TOWARD AN IMPROVED RAPID URBAN SITE INDEX

By

Luke L. Scheberl

A Thesis

Submitted in partial fulfillment of the

requirements of the degree

MASTER OF SCIENCE
IN
NATURAL RESOURCES
(Soil Science)

College of Nature Resources

UNIVERSITY OF WISCONSIN
Stevens Point, Wisconsin

May 2018

APPROVED BY THE GRADUATE COMMITTEE OF:

Dr. Bryant C. Scharenbroch, Committee Chairman
Assistant Professor of Soil Science

Dr. Jacob R. Prater
Associate Professor of Soil Science

Dr. Les P. Werner
Professor of Forestry

ABSTRACT

The ability of the rapid urban site index (RUSI) model to predict urban tree health was tested in three cities in Wisconsin, USA. While the RUSI model was found to significantly correlate to tree growth and health (P = <0.01; R^2 = 0.09-0.10), it did so while explaining less variation than the previous study (P = <0.0001; R^2 = 0.18-0.40). To increase the strength of this correlation, weighting schemes on RUSI parameters were investigated but resulted in no significant correlation with tree performance. The RUSI models' sensitivity to the application of biosolids was also tested. To increase this sensitivity, four different labile organic carbon assessments were added. Only the RUSI + permanganate oxidizable carbon model showed a significant mean change as a result of the soil amendment application (P = 0.04; F = 3.47). Future research should continue to expand the models geographic extent and tree species evaluated as well as investigate other potential parameters to aid in identifying site quality.

This thesis continues with an evaluation of popular low-cost soil pH and moisture field sensors. Twenty-two soil pH and moisture sensors were tested for their ability to accurately and precisely measure soil pH, volumetric soil moisture content (VMC), or both. This research was conducted on four different soil texture classes (loamy sand, sandy loam, clay loam, and clay) at three different moisture levels (air dry, ≈ 0.5 field capacity, and ≈ field capacity). Glass-electrode pH sensors measuring a 1:2 (soil:deionized water) solution were found to be both accurate and precise (P = <0.0001; ρ_c = >0.95). However, metal electrode sensors inserted into the soil had no significant correlation to soil pH levels (P = >0.1; ρ_c = <0.2). When selecting a soil pH sensor, measurement method may be the most important variable. Soil VMC sensors performed

best when measuring time domain reflectometry and frequency domain reflectometry (P = <0.0001; ρ_c = >0.76). Sensors measuring electrical conductivity were highly variable in cost, accuracy, and precision. When selecting a soil VMC sensor, measurement method and cost are both important variables. These field sensors may improve urban site management and could lead to the addition of an available water holding capacity parameter to the RUSI model.

ACKNOWLEDGMENTS

My most sincere thanks goes to Dr. Bryant Scharenbroch who provided constant motivation and countless hours of guidance and feedback. The knowledge and skills he has helped me gain are priceless.

Special thanks to my graduate committee members, Dr. Les Werner and Dr. Jacob Prater, for their time, availability, and guidance. To Alyssa Gunderson for her field, life, and laboratory assistance throughout this research, as well as all of the other staff and students within the College of Natural Resources at UWSP.

Lastly, I want to thank my family for their support, my parents, John and Marla, for a lifetime of outdoor exploring and interest as well as for the free childcare. To my son, Charlie, for his love and for reminding me of what is most important in life. Finally and most importantly, thank you to my wife, Jenny, who agreed to take on this endeavor with me and for all of her love and support throughout our lives.

Table of Contents

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

INTRODUCTION

1.1 INTRODUCTION

Arborists and urban foresters need an efficient tool to assess site conditions and observe the effectiveness of soil amendments. To address this need, the rapid urban site index (RUSI) was developed by Scharenbroch et al. (2017). This research found the RUSI model to accurately predict tree health but suggested continued development to improve the model. Development suggestions included testing the model in new geographical areas and spatial scales as well as the exploration of parameter weighting and the introduction of new parameters to improve the model's correlation with tree performance.

This thesis seeks to address these suggestions and includes an evaluation of the RUSI model in three communities in Wisconsin as well as assessing weighting schemes. Also tests was the addition of a labile organic carbon parameter on the models ability to predict tree performance and sensitivity to an organic soil amendment. A pilot study on the development of a field method for the evaluation of plant available water is then presented. Finally, field sensors were evaluated for their ability to accurately and precisely measure soil pH and/or soil moisture in an attempt to identify sensors for use in an urban site assessment. Accurate assessments may allow arborists and urban foresters to identify and address site quality concerns, thereby improving the health and sustainability of the urban forest. A site index tool may also be used to increase tree species diversity and individual tree performance. The rest of the introduction section provides a literature overview supporting the need for this research as well as providing the current knowledge on the topic.

