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A rapid urban site index for assessing the quality of street tree planting sites

Bryant C. Scharenbroch[a,b,*], David Carter[c], Margaret Bialecki[d], Robert Fahey[b,e], Luke Scheberl[a], Michelle Catania[b], Lara A. Roman[f], Nina Bassuk[g], Richard W. Harper[h], Les Werner[a], Alan Siewert[i], Stephanie Miller[j], Lucy Hutyra[k], Steve Raciti[l]

[a] College of Natural Resources, University of Wisconsin-Stevens Point, 800 Reserve Street, Stevens Point, WI 54481, USA
[b] The Morton Arboretum, 4100 Illinois Route 53, Lisle, IL 60532, USA
[c] Department of Forest Resources, University of Minnesota, Green Hall, 2005 Upper Buford Circle, St. Paul, MN 55108, USA
[d] Department of Geography, Environment, and Society, University of Minnesota, 414 Social Sciences 19th Avenue S., Minneapolis, MN 55455, USA
[e] Department of Natural Resources and the Environment, University of Connecticut, 1376 Storrs Road, Storrs, CT 06269, USA
[f] US Forest Service, Philadelphia Field Station, 100 N. 20th Street, Philadelphia, PA 19103, USA
[g] Urban Horticulture Institute, Horticulture Section, School of Integrative Plant Science, Cornell University, 134A Plant Science, Ithaca, NY 14853, USA
[h] Department of Environmental Conservation, University of Massachusetts, 160 Holdsworth Way, Amherst, MA 01003, USA
[i] Ohio DNR Division of Forestry, Region 3, 11800 Buckeye Drive, Newbury, OH 44065, USA
[j] Ohio DNR Division of Forestry, Region 4, 952-B Lima Avenue, Findlay, OH 45840, USA
[k] Department of Earth & Environment, Boston University, 685 Commonwealth Avenue, Boston, MA 02215, USA
[l] Department of Biology, Hofstra University, 227 Gittleson Hall, Hempstead, NY 11549, USA

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ABSTRACT

Urban trees experience site-induced stress and this leads to reduced growth and health. A site assessment tool would be useful for urban forest managers to better match species tolerances and site qualities, and to assess the efficacy of soil management actions. Toward this goal, a rapid urban site index (RUSI) model was created and tested for its ability to predict urban tree performance. The RUSI model is field-based assessment tool that scores 15 parameters in approximately five minutes. This research was conducted in eight cities throughout the Midwest and Northeast USA to test the efficacy of the RUSI model. The RUSI model accurately predicted urban tree health and growth metrics ($P < 0.0001$; R^2 0.18–0.40). While the RUSI model did not accurately predict mean diameter growth, it was significantly correlated with recent diameter growth. Certain parameters in the RUSI model, such as estimated rooting area, soil structure and aggregate stability appeared to be more important than other parameters, such as growing degree days. Minimal improvements in the RUSI model were achieved by adding soil laboratory analyses. Field assessments in the RUSI model were significantly correlated with similar laboratory analyses. Other users may be able to use the RUSI model to assess urban tree planting sites (< 5 min per site and no laboratory analyses fee), but training will be required to accurately utilize the model. Future work on the RUSI model will include developing training modules and testing across a wider geographic area with more urban tree species and urban sites.

1. Introduction

1.1. Urban tree stress and mortality

Poor site conditions can cause urban tree stress leading to reduced establishment, growth, health and ultimately premature mortality. Roman and Scatena (2011) found that street trees typically live only 20 years. It is unclear exactly how much urban tree stress is attributable to site conditions, but Patterson (1977) suggested that as much as 90% of all urban tree health issues are soil-related. Regardless, urban trees in poor site conditions are predisposed to other tree stress agents, like diseases or insects (Cregg and Dix, 2001). Site conditions in streetscapes

Abbreviations: AHOR, A horizon; EC, electrical conductivity; ERA, estimated rooting area; EXP, exposure; GDD, growing degree days; INFR, infrastructure; MAI, mean annual increment; PEN, penetration; PPT, precipitation; RUSI, rapid urban site index; RAI, recent annual increment; SOM, soil organic matter; STRC, structure; SURF, surface; TRAF, traffic; TC, tree condition; TCI, tree condition index; UTH, urban tree health; WAS, waterstable aggregates

* Corresponding author at: College of Natural Resources, University of Wisconsin – Stevens Point, 800 Reserve Street, Stevens Point, WI 54481, USA.
E-mail addresses: Bryant.Scharenbroch@uwsp.edu, bscharenbroch@mortonarb.org (B.C. Scharenbroch), david.r.j.carter@gmail.com (D. Carter), biale009@umn.edu (M. Bialecki), rfahey@mortonarb.org, robert.fahey@uconn.edu (R. Fahey), Luke.L.Scheberl@uwsp.edu (L. Scheberl), mcatania@mortonarb.org (M. Catania), lroman@fs.fed.us (L.A. Roman), nlb2@cornell.edu (N. Bassuk), rharper@umass.edu (R.W. Harper), Les.Werner@uwsp.edu (L. Werner), alan.siewert@dnr.state.oh.us (A. Siewert), Stephanie.Miller@dnr.state.oh.us (S. Miller), lrhutyra@bu.edu (L. Hutyra), steve.raciti@gmail.com (S. Raciti).

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are particularly poor (Jim, 1998) and these landscapes often have the most severe site limitations inhibiting establishment, growth, health and longevity of urban trees.

