious surface (100 m buffer) and $\log_{10}(x+1)$ transformed 2014 scale density to predict the probability that a tree was in Excellent/Good condition in 2015. We repeated this process with 2016 scale counts and 2017 condition ratings.

We repeated the binomial logistic regression procedure for the cumulative scale counts, using the sum of live scale insects on 2014 and 2015 branch growth, standardized to number per 15 cm, as a predictor, and 2017 condition as a response.

Table 2. Generalized linear models predicting scale density on branch growth from A) 2014 and B) 2015, based on cumulative scale counts conducted in 2016

	Estimate	SE	z value	*P* value
A. Scale density on branch growth from 2014				
Intercept	−2.725	0.505	−5.396	**<0.0001**
Impervious surface (100 m)	−0.0357	0.0528	−0.676	0.499
Years since planting (11)	0.723	0.707	1.023	0.307
Years since planting (13)	1.594	0.702	2.272	**0.0231**
Impervious surface × years since tree planting (11)	0.219	0.0806	2.713	**0.00668**
Impervious surface × years since tree planting (13)	0.0985	0.0667	1.277	0.140
B. Scale density on branch growth from 2015				
Intercept	−3.269	0.501	−6.524	**<0.0001**
Impervious surface (100 m)	−0.0628	0.0511	−1.229	0.219
Years since planting (11)	1.122	0.695	1.615	0.106
Years since planting (13)	2.342	0.680	3.443	**0.0006**
Impervious surface × years since tree planting (11)	0.245	0.0781	3.142	**0.0017**
Impervious surface × years since tree planting (13)	0.127	0.0639	1.981	**0.0476**

Models include data from the three oldest planting groups (n = 33). The number of years since tree planting was treated as a categorical variable with a baseline of 7 yr since tree planting. Impervious surface is the amount of impervious surface in a 100 m buffer and is mean-centered. Significant *P* values (< 0.05) are bolded.

Fig. 3. Scale insect density from cumulative counts in high and low impervious surface. Scale density was analyzed separately on 2014 and 2015 branch growth (Table 2) but is shown here as the sum of scale abundances on 2014 and 2015 branch growth, standardized down to 15 cm and then $\log_{10}$(x+1) transformed. The two youngest planting groups are excluded. Impervious surface is the percent impervious surface in a 100 m radius buffer around the tree. Trees are divided into those surrounded by less than 30% impervious surface within 100 m (n = 16) and those surrounded by more than 30% impervious surface within 100 m (n = 17).

Trees from the youngest planting groups were excluded from prior condition analyses because of low scale abundance, but we were still interested in whether their condition showed patterns across the impervious surface gradient. We used binomial logistic regression to test whether the probability that a tree was in good condition in 2015 or, separately, 2017 changed with impervious surface.

Results

Gloomy Scale Colonization on Nursery Trees

We did not find live gloomy scales on any of the 72 red maples we inspected at nurseries that supply trees to the Neighborwoods tree planting program.

Gloomy Scale Infestation Development on Street Trees

The amount of impervious surface within a 100 m buffer ranged from 5.40% to 56.19% with a mean (± SEM) of 30.84% (± 1.58%).

Gloomy scale density on branches

Over 3 yr of sampling, the number of gloomy scales per 15 cm of new branch growth increased and ranged from 0 to 31.90.

Based on a model fitted to data from all 3 yr of sampling, the number of scales on branches increased with years since tree planting and with impervious surface area in a 100 m buffer as in previous studies (Dale and Frank 2014b, Just et al. 2018; Fig. 1; Table 1). Absolute rates of change in scale density on tree branches, calculated by subtracting 2014 density from 2016 density on the same tree, ranged from −1.82 to 56.32 scales per 2-yr period for trees in the two oldest planting groups. The rate was higher for trees with more impervious surface within a 100 m buffer (Wilcoxon W = 25.5, P = 0.0246; Fig. 2; Supp Table S2 [online only]). Results were similar (P < 0.1) at all thresholds used to divide trees into high and low impervious surface groups (Supp Table S2 [online only]).

For the cumulative counts of scales on 3 yr of branch growth, the density of scales ranged from 0 to 136.8 scales per 15 cm of branch. There was a significant interaction between impervious surface (100 m) and the number of years since tree planting in predicting scale density on 2014 and 2015 branch growth. For trees in high impervious surface, the difference between scale abundance in the seventh growing season and scale abundance in the older two growing seasons was larger than for trees in low impervious surface (Table 2; Fig. 3).

Gloomy scale density on trunks

The number of gloomy scales per 20 cm^2 of trunk ranged from 0 to 178 and increased with years since tree planting but not with impervious surface (Fig. 1; Table 1).

The interaction between impervious surface and the number of scales in the trunk patches in 2014 was not a significant predictor of the number of scales in the trunk patches in 2016 (χ^2 = 0.209, df = 1, P = 0.648). When we removed the interaction, the number of scales in trunk patches in 2014 was the only significant predictor of 2016 abundance (Table 3).