1.2 URBAN FORESTS IMPORTANCE

1.2.1 Urban Tree Health and Growth

Reduced urban forest populations and species diversity is often a result of poor tree that can result in decreased community benefits (Thompson et al., 2009; Blood et al., 2016). The benefits of urban trees are maximized when they are allowed to reach maturity and beyond (Roy et al., 2012). Nowak (1994) found that tree diameter at breast height was correlated to a trees ability to remove air particulates and that large trees (>77 cm) removed approximately 60-70 times the air pollutants of small trees (<8 cm). These larger species can only provide increased environmental and economic benefits when located on sites that allow them to reach maturity and maximize their genetic potential (Subburayalu and Sydnor, 2012). Genetic potential is often unrealized in poor urban site conditions that result in reduced tree performance (Roman and Scatena, 2011; Koeser et al., 2013). Tree performance includes growth, both primary and secondary, as well as health which is defined as the ability to resist strain (Shigo, 1986). Urban forest benefits may be increased with site quality management that promotes tree survival and longevity while also aiding in diversifying species selection.

1.2.2 Urban Forest Diversity

Urban forest diversity may be limited due to the negative effects that urban development and maintenance can have on site a sites ability to support healthy trees. This urbanization alters native forest species resulting in changes in the soil characteristics (Whittaker et al., 2001; Clarke et al., 2013) resulting in alterations to the structure and composition of these forests (Wear, 2013). These alterations may result in decreased tree species diversity and may make urban forests more susceptible to losses from pest and pathogen outbreaks (Raupp et al., 2006). For example, limited diversity in New York City, NY and Chicago, IL, combined with the potential infestation of just a single species of beetle (*Anoplophora glabripennis*), could result in 12-61% canopy loss at a cost of $72 million-$2.3 billion (Nowak et al., 2001). Koeser et al. (2013) suggest that a site index that maximized tree longevity would improve species diversity by increasing selection option and limiting tree loss. Such a site index could also aid in managing urban site limitations and the urban forest.

1.3 URBAN SITE CONSIDERATIONS

1.3.1 Site Factor Limitations of the Urban Forest

Many urban site characteristics affect tree performance including climate, urban, soil physical, soil chemical, and soil biological factors. Urban development and maintenance modify these factors creating unique and variable microclimates throughout the landscape (Arnfield, 2003). Construction activities like cutting, filling, and grading can alter the native soils and increase urban heterogeneity (Effland and Pouyat, 1997; De Kimpe and Morel, 2000). In order to assess these alteration, soil forming factors need to be considered on a much smaller scale (Pickett and Cadenasso, 2009). An urban site index could use these site characteristics to address the high levels of heterogeneity and identify site quality and improve it to promote for tree health.

1.3.2 Climate Influence

Important climate considerations for urban trees include solar radiation, temperature, and precipitation. Solar radiation is positively correlated with tree leaf nutrient content and photosynthesis (Field, 1983). Photosynthetic rates are also affected by air temperature (Schwarz et al., 1997). They are generally positively correlated however; very high temperatures may cause a reduction in photosynthesis and therefore tree growth (Cregg and Dix, 2001). The impact of temperature on growth rate can be estimated using growing degree days. Growing degree days (GDD) are calculated by subtracting the mean daily temperature from the base temperature needed for growth of the tree ($GDD = (T_{max} + T_{min}) / 2 - T_{base}$) (Prentice et al., 1992). Soil moisture is also important for photosynthesis, with rates decreasing under drought conditions as trees close their stomata to conserve water (Flexas and Medrano, 2002). Too much water may also reduce growth as saturated soils can limit the amount of oxygen available for root respiration (Percival and Keary, 2008). Urban trees with a proper balance of moisture, sunlight, and temperature can be expected to be healthier and survive longer.

Climate factors may be highly altered in urban settings. Temperatures within urban areas can be elevated due to the urban heat island effect (Oke, 1995). Tall buildings increase this effect as well as influence weather patterns and may shade urban trees (Arnfield, 2003). Altered weather patterns and limited water infiltration can result in flooding in some areas while others nearby remain dry (Smith et al., 2005). Due to this increased variability, these climate factors need to be assessed at individual planting sites.