Streetscape trees are negatively affected by a wide variety of site constraints. These landscapes have limited above- and belowground growing space (Jim, 1997), leading to reduced tree growth (Sanders and Grabosky, 2014). Poor soil structure, high bulk densities, low hydraulic conductivity and low aeration from compaction can negatively impact trees in these landscapes (Day and Bassuk, 1994). Streetscapes are often underlain by engineered soils comprised of coarse materials optimal for supporting infrastructure, but with poor water and nutrient holding capacities (Grabosky and Bassuk, 1995). Nutrient availability for trees may be affected by alterations in organic matter cycling and biological activity in streetscapes (Scharenbroch and Lloyd, 2004; Scharenbroch et al., 2005). Streetscape soils often are often alkaline due to weathering of concrete (Ware, 1990). The salinities of these soils are often high due to application of de-icing salts (Hootman et al., 1994; Czerniawska-Kusza et al., 2004). Management activities to maintain infrastructure (e.g., road salts, tree trimming) in these landscapes may induce urban tree stress (Randrup et al., 2001). The aforementioned scenarios outline some of the major site conditions limiting trees in streetscapes. Although site conditions are often degraded in streetscape plantings, this is not always the case and a wide range of site qualities exist in streetscapes (Scharenbroch and Catania, 2012).

1.2. Improving the urban forest through site assessment

The ability to detect differences across the range of site qualities in streetscapes would benefit both the planning and management of the urban forest. Furthermore, urban tree species have a wide range of tolerances to site conditions (Bassuk, 2003; Sjöman and Nielsen, 2010). Better matching of species tolerances with site conditions may increase urban forest health and diversity. Trees with low hardiness might be planted in high quality sites. By doing so, these trees will have better chance to establish and grow to maturity. New tree species to the urban environment might be planted in the highest quality sites, since limited information may be known on their tolerances to urban site conditions. Trees with high tolerances to urban stress might be planted in the lowest quality sites, thereby maximizing the total canopy cover of the urban forest.

The ability to detect site quality differences would also benefit individual urban trees. Soil management is often required for urban trees since so many urban landscapes are degraded (De Kimpe and Morel, 2000), and these soil treatments have been shown to enhance tree growth and health (Scharenbroch and Watson, 2014; Layman et al., 2016). However, assessment tools are limited and inaccurate to assess the efficacy of these management actions towards improving soil quality for urban trees (Scharenbroch et al., 2014). Improved assessment tools will enhance soil management efforts, which in turn will promote the health and growth of trees in urban landscapes.

1.3. Site indices for urban trees

A practical and accurate site index for urban trees does not currently exist. Site indices are available for agronomic plants (Doran and Parkin, 1994; Doran et al., 1996) and timber species (Amacher et al., 2007). Agronomic site indices employ site indicators and interpret score values into integrated indices (Andrews et al., 2004; Idowu et al., 2009) to relate site conditions affecting plants in these landscapes. Forest site index reflects primary growth potential in dominant and co-dominant trees for a given species at an established reference age (i.e. 50 y). Such growth-based indices inherently reflect the collective influence of site and soil characteristics on growth. Indices from agriculture and forestry may have limited application for urban trees since the species and site conditions differ substantially in urban landscapes.

Efforts have been made to develop site indices for urban trees (Siewert and Miller, 2011; Scharenbroch and Catania, 2012). The Urban Site Index (USI) by Siewert and Miller (2011) is a field-based assessment comprised of eight observations producing a score of 0–20. Specific parameters in the USI include: vegetation, surface compaction, probe penetration, soil development, traffic speed, street lanes, parking, and length between traffic control devices. The USI model has not been tested outside of Ohio, USScharenbroch and Catania (2012) published a soil quality minimum data set (MDS) that predicted urban tree attributes on 84 sites throughout DuPage County, IL USA. The MDS included soil texture, aggregation, density, pH, conductivity, total soil organic matter (OM), and labile OM. The MDS is mostly field-based, includes only soil properties and does require some laboratory characterization. The MDS has not been tested outside of DuPage County, IL, USA.

An urban site index to assess streetscapes would be a useful tool for urban tree managers. Toward this goal, a team of scientists and practitioners developed a model called Rapid Urban Site Index (RUSI). The RUSI model was developed based on other urban (Siewert and Miller, 2011; Scharenbroch and Catania, 2012) and non-urban sites indices (Doran and Parkin, 1994; Doran et al., 1996; Andrews et al., 2004; Amacher et al., 2007; Idowu et al., 2009). This research was conducted to answer five questions on the RUSI model:

1. Can the RUSI accurately predict urban tree performance across different sites, species and cities?
2. Are all fifteen RUSI parameters useful for predicting urban tree performance?
3. Can additional laboratory analyses improve the ability of the RUSI model to predict urban tree performance?
4. Are the RUSI field assessments accurate in comparison to laboratory analyses?
5. Is the RUSI model accurate and practical for other users?

2. Materials and methods

2.1. Study areas and sample plots

Descriptions and data on human and tree populations, climates and geologies of the eight cities are provided in the Appendix. The first four questions were tested in five USA cities: Boston, MA; Chicago, IL; Cleveland, OH; Springfield, MA and Toledo, OH. These cities were selected based the wide range of urban tree species and site conditions and minimal logistical concerns to facilitate efficient sampling. The fifth question was tested in four USA cities: Chicago, IL; Ithaca, NY; New York City, NY and Stevens Point, WI.