Table 3. Coefficients for model predicting the number of scales recolonizing trunk patches between 2014 and 2016

	Estimate	SE	*t* value	*P* value
Intercept	0.554	0.336	1.649	0.109
Impervious surface (100 m)	−0.0108	0.0098	−1.107	0.277
$\log_{10}$ (x+1) 2014 scale density	0.345	0.123	2.814	**0.009**

The response, scales per 20 cm^2, is $\log_{10}$(x+1)-transformed. Model includes trees from the three oldest planting groups (n = 33). Significant P values (<0.05) are bolded.

Table 4. Binomial logistic regression models predicting tree condition

	Estimate	SE	z value	*P* value
A. *Response: 2015 tree condition (Good = 1, Fair/Poor = 0)*				
data: branches; two oldest planting groups				
intercept	1.235	1.540	0.802	0.230
impervious surface (100 m)	-0.018	0.048	-0.386	0.700
$\log_{10}$ (x+1) scale density per 15 cm (2014)	-0.857	1.546	-0.554	0.579
B. *Response: 2017 tree condition (Good = 1, Fair/Poor = 0)*				
data: branches; two oldest planting groups				
intercept	0.473	1.646	0.288	0.774
impervious surface (100 m)	0.030	0.054	0.555	0.579
$\log_{10}$ (x+1) scale density per 15 cm (2016)	-4.079	2.014	-2.025	**0.043**
C. *Response: 2015 tree condition (Good = 1, Fair/Poor = 0)*				
data: trunk; two oldest planting groups				
intercept	1.276	1.672	0.763	0.445
impervious surface (100 m)	-0.0285	0.0440	-0.648	0.517
$\log_{10}$ (x+1) scale density per 20 cm^2 (2014)	0.0460	0.539	0.085	0.932
D. *Response: 2017 tree condition (Good = 1, Fair/Poor = 0)*				
data: trunk; two oldest planting groups				
intercept	1.560	1.671	0.934	0.350
impervious surface (100 m)	-0.0438	0.0456	-0.961	0.337
$\log_{10}$ (x+1) scale density per 20 cm^2 (2016)	-0.230	0.653	-0.352	0.725
E. *Response: 2017 tree condition (Good = 1, Fair/Poor = 0)*				
data: branch growth from previous years; three oldest planting groups				
intercept	1.122	0.537	2.089	**0.037**
$\log_{10}$ (x+1) scale density per 15 cm (sum of scales on growth from 2014 and 2015)	-1.527	0.739	-2.068	**0.039**

A is a model predicting the 2015 condition of trees planted in 2004 and 2006 (n = 22), using $\log_{10}$(x+1)-transformed 2014 branch scale insect density and impervious surface (100 m) as predictors. B is the same as A except the condition rating is from 2017 and scale insect density is from 2016. C is a model predicting the 2015 condition of trees planted in 2004 and 2006 (n = 22), using $\log_{10}$(x+1)-transformed 2014 trunk scale insect density and impervious surface (100 m) as predictors. D is the same model as C except the condition rating is from 2017 and scale insect density is from 2016. E is for the cumulative samples and is a model predicting the 2017 condition of trees planted in 2004, 2006, and 2010 (n = 33). The predictors are $\log_{10}$(x+1)-transformed scale insect density, summed over the 2014 and 2015 branch growth, and impervious surface (100 m). Significant P values (< 0.05) are bolded.

Gloomy scale scouting locations

Yearly branch scale counts and trunk scale counts were not correlated in 2014 ($F_{1,47}$ = 0.173, P = 0.680), 2015 ($F_{1,47}$ = 0.208, P = 0.651), or 2016 ($F_{1,47}$ = 0.479, P = 0.492). Cumulative scale counts were not correlated with trunk counts (2014 branch growth: $F_{1,31}$ = 0.086, P = 0.771; 2015 branch growth: $F_{1,31}$ = 0.124, P = 0.727).

For cumulative scale counts, gloomy scale density on new growth was correlated with density on 2015 growth ($F_{1,31}$ = 37.08, P < 0.0001, R^2_{adjusted} = 0.53) and 2014 growth ($F_{1,31}$ = 32.74, P < 0.0001, R^2_{adjusted} = 0.50).

Supplemental trees in their eighth growing season

On the supplemental sample of trees in their eighth growing season, scale density on branches was higher than on trees in their seventh growing season (Wilcoxon W = 33, P = 0.002) but not different from trees in their ninth growing season (Wilcoxon W = 111, P = 0.416; Fig. 1). On trunks, scale density on trees in their eighth growing season was not different from trees in their seventh growing season (Wilcoxon W = 72, P = 0.283) or trees in their ninth growing season (Wilcoxon W = 117.5, P = 0.250; Fig. 1).

Tree Condition

Tree condition did not change with impervious surface for any tree planting groups in 2015 or 2017 (Table 4, Supp Table S3 [online only]). On trees in the two oldest planting groups, there was not a significant relationship between 2015 tree condition and 2014 branch scale density (Table 4). In 2017, the probability that a tree was in good condition declined with 2016 branch scale density (Table 4, Fig. 4). Likewise, for cumulative branch counts conducted in 2016, the probability that a tree was in good condition in 2017 decreased with scale density (Table 4). There was not a significant relationship between tree condition and scale density on tree trunks in 2015 or 2017 (Table 4).