1.3.3 Anthropogenic Influence

Human activities such as vehicle traffic, infrastructure development, and surface vegetation management, alter urban tree performance. Streets with curbs reduce water infiltration by directing surface water to storm sewers, altering drainage patterns (Arisz and Burrell, 2006). These alterations may limit soil moisture resulting in decreased microbial activity and nutrient uptake resulting in decreased tree performance (Stark and Firestone, 1995). However, human activities such as organic mulch additions can improve site quality by increasing the soil carbon content (Bronick and Lal, 2005) in addition to stabilizing soil temperature and moisture (Chalker-Scott, 2007).

Pickett and Cadenasso (2009) theorize that within a city, soil characteristics and function may follow the same spatial heterogeneity as land use. Many urban land uses, such as transportation and infrastructure, can result in surface alteration such as sealing of the soil surface resulting in decreased plant available water (Pickett and Cadenasso, 2009). Other uses, such as high traffic roads, may result in nutrient and salt deposition and microbial activity rates, altering plant nutrient availability (Pickett and Cadenasso, 2009). These human activities need to be accurately assessed at each planting site to improve urban tree and forest management.

1.3.4 Soil Physical Factors

Important soil physical factors for tree performance include texture, compaction, and structure. Soil texture influences the availability of water, air, and nutrients (Saxton et al., 1986; Kaiser et al., 1992). Coarse-textured soils have reduced water holding and cation exchange capacity often resulting in low nutrient storage and availability (Saxton et al., 1986). Fine-textured soils hold more water and nutrients but are more sensitive to compaction (Patterson, 1977). Compaction alters soil structure resulting in increased bulk density that limits tree root penetration (Kozlowski, 1999).

Physical parameters are often altered during urban development, which may limit a site's ability to support trees. Construction often requires soils to be compacted, which increase their strength and provides proper load bearing of buildings (Scharenbroch and Watson, 2014). The rate of this compaction can be variable based on the machinery used as well as the soil moisture and texture conditions, resulting in the increased heterogeneity of developed areas (Watson et al., 2014). To improve a sites quality, different construction materials, such as manufactured soils, may be used to support infrastructure while maintaining soil structure and increasing plant performance (Smiley et al., 2006). A site's physical soil factors may vary widely based on the type of development and management requiring them to be included in a urban site assessment.

1.3.5 Soil Chemical Factors

Soil chemical factors such as electrical conductivity (EC), pH, and organic matter play an important role in the availability of water and nutrients. Soil EC is related to the total amount of cations and anions in the soil and may also indicate soil salinity and nutrient availability (Smith et al., 1996). Increased soil salinity often adversely affects soil structure resulting in decreased plant available water and tree performance (Hootman et al., 1994). Tree performance is also influenced by soil pH due to its influence on all soil physical, chemical, and biological properties (Brady and Weil, 2002) One specific example is soil pH's importance in the availability of essential nutrients with ideal values being between 6 and 7 pH units (Thomas, 1996). High and low levels of soil pH may result in decreased tree performance due to limitations or toxic levels of certain elements in the soil solution (Brady and Weil, 2002). Both soil pH and EC may be influenced by the addition of organic matter, which stimulates biological activity as well as increasing the total soil carbon content. Organic matter serves to hold moisture as well as fuel biological activity, which provides and holds nutrients while aiding in soil structure creation (Sikora et al., 1996). Soil chemical factors impact tree growth and health and are necessary parameters for predicting site quality.

Soil chemical properties are often variable in urban landscapes as a result of anthropogenic parent material and management practices. The weathering of manmade materials may result in elevated soil pH in urban areas (Watson et al., 2014). Heavily managed urban areas may also experience changes in pH related to the removal of plant litter, decreased soil organic matter levels, and improper irrigation (Craul, 1999). On the other hand, proper management including the application of compost, mulch, and proper irrigation will elevate soil organic matter content (Scharenbroch and Watson, 2014). Irrigation may also affect soil chemistry depending on the salinity and application rate of the irrigation water (Watson et al., 2014). Soil chemical parameters greatly affect the availability of plant nutrients and are required when predicting tree performance.