Forty sample plots were identified in each city by first sorting respective city tree inventories to identify two of the most common street trees in each city. *Acer rubrum* L. was the 1st to 2nd most common species in all five cities, therefore twenty sample plots in each city had *Acer rubrum* trees. The remaining twenty plots in each city had either *Quercus rubra* L. or *Tilia cordata* Mill. trees. *Quercus rubra* was selected as the second species in Chicago, IL; Boston, MA and Springfield, MA and *Tilia cordata* was selected as the second species in Cleveland, OH and Toledo, OH.

Sample plots had to meet criteria of at least three trees of the same species and size (within 10 cm in diameter at breast height) on a location. A sample location was defined as a uniform site on one side of the block bounded by cross streets. Locations were commonly found between the street and the sidewalk. Google Earth was used to examine and verify the potential locations. Locations that did not meet the above criteria were excluded. A common reason to exclude a location was that a tree had died or was replanted and this change was not reflected in the current street tree inventory. Forty random plots in each city (twenty for each species) were selected from the locations that had met all criteria. An additional ten plots (five for each species) were selected in each city to be used as backup plots if field verification found that the location did not meet the criteria. Due to the relatively smaller street tree population in Stevens Point, WI, segments of the sample criteria, such as three trees per plot were not met. Consequently, the Stevens Point, WI survey did not follow previously described sampling protocol. For Stevens Point, WI, 360 sample plots were randomly selected from all street trees.

2.2. Field sampling and laboratory analyses

On each sample plot, site quality was assessed using the RUSI model and urban tree performance was assessed using metrics related to urban tree health and growth. The start and stop times were recorded to track the time required to complete the assessment. The tree health assessments were performed for each tree on the plot and a plot mean was computed. Only one tree per plot was assessed for growth using an increment core.

To limit subjectivity bias, all sampling for the first four questions were conducted by the project primary investigator. The fifth question examined the ability of other users to utilize the RUSI model in two pilot projects. The first pilot project involved five minimally trained users in Chicago, IL; New York, NY and Ithaca, NY on a total of 100 plots. The minimally trained users were paid undergraduate interns studying a range of topics in environmental sciences. The users received one-hour of field instruction on the RUSI model. The users were instructed to only collect the parameters that they felt confident assessing. The second pilot test was carried out with ten user groups given six hours of training on the RUSI model. The users for this pilot test with unpaid undergraduate students in studying a range of topics in environmental sciences. The users worked in groups of four to five and assessed 360 randomly located urban trees and planting sites in Stevens Point, WI USA. The users for the second pilot test were instructed to work as a team to derive scores and not exclude any of the RUSI parameters.

2.3. Rapid urban site index (RUSI) model

The RUSI model had five factors and 15 parameters (Fig. 1). The five factors were climate, urban, soil physical, soil chemical and soil biological. Each of these factors had three parameters which were measured and scored (s) 0–3 based on scoring functions which are described in the Appendix (Table A3). The climate parameters were precipitation (PPT), growing degree days (GDD), exposure (EXP). The urban parametes were traffic (TRAF), infrastructure (INFR) and surface (SURF). Soil physical parameters were texture (TEXT), structure (STRC), penetration (PEN). Soil chemical parameters were pH, electrical conductivity (EC), soil organic matter (SOM). Soil biological parameters were estimated rooting area (ERA), A horizon (AHOR) and water-stable aggregates (WAS). The scoring functions for each of the 15 parameters were determined from discussions with experts and practitioners as well as from the literature (Doran and Parkin, 1994; Doran et al., 1996; Andrews et al., 2004; Amacher et al., 2007; Idowu et al., 2009; Siewert and Miller, 2011; Scharenbroch and Catania, 2012). The scores for the 15 parameters were summed for Σs, which was then divided by the maximum possible total for the number of parameters measured (3n) and multiplied by 100 for the RUSI score (Eq. (1)).

$$RUSI = (\Sigma s/3n)*100, \quad (1)$$

where s = is the score (0–3) of the parameters and n = the number of the individual RUSI parameters

2.4. Urban tree performance

Six metrics were used to assess urban tree health and growth. The three urban tree health metrics: tree condition (TC), tree condition index (TCI) and urban tree health (UTH) were determined from the discussions with experts and practitioners as well as from the literature (Webster, 1979; Bond, 2012; Scharenbroch and Catania, 2012). Descriptions of the three urban tree health metrics and their scoring functions are provided in the Appendix (Tables A4, A5 and A6). Tree condition index and UTH are computed with Eqs. (2) and (3), respectively.