Discussion

Gloomy scale is the primary pest of urban red maples in the Southeast United States, yet there is no existing information about how gloomy scale infestations begin and develop on trees. We found that gloomy scale densities increase faster on red maples surrounded by more impervious surface cover and erupt after the seventh year

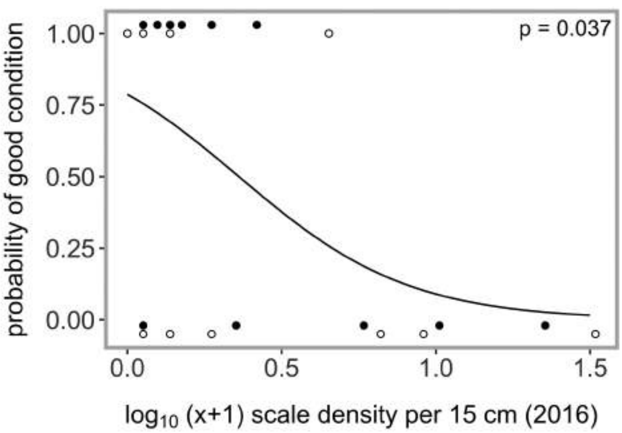

Fig. 4. Logistic regression model of the probability that a tree is in good condition in 2017. Trees are assigned a 1 (good condition) or 0 (fair/poor) condition. Figure includes trees from the two oldest planting groups. Closed circles are trees planted in 2004 (n = 11) and open circles are trees planted in 2006 (n = 11). Points are offset slightly from 0.0 and 1.0 for improved visibility.

following tree planting. This provides a critical age to begin gloomy scale monitoring. Further, gloomy scale scouting should focus on tree branches, where population growth is related to impervious surface and condition, rather than trunks.

We did not find live gloomy scales in the nurseries that supplied trees to Raleigh's municipal tree planting program. Gloomy scale is not known as an important nursery pest (S.D.F., personal observation), which is also corroborated by the overall low scale densities on young trees in our study. For 7 yr after tree planting, mean gloomy scale densities were less than 1.2 scales per 15 cm of branch and less than two scales per 20 cm^2 of trunk. The low density of gloomy scales on young trees indicates that early maintenance efforts should focus on practices such as watering and pruning that improve tree establishment or on monitoring for pests that target young trees, such as flat headed appletree borer or potato leafhopper, rather than monitoring for gloomy scale (Seagraves et al. 2013).

We found that 75% of trees in the two youngest planting groups had detectable scale populations by their fourth growing season, but gloomy scale densities never exceeded two scales per 15 cm of branch on trees within the first 7 yr after planting. However, gloomy scale densities increased more than sixfold between 7 and 10 yr after tree planting on branches and trunks, after which many trees developed darkened branches and trunks characteristic of gloomy scale infestations. We do not know the mechanism for this rapid population increase, but populations increased even faster on trees that were surrounded by impervious surface. Water stress, which increases with impervious surface (Savi et al. 2015), may contribute to the flare we observed in gloomy scale populations on trees after their seventh growing season if, for example, water demand increases as trees grow and trees have restricted root zones or poor soil. Dale and Frank (2017) found an additive positive effect of temperature and water stress on gloomy scale embryo production such that scales on hot water stressed trees produce around 50% more embryos than on watered trees 2.5°C cooler. Watering trees, especially those in high impervious surface areas, may be a useful IPM tactic for avoiding gloomy scale infestations.

Tree condition was worse on trees with high scale densities on their branches in 2016. This pattern was not evident in 2014 despite high gloomy scale densities on some trees, suggesting a lag in the decline in tree condition following infestation with scales. Trees have a very low chance of recovery after their condition has declined (Sinclair and Hudler 1988, Dale and Frank 2017) and may have shorter lifespans than pest-free trees if they experience other stressors (Metcalf 1922). Thus, monitoring for gloomy scale should begin prior to a visible decline in tree condition or darkening of tree bark. We recommend that monitoring begin around the seventh growing season after tree planting to allow time for corrective action prior to a decline in condition, or earlier if trees are planted in a landscape with existing gloomy scale populations. We found no relationship between the scale densities on a tree's trunk and branches, and since gloomy scale densities on the tree trunk did not track impervious surface or affect tree condition, they are not good targets for monitoring infestation development. In our cumulative counts on tree branches, gloomy scale densities were correlated on all 3 yr of branch growth but were much lower on new growth. Therefore, gloomy scale will be easier to detect on growth from previous years.

Scale insect infestations are difficult to control once established (Fulcher et al. 2012, Quesada et al. 2018). Therefore, monitoring should be conducted before gloomy scales reach high population densities and reduce tree condition. We provide new guidelines for monitoring gloomy scales in urban landscapes to allow time for management action. The lifetime benefits provided by urban trees are maximized when trees survive and develop large, healthy canopies (Maco and McPherson 2003, Roman et al. 2014). Our results highlight the need to match red maple trees with planting sites where those trees can thrive with minimal pest infestations.

Supplementary Data

Supplementary data are available at *Environmental Entomology* online.

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