1.3.6 Soil Biological Factors

Urban development may limit biological activity by decreasing the soil volume and altering aggregation. Urban planting beds may have a limited soil volume and are often confined by impervious surfaces (Sanders and Grabosky, 2014). Impervious surfaces can alter biological activity resulting in decreases in soil aggregate strength (Loch, 1994).

Weak aggregates may further degrade causing a decrease in water infiltration, soil aeration, and root growth (Nimmo and Perkins, 2002). The destruction of aggregates within an already limited soil volume further reduces tree root growth and performance.

Soil biological properties are highly variable within urban communities. Urban development, including the installation and repair of infrastructure, often requires vegetation, organic matter (O horizon) and topsoil (A horizon) removal (Randrup et al., 2001; Scharenbroch and Watson, 2014). The removal, handling, and reapplication of this material can greatly reduce soil aggregation resulting in soil degradation and decreased site quality (Bronick and Lal, 2004). This decrease is also a result of the complete removal of the O horizon and reduction of the A horizon, which alters soil properties and reduces soil organic contents (Scharenbroch and Watson, 2014). Methods of urban development and time since repair are highly variable resulting in a patchwork of soil quality within urban areas (Pickett and Cadenasso, 2009). A site quality index would allow frequent observation of these important and highly variable factors to maximize tree performance.

1.4. SITE INDICES

1.4.1 Site Index Benefits

Site indices are used to characterize the quality of a site for a specific function such as plant productivity or yield. Site assessment tools have been developed for use in agriculture (Doran and Parkin, 1994) and rural forestry (Schoenholtz et al., 2000). Agronomic indices score site indicators and rate current conditions for their ability to support crops (Idowu et al., 2009). Forest indices are used to identify the growth potential for a given species at a given age (Schoenholtz et al., 2000). These tools may have limited usefulness in urban landscapes because of unique urban site conditions, high levels of heterogeneity, and differences in plant type and species (Rahman et al., 2014).

Urban sites often suffer from poor site conditions, although a wide range of site qualities exists (Scharenbroch and Catania, 2012). Variability in site quality may be addressed by maintaining a diverse urban forest, as a tree's species can influence its ability to adapt to site conditions found in urban areas (Bassuk, 2003; Sjöman and Nielsen, 2010). Managers with knowledge of existing conditions can better match species to planting sites increasing urban forest health, as well as aiding in the introduction of new tree species to match site conditions as well as diversify our urban forests.

1.4.2 Current Urban Site Indices.

There have been many efforts to create an urban site index including the Ohio urban site index (Siewert and Miller, 2011), the site quality index (Scharenbroch and Catania, 2012), and the rapid urban site index (Scharenbroch et al., 2017). These models were specifically developed to relate urban site conditions to tree performance making them more suitable for urban tree planning. Urban tree species selection guides (e.g. the Virginia urban tree selector, Cornell woody plant database) have also been developed. However, these tools have limited geographical application and focus more on simply matching tree species by mature height or growth form as well as current conditions such as sun exposure and USDA hardiness zone. For that reason, the focus of this thesis on urban site indices that attempt to quantitatively identify site quality and may also be used for site quality management.

1.4.3 The Ohio Urban Site Index

The USI model, developed by the Ohio Division of Forestry, is based on scores from soil and street factors (Fig. 1.1) (Siewert and Miller, 2011). Soil factors include vegetation, compaction, probe penetration, and soil development. Street factors include speed limit, number of lanes, availability of parking, and length between stop signs. This model is field-based and user-friendly, but its accuracy to detect urban tree performance has not been tested outside of Ohio, USA.