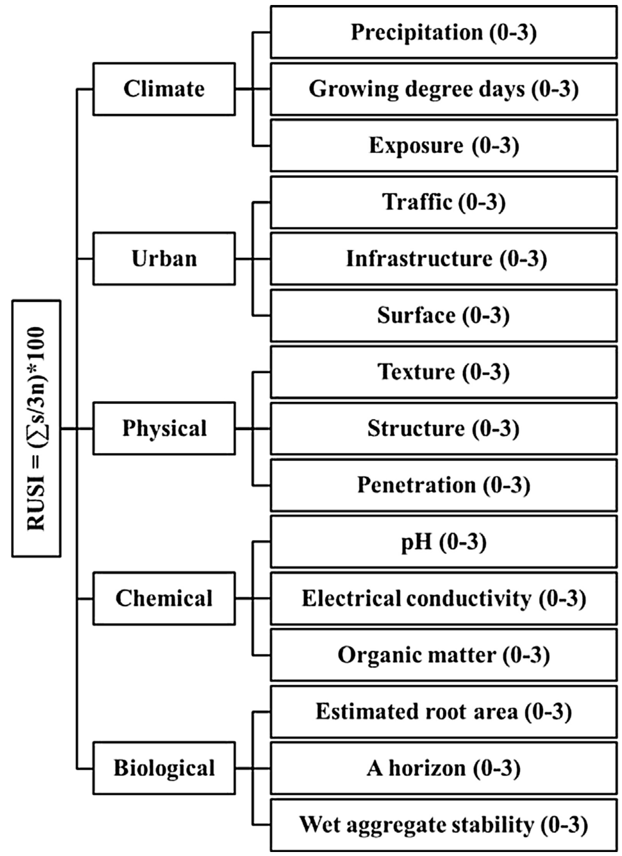

Fig. 1. Factors and parameters for the rapid urban site index (RUSI) model.

$$TCI = (\Sigma s/3n)*100, \quad (2)$$

where s = is the score (0–3) of the parameters and n = number of individual TCI parameters

$$UTH = (\Sigma s/5n)*100, \quad (3)$$

where s = is the score (0–5) of the parameters and n = number of individual UTH parameters

Tree assessments included three growth metrics. One increment core was extracted at 1.37 m in height and at a random azimuth on the stem. Increment cores were dried, mounted, and sanded with progressively finer sand paper following standard methods by International Organization for Standardization (Orvis and Grissino-Mayer, 2002) and standard dendrochronological techniques (Stokes and Smiley, 1996). Annual rings widths were measured to the nearest 0.001-mm on a slide-stage micrometer (Velmex, Inc., Bloomfield, NY USA) interfaced with the Measure J2X software program. The mean annual increment (MAI) (mm yr^{-1}) was by computed as the mean width for all annual rings measured. The recent annual increment (RAI) (mm yr^{-1}) was computed using the annual increment over the most recent ten years. The diameter (cm) at breast height (DBH) of all trees was measured at 1.37 m. The annual rings were counted to estimate the tree age and pith was present on all increment cores. The DBH/age (cm yr^{-1}) was computed as the third metric to assess tree growth.

2.5. Soil laboratory analyses

Soil laboratory analyses were used to answer the questions of whether field measures are accurate and if additional soil testing would improve the RUSI model. The remaining soil from the RUSI field assessment was bagged, labelled and stored on ice for laboratory characterization. In the laboratory, moist soils were passed through a 6-mm screen for homogenization. Gravimetric soil moisture content was determined by the mass loss after drying soil sub-samples at 105 °C for 48 h (Topp and Ferré, 2002). Wet-aggregate stability (WAS) was determined on the 1–2 mm fraction following Nimmo and Perkins (2002). Soil pH and electrical conductivity (EC) were measured in 1:1 (soil:deionized) water pastes (Model Orion 5-Star, Thermo Fisher Scientific Inc., Waltham, MA USA) (Rhoades, 1996; Thomas et al., 1996). Extractable soil P was determined using Olsen or Bray methods depending on the soil pH (Kuo, 1996). Total soil C and N concentrations and the C/N ratio were determined using an automated dry combustion gas analyzer (Vario ELIII, elementar Analysensysteme, Hanau, GER) (Bremner et al., 1996; Nelson et al., 1996). Total organic matter was determined by loss-on-ignition at 360 °C for 6 h (Nelson et al., 1996). Particulate organic matter (POM), which is relatively labile, physically un-complexed OM, was determined by particle size fractionation following methods of Gregorich et al. (2006). The chloroform fumigation-extraction method (Vance et al., 1987) with a K_{EC} of 0.45 (Joergensen, 1996) was used to determine microbial biomass C (MBC).

2.6. Statistical analyses

Summary statistics were computed to describe the RUSI model and urban tree performance among all cities and species and within each city and by species. Analysis of variance (ANOVA) was used to examine differences by city and species. Prior to running the ANOVA's, data distributions were checked for normality using the Shapiro-Wilk test. Transformations of non-normal data were performed when necessary. Mean separations were carried out with the Tukey's HSD test. Linear regression analyses were used to test whether the RUSI model and its parameters predicted urban tree performance. When necessary, P-values were adjusted for multiple comparisons. Principal component analyses were used to identify RUSI parameters explaining most variance in the entire data set (Fox and Metla, 2005). Standard least squares modeling was used to determine if adding laboratory soil analyses improved the RUSI model for predicting urban tree performance. All significant differences for statistical analyses were determined at the 95% confidence level. All statistical analyses were conducted using SAS JMP 7.0 software (SAS Inc., Cary, NC USA).

3. Results and discussion

3.1. RUSI significantly correlates with urban tree performance

The RUSI scores significantly correlated with four of the six urban tree performance metrics (Fig. 2). The RUSI scores explained 40% of the variance in TCI, 28% of variance in UTH and 18% of the variance in TC. The RUSI scores were not significantly correlated with DBH/age or MAI, but were significantly correlated with RAI. No significant interaction effects of city or species were detected for the relationships of RUSI and urban tree performance attributes. Models that were significant between RUSI and urban tree performance metrics across all cities and species were also significant within each city and species. Overall, the answer to the first question was that the RUSI model did significantly correlate with urban tree performance.

The RUSI scores were better predictors of tree health (TC, TCI and UTH) compared to tree growth (DBH/age, MAI and RAI). This finding raises at least two questions to consider and discuss. The first question being why were RUSI scores better correlated with tree health compared to tree growth? The second question, is it preferred for a site

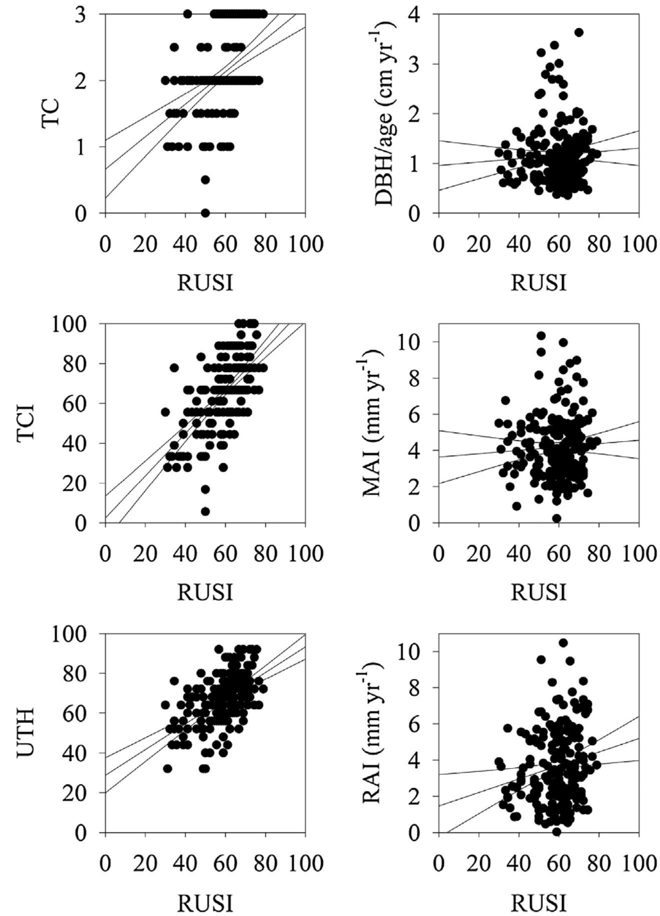

Fig. 2. Linear regressions and 95% confidence intervals for rapid urban site index (RUSI) and tree condition (TC) [$P < 0.0001$; $R^2 = 0.18$; TC = 0.66 + 0.025*RUSI], tree condition index (TCI) [$P < 0.0001$; $R^2 = 0.40$; TCI = 2.4 + 1.1*RUSI], urban tree health (UTH) [$P < 0.0001$; $R^2 = 0.28$; UTH = 29 + 0.65*RUSI], diameter at breast height by age (DBH/age) [$P = 0.4086$; $R^2 = 0.00$], mean annual increment (MAI) [$P = 0.5700$; $R^2 = 0.00$] and recent annual increment (RAI) [$P = 0.0118$; $R^2 = 0.03$; RAI = 1.5 + 0.037*RUSI]. Data from Boston, MA; Chicago, IL; Cleveland, OH; Springfield, MA and Toledo, OH USA (N = 200).

assessment tool to relate to tree health or growth potential? Four reasons are provided to explain the greater correlation between tree health and RUSI compared to tree growth and RUSI followed by a discussion on whether it is preferred for a site index to relate tree health and/or growth.

The first reason on why tree health correlated better with RUSI than tree growth is that the subjective nature of the tree health assessments might have biased the results. Sites given low RUSI scores might have inadvertently and subconsciously also been given low TC, TCI and UTH scores. This bias potential was recognized in designing the experiment and the researchers randomly chose the order of the evaluation metrics at each site in an attempt to minimize the bias.

The second reason on why tree health correlated better with RUSI than tree growth is that the tree growth sampling might have been too crude to detect changes in tree growth due to site quality. Only one increment core sample was allowed to be taken from each tree and only one tree was allowed to be sampled from each site. If it was possible, multiple trees on each site and multiple increment cores from each tree would have been taken. Tree growth is asymmetric and it might be that the location of the increment core was such that changes in annual ring growth due to site conditions were missed. Random tree selections within sites and random azimuths for coring were used to limit the potential errors created from using one tree per site and one increment core per tree. The DBH/age growth assessment was included to integrate growth of the entire stem over the tree's lifespan. Certain stressors such as drought or defoliation cause immediate reactions and may not be detectable by examining the stem growth over the tree's lifespan (Dobbertin, 2005). To attempt to control for this, the RAI was also computed to assess the tree growth over the last decade. In comparison to the MAI or DBH/age the RAI was significantly correlated to the RUSI model. However, it might be that the ten-year increment for RAI was still too coarse to detect immediate responses of the tree to site induced stress.

The third reason on why tree health correlated better with RUSI than tree growth is that stem growth does not respond to site quality. This reason is proposed, but unlikely. In a closed canopy under competition for light, height rather than diameter growth might be preferred to assess growth. However, all of the sample trees were open-grown and competition for light was unlikely. Stem growth was chosen to evaluate tree growth because it has been found to be responsive to stress (Waring, 1987). Under stress, photosynthesis is reduced, and since stem growth is not directly vital to the tree, it may be reduced early on as carbon allocated to other processes such as foliage or root growth (Dobbertin, 2005).