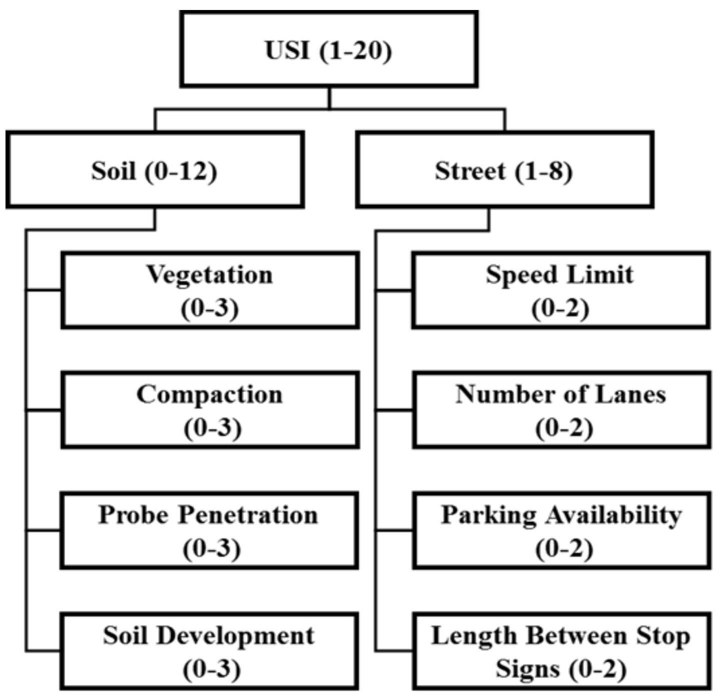


Fig. 1.1. Factors and parameters for the urban site index (USI) model.

1.4.4 Site Quality Index

Scharenbroch and Catania (2012) identified soil factors with the greatest influence on urban tree performance. Soil factors included in the soil quality index were texture, aggregation, bulk density, pH, electrical conductivity, and organic matter. This index was significantly correlated to tree height, canopy density, leaf chlorophyll content, and tree condition index. However, the number of variables and lab techniques required limit the practicality and accessibility of this model. The geographical extent of this study was also limited and the model has not been tested outside of DuPage County, IL USA.

1.4.5 Rapid Urban Site Index

To address the need for accuracy and practicality in an urban site index, previous urban and rural indices were combined to create the rapid urban site index (RUSI) model (Scharenbroch et al., 2017). The RUSI model contains five factors each with three parameters (Fig. 1.2). Each of these parameters is given a score of 0-3 based on field observations. Scores are then summed, divided by the maximum possible value, and multiplied by 100 to provide the final score. The RUSI model is a practical assessment tool that has been found to correlate with urban tree health (Scharenbroch et al., 2017).