The forth reason why tree health correlated better with RUSI than tree growth is that the tree health metrics may be better indicators of stress compared to the tree growth metrics. Tree health metrics may better indicate site-induced stress since they were more complete tree evaluations. The tree health assessments examined the crown, stem and roots of the trees, whereas the growth assessments were on only the stem. Many site-related stress agents are present in urban sites and not all of them impact tree growth. Berrang et al. (1985) found that street trees in New York City exhibited a variety of tree health symptoms relative to a variety of urban site stress agents, and many of these responses were not related to secondary growth. Additional support for the forth reason is that correlations improved with RUSI with more detailed assessments of tree health. The TCI and UTH metrics were more comprehensive assessments of the tree and better correlated with RUSI compared to the rather coarse TC assessment.

Ideally a site index would relate both tree health and growth. However, if a site index is to predict one or the other, tree health is preferred. Tree health is a better metric of urban tree performance for at least three reasons. First, it is unclear whether faster growth is preferred for urban trees. Urban trees grow in limited spaces (Jim, 1997) and it is problematic if the trees outgrow the limited growing spaces provided for them. Faster growing trees might require more maintenance (e.g., pruning, sidewalk repair). Increased growth might come at the expense of reduced defense to pests (Herms and Mattson, 1992). Faster aboveground growth may lead to an imbalance in the root:shoot ratio and predispose that tree to failure for a variety of reasons, including drought (Lloret et al., 1999). Faster growth is preferred to help trees establish in urban sites (Zisa et al., 1979), but after establishment moderate growth rates might be ideal for urban trees. Second, urban tree health assessments often include a measure of, or are influenced by, tree growth. For instance, the UTH metric includes a growth parameter that evaluates and scores the annual twig extension. Third, urban tree longevity is the ultimate goal for urban tree managers. This goal is more likely to be attained with healthy trees, not faster growing trees. The commonly held belief that faster growing trees in urban environments are preferred is one that should be re-evaluated and further debated. Rather, establishing and maintaining healthy urban trees should be a primary objective and a site index aimed at furthering our understanding of the relationship of potential urban tree health and urban growing conditions should be the goal.

3.2. All RUSI parameters do not have equal importance

All RUSI parameters did not have equal importance for predicting urban tree performance. Estimated root area (ERA) explained the most variance in TC, TCI and UTH (Table 1). The second most informative RUSI parameter appeared to be STRC. Many of the RUSI parameters had significant correlations with TC, TCI and UTH, but lower R^2 values. The RUSI parameter that appeared to be least informative for urban tree performance was GDD. The principal component analysis also found ERA and STRC to be important properties in the RUSI model (Appendix, Table A10). The first principal component explained 33% of the variance in the urban tree performance metrics, RUSI model and parameters data set. The five eigenvectors with the most influence on the first principal component were RUSI, TCI, ERA, STRC and WAS.

Table 1

R^2 and *P*-values ($P < 0.0001$***; $P < 0.01$ to 0.0001**; $P < 0.05$ to 0.01*) for linear regression models for RUSI parameters and tree condition (TC), tree condition index (TCI) urban tree health (UTH), DBH/age, mean annual increment (MAI) and recent annual increment (RAI). Data from Boston, MA, Chicago, IL, Cleveland, OH, Springfield, MA and Toledo, OH (N = 200).

RUSI parameter	TC (0–3)	TCI (0–100)	UTH (0–100)	DBH/age (cm yr^{-1})	MAI (mm yr^{-1})	RAI (mm yr^{-1})
PPT (0–3)	0.12***	0.14***	0.08**	0.01	0.01	0.04*
GDD (0–3)	0.00	0.00	0.00	0.00	0.00	0.00
EXP (0–3)	0.08**	0.07**	0.06**	0.01	0.00	0.02
TRAF (0–3)	0.02	0.03*	0.03*	0.01	0.01	0.00
INFR (0–3)	0.14***	0.22***	0.16***	0.01	0.01	0.08**
SURF (0–3)	0.09**	0.21***	0.13***	0.00	0.00	0.00
TEXT (0–3)	0.01	0.06**	0.05*	0.00	0.00	0.00
STRC (0–3)	0.18***	0.25***	0.19***	0.01	0.01	0.03*
PEN (0–3)	0.00	0.07**	0.03*	0.00	0.00	0.00
pH (0–3)	0.00	0.00	0.00	0.00	0.00	0.00
EC (0–3)	0.00	0.00	0.00	0.02	0.01	0.01
SOM (0–3)	0.09**	0.16***	0.12***	0.00	0.02	0.03*
ERA (0–3)	0.23***	0.41***	0.29***	0.01	0.01	0.05*
AHOR (0–3)	0.04	0.11***	0.06*	0.00	0.00	0.01
WAS (0–3)	0.10	0.18***	0.13***	0.02	0.01	0.04*

Finding ERA, STRC and WAS to have high importance in the RUSI model is not surprising given primary constraints on urban tree health are limited soil volumes and compaction (Jim, 1998). The belowground growing space is known to be a major factor driving site quality and urban tree performance. Increasing rooting volumes has been an emphasis in urban tree research for more than 25 years (Grabosky and Bassuk, 1995; Smiley et al., 2006). Both STRC and WAS integrate physical, chemical and biological soil properties, which are defining attributes of highly effective soil quality indices (Doran and Parkin, 1994). Both STRC and WAS relate the effects of compaction, biological activity and soil chemistry. Compaction is a major constraint to urban tree health (Jim, 1993; Day and Bassuk, 1994; Scharenbroch and Watson, 2014). The loss of soil structure and water-stable aggregates that results from compaction creates physical barriers for root growth and negatively affects pore space dynamics in soils. Trees struggle in compacted soils due to low oxygen contents from the loss of macropore spaces (Watson and Kelsey, 2006). Aggregation and soil structure are created or restored through biological (root and microbial activity), chemical (cation and clay bridging) and physical (freeze-thaw, shrink-swell) processes (Harris et al., 1966).