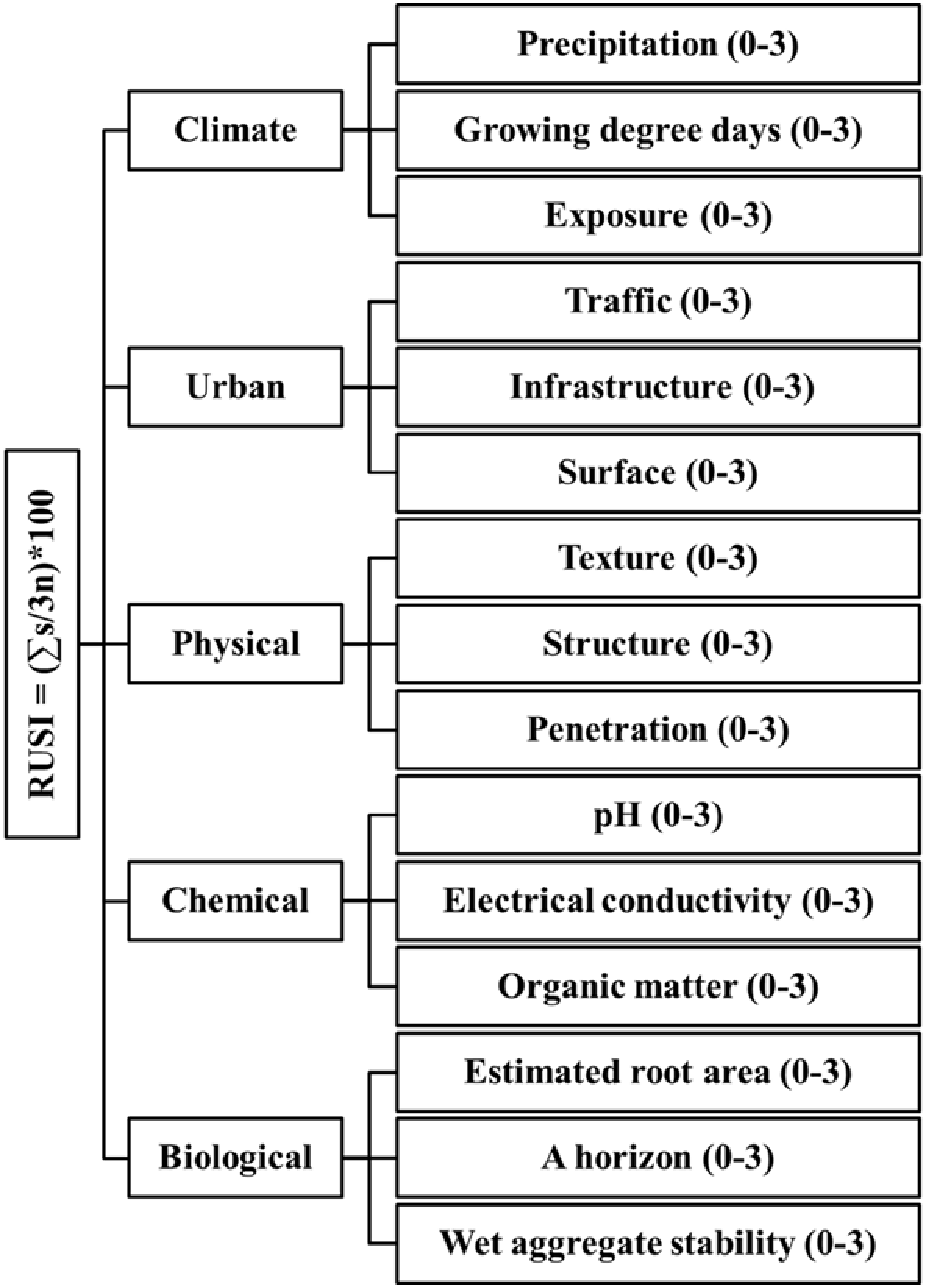


Fig. 1.2. Factors and parameters for the rapid urban site index (RUSI) model.

1.5 SUMMARY

The urban forest performs many important ecosystem services. To maximize these services, urban forests should be made up of diverse species and individual trees should be managed for health and longevity. To achieve this, urban forest managers need an urban site index that can quickly and accurately assess the quality of planting sites. Previous attempts at an urban site index were either too simplistic or overly complicated. A new site index, the rapid urban site index (RUSI) model, was created to address these shortcomings.

This thesis includes continued evaluation of the RUSI models' ability to predict urban tree performance within Wisconsin, USA, as well as testing its responses to soil management. Also evaluated are the effects of weighting RUSI parameters, the addition of a labile organic carbon parameter, and the exploration of a field evaluation of plant available water. Lastly, multiple field sensors were evaluated for their ability to accurately and precisely measure soil pH and/or soil moisture in an attempt to identify sensors for use in an urban site assessment. Accurate assessments may allow managers to identify and address site quality concerns, improving their ability to manage the urban forest. A site index tool may then be used to increase species diversity and individual tree performance.

1.6 REFERENCES

Arnfield, A.J., 2003. Two decades of urban climate research: A review of turbulence, exchanges of energy and water, and the urban heat island. International Journal of Climatology 23, 1-26.

Arisz, H., Burrell, B., 2006. Urban drainage infrastructure planning and design considering climate change. 2006 IEEE EIC Climate Change Conference 1-9.

Bassuk, N., 2003. Recommended urban trees: Site assessment and tree selection for stress tolerance. Cornell University, Urban Horticulture Institute.

Blood, A., Starr, G., Escobedo, F., Chappelka, A., Staudhammer, C., 2016. How do urban forests compare? Tree diversity in urban and periurban forests of the southeastern US. Forests 7, 1-15.

Brady, N.C. and Weil, R.R., 2010. Elements of the nature and properties of soils. Pearson Educational International.

Bronick, C.J., Lal, R., 2005. Soil structure and management: A review. Geoderma 124, 3-22.

Chalker-Scott, L., 2007. Impact of mulches on landscape plants and the environment - A review. Journal of Environmental Horticulture 25, 239-249.

Clarke, L.W., Jenerette, G.D., Davila, A., 2013. The luxury of vegetation and the legacy of tree biodiversity in Los Angeles, CA. Landscape and Urban Planning 116, 48-59.

Cregg, B.M., Dix, M.E., 2001. Tree moisture stress and insect damage in urban areas in relation to heat island effects. Journal of Arboriculture 27, 8-17.

Craul, P.J., 1999. Urban soils: applications and practices. John Wiley and Sons. Hoboken, NJ.

De Kimpe, C.R., Morel, J.L., 2000. Urban soil management: A growing concern. Soil Science 165, 31-40.

Doran, J.W., Parkin, T.B., 1994. Defining and assessing soil quality. Defining soil quality for a sustainable environment, Soil Science Society of America, pp.1-21.

Effland, W.R., Pouyat, R.V, 1997. The genesis, classification, and mapping of soils in urban areas. Urban Ecosystems 1, 217-228.