Further evaluation of the RUSI model is necessary to see if weighting factors should be included and parameter scoring functions can be revised to better predict urban tree performance. Weighting would place more emphasis on factors like ERA, STRC and WAS; and, less emphasis on factors like GDD. Prior to applying weighting factors, it will be necessary to evaluate the RUSI model in more cities and with more urban tree species. RUSI parameters appearing to have less importance like GDD might be improved to better relate urban tree performance. The data range for GDD in these five cities was too narrow (Appendix, Table A7), as all 200 plots received a GDD score of 2. Future research should also examine the breakpoints in the scoring function of GDD to better represent the range of this parameter for urban trees. The scores for pH and EC ranged from 0 to 3, but the range in raw data for

Table 2
P-values and R^2 values for linear regression models for rapid urban site index (RUSI), SOIL and RUSI + SOIL and metrics of urban tree performance and tree condition (TC), tree condition index (TCI), urban tree health (UTH), diameter at breast height (DBH) by age, mean annual increment (MAI) and recent (last 10 years) annual increment (RAI). Data from Boston, MA, Chicago, IL, Cleveland, OH, Springfield, MA and Toledo, OH (N = 200).

Variable (y)	RUSI		SOIL		RUSI + SOIL	
	P-value	R^2	*P*-value	R^2	*P*-value	R^2
TC (0–3)	< 0.0001	0.18	< 0.0001	0.17	< 0.0001	0.29
TCI (0–100)	< 0.0001	0.40	< 0.0001	0.22	< 0.0001	0.45
UTH (0–100)	< 0.0001	0.28	0.0003	0.15	< 0.0001	0.33
DBH/age (cm yr^{-1})	0.4086	0.00	0.8868	0.03	0.9348	0.03
MAI (mm yr^{-1})	0.5700	0.00	0.3019	0.06	0.3896	0.06
RAI (mm yr^{-1})	0.0118	0.03	0.0184	0.10	0.0434	0.11

these values was narrow for these five cities.

3.3. Additional soil analyses do improve RUSI, but it might not be worth the effort

Additional laboratory analyses marginally improve the ability of the RUSI model to predict urban tree performance (Table 2). The soil laboratory analyses tested to improve the RUSI model (RUSI + SOIL) included soil moisture (GSM), pH, electrical conductivity (EC), extractable phosphorus (P), total nitrogen (N), soil organic carbon (SOC), soil C/N, total organic matter (SOM), particulate organic matter (POM) and microbial biomass C (MBC). These ten soil properties were selected since they are the chemical, physical and biological soil properties most often included in soil quality assessments (Doran and Parkin, 1994; Doran et al., 1996). The RUSI model was a better predictor of urban tree performance compared to the ten soil properties alone. Adding the ten soil properties to the RUSI model explained an additional 2–9% of the variance in urban tree performance metrics.

Although adding the soil properties improved the RUSI model, the soil analyses come with an additional cost and effort. The RUSI model is a field-based assessment tool and the average time to complete the assessment on a site was 4.7 min (Appendix, Table A7). Adding soil laboratory analyses to the RUSI model will require users to spend additional time collecting soil samples in the field and spending money to have the samples processed by a laboratory. On average, the additional time to collect the soil samples was 4.2 min. Costs for the laboratory analyses might range from approximately $25 to $100 US D per sample. A major advantage of the RUSI model is that it is field-based and low cost. Consequently, the additional soil laboratory analyses do not appear to be merited given the minimal improvement in the model's ability to predict urban tree performance.

3.4. Field assessments for RUSI are accurate

Field assessments were found to correlate with laboratory techniques. Soil organic matter and SOC were significantly correlated with SOM assessed by color and scored in the RUSI model (SOM% = 20.6 + 21.7*RUSI-SOM; $R^2 = 0.16$; $P < 0.0001$) (SOC% = 3.0 + 0.56*RUSI-SOM; $R^2 = 0.04$; $P = 0.0010$). Soil pH measured in the laboratory was significantly correlated with soil pH assessed in the field scored in the RUSI model (pH = 8.0–0.55*RUSI-pH; $R^2 = 0.20$; $P < 0.0001$). Soil EC measured in the laboratory was significantly correlated with soil EC assessed in the field and scored in the RUSI model (EC = 77–33*RUSI-EC; $R^2 = 0.19$; $P < 0.0001$). Other researchers have been able to correlate rapid field methods with laboratory analyses. Konen et al. (2002) used soil value (lightness and darkness) to predict organic matter contents of soils in north-central USA.

Wet-aggregate stability measured in the laboratory did not significantly correlate with WAS assessed in the field and scored in the RUSI model ($R^2 = 0.00$; $P = 0.7855$). However, WAS assessed in the field and scored in the RUSI model did correlate with microbial biomass C (MBC = 74 + 113*RUSI-WAS; $R^2 = 0.19$; $P < 0.0001$) A. and soil N (N% = 0.14 + 0.04*RUSI-WAS; $R^2 = 0.09$; $P < 0.0001$). The field-WAS measurement is intended to be an indicator of soil biological activity, so these correlations confirm its usefulness. Future RUSI work should be directed at improving the WAS field assessment so that it correlates well with the accepted laboratory procedure. Methodological improvements may include changing the soak and swirl intervals and refining the scoring function intervals since the WAS score distribution was slightly skewed to the right. Capillary wetting might also be considered to limit disturbance created by rapid wetting of soil aggregates (Beare and Bruce, 1993).

3.5. Additional training may be required for RUSI users

More extensive training is required for additional users to use the RUSI model to assess quality of the urban tree planting sites. The results from two pilot projects were used to make this conclusion.

The first pilot test found that one-hour of training was not sufficient to utilize the RUSI model. There were no significant relationships for the RUSI model and urban tree performance metrics in this pilot test (Table 3). The users in this pilot test were given a one-hour field training and instructed to exclude RUSI parameters that they did not feel comfortable in accurately assessing. Most often the users excluded soil TEXT, STRC and WAS, two of which were found to be important RUSI parameters for predicting urban tree performance. It is likely that by excluding these important RUSI parameters, the model's ability to predict urban tree performance was substantially reduced.

The second pilot test found evidence that six hours of training may be sufficient for users to accurately apply the RUSI model. The RUSI model significantly correlated with both tree metrics measured in this pilot test (Table 4). Tree species and tree size diversity in this pilot test likely contributed to the loss of RUSI accuracy to predict urban tree performance. Correlations between the RUSI model and urban tree performance were high with certain genera and also certain size classes and weak with others. Correlations were greater with *Tilia* (TCI = 15 + 0.88*RUSI; $R^2 = 0.19$; $P = 0.0234$) compared to *Acer* (TCI = 48 + 0.31*RUSI; $R^2 = 0.01$; $P = 0.2313$). Correlations were greater with the larger trees (> 30 cm DBH) (TCI = 27 + 1.5*RUSI; $R^2 = 0.36$; $P < 0.0001$) compared to smaller trees (< 30 cm DBH) (TCI = 44 + 0.36*RUSI; $R^2 = 0.02$; $P = 0.0075$). In this pilot test the RUSI model appears to show some sensitivity to species and age with larger trees and *Tilia* being more sensitive to site quality compared to smaller trees and *Acer*.

The results of these two pilot tests suggest that more than one hour of field training must be offered for users to successfully apply the RUSI model. Results from study utilizing a similar demographic to collect urban tree data found that training sessions of six to seven hours were also required for accurate data (Roman et al., 2017). The premise that

Table 3
Linear regression models, *P*-values and R^2 values for rapid urban site index (RUSI) and tree condition (TC), tree condition index (TCI), urban tree health (UTH), diameter at breast height (DBH) by age, mean annual increment (MAI) and recent (last 10 years) annual increment (RAI). Data from pilot test one with minimally-trained users in Chicago, IL, Ithaca, NY and New York City, NY (N = 100).

Variable (y)	*P*-value	R^2	Fit y by x
TC (0–3)	0.9341	0.00	Not significant
TCI (0–100)	0.9288	0.00	Not significant
UTH (0–100)	0.1527	0.03	Not significant
DBH/age (cm yr^{-1})	0.5926	0.00	Not significant
MAI (mm yr^{-1})	0.0952	0.04	Not significant
RAI (mm yr^{-1})	0.0790	0.04	Not significant

Table 4
Linear regression models, *P*-values and R^2 values for rapid urban site index (RUSI) and tree condition (TC) and tree condition index (TCI). Data from pilot test two with users receiving six hours of training in Stevens Point, WI (N = 360).

Variable (y)	*P*-value	R^2	Fit y by x
TC (0–3)	0.0174	0.02	TC = 1.4 + 0.011*RUSI
TCI (0–100)	< 0.0001	0.05	TCI = 35 + 0.51*RUSI

certain parameters may be excluded from the RUSI model based on the user's skill is not supported. It appears that all, or at least specific highly-important parameters (ERA, STRC and WAS) must be assessed for the RUSI model to accurately predict urban tree performance. Future work on the RUSI model will include developing training workshops, more detailed instruction manuals to be complimented by online videos and tutorials.

4. Conclusion

For an urban site index to have value for urban forestry and arboriculture it must be practical and accurate. Practical considerations include the time and expertise required to use the tool. The RUSI model is a relatively simple, field-based and rapid tool to evaluate urban planting sites. Accuracy pertains to how effective the tool is at categorizing sites for urban tree performance. The current RUSI model can accurately predict urban tree health, but some improvements are necessary. Specifically, more effective and efficient training methods need to be developed for the RUSI model. Most potential RUSI users have minimal training in soil assessment, so these field evaluation techniques should be the focus of training materials.

Future research efforts on the RUSI model should be directed towards the following four objectives. First, the efficacy of new training methods with other users needs to be tested. Secondly, the geographic range and species palate needs to be expanded upon to see if RUSI will predict urban tree performance more broadly than has been tested in the current study. Thirdly, the potential of other data sources should be examined for utilization in the RUSI model. For example soil surveys in urban areas might have useful information for a tree site index. In the United States, a few major urban areas (e.g., New York City, Baltimore) have been mapped or partially mapped by National Resources Conservation Service (USDA-NRCS, 1998, 2005). This mapping includes accessible databases on soil physical and chemical properties (e.g., texture, pH, cation exchange capacity, organic matter), which might be useful in the RUSI model. However, most urban areas in United States are not currently mapped and is it unknown if these maps would provide useful data at the mapped scale (1:24,000) for this application. Furthermore, this data is not available for urban areas outside of the United States. Lastly, the RUSI might relate other functions aside from urban tree performance and future research might look to evaluate RUSI for these additional functions.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ufug.2017.08.017.

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