Field, C., 1983. Allocating leaf nitrogen for the maximization of carbon gain: Leaf age as a control on the allocation program. Oecologia 56, 341-347.

Flexas, J., Medrano, H., 2002. Drought-inhibition of photosynthesis in C3 plants: Stomatal and non-stomatal limitations revisited. Annals of Botany 89, 183-189.

Hootman, R.G., Kelsey, P.D., Reid, R., Von Der Heide-Spravka, K., 1994. Factors affecting accumulation of deicing salts in soils around trees. Journal of Arboriculture 20, 196.

Idowu, O.J., Van Es, H.M., Abawi, G.S., Wolfe, D.W., Schindelbeck, R.R., Moebius-Clune, B.N., Gugino, B.K., 2009. Use of an integrative soil health test for evaluation of soil management impacts. Renewable Agriculture and Food Systems 24, 214-224.

Kaiser, E.A., Mueller, T., Joergensen, R.G., Insam, H., Heinemeyer, O., 1992. Evaluation of methods to estimate the soil microbial biomass and the relationship with soil texture and organic matter. Soil Biology and Biochemistry 24, 675-683.

Koeser, A., Hauer, R., Norris, K., Krouse, R., 2013. Factors influencing long-term street tree survival in Milwaukee, WI, USA. Urban Forestry and Urban Greening 12, 562-568.

Kozlowski, T.T., 1999. Soil compaction and growth of woody plants. Scandinavian Journal of Forest Research 14, 596-619.

Loch, R.J., 1994. A method for measuring aggregate water stability of dryland soils with relevance to surface seal development. Soil Research 4, 687-700.

Nimmo, J.R., Perkins, K.S., 2002. Aggregate stability and size distribution. Methods of soil analysis. Part 4-Physical methods. Soil Science Society of America, pp. 317-328.

Nowak, D.J., 1994. Air pollution removal by Chicago's urban forest. Chicago's urban forest ecosystem: Results of the Chicago urban forest climate project, pp. 63-81.

Nowak, D.J., Pasek, J.E., Sequeira, R.A., Crane, D.E., Mastro, V.C., 2001. Potential effect of *Anoplophora glabripennis* (Coleoptera: Cerambycidae) on urban trees in the United States. Journal of Economical Entomology 94, 116-122.

Oke, T., 1995. The heat island of the urban boundary layer: characteristics, causes and effects. Wind climate in cities. Springer, Dordrecht, pp. 81-107.

Patterson, J.C., 1977. Soil compaction - Effects on urban vegetation. Journal of Arboriculture 3, 161-167.

Percival, G.C., Keary, I.P., 2008 The influence of nitrogen fertilization on waterlogging stresses in *Fagus sylvatica* L. and *Quercus robur* L. Arboriculture and Urban Forestry 34, 29-39.

Pickett, S.T.A., Cadenasso, M.L., 2009. Altered resources, disturbance, and heterogeneity: A framework for comparing urban and non-urban soils. Urban Ecosystems 12, 23-44.

Prentice, I.C., Cramer, W., Harrison, S.P., Leemans, R., Monserud, R.A., Solomon, A.M., 1992. A global biome model based on plant physiology and dominance, soil properties and climate. Journal of Biogeography 19, 117-134.

Rahman, M.A., Armson, D., Ennos, A.R., 2014. Effect of urbanization and climate change in the rooting zone on the growth and physiology of *Pyrus calleryana*. Urban Forestry and Urban Greening 13, 325-335.

Randrup, T.B., McPherson, E.G., Costello, L.R., 2001. A review of tree root conflicts with sidewalks, curbs, and roads. Urban Ecosystem 5, 209-225.

Raupp, M.J., Cumming, A.B., Raupp, E.C., 2006. Street tree diversity in eastern North America and its potential for tree loss to exotic borers. Arboriculture and Urban Forestry 32, 297-304.

Roman, L.A., Scatena, F.N., 2011. Street tree survival rates: Meta-analysis of previous studies and application to a field survey in Philadelphia, PA, USA. Urban Forestry and Urban Greening 10, 269-274.

Roy, S., Byrne, J., Pickering, C., 2012. A systematic quantitative review of urban tree benefits, costs, and assessment methods across cities in different climatic zones. Urban Forestry & Urban Greening 4, 351-363.

Sanders, J.R., Grabosky, J.C., 2014. 20 years later: Does reduced soil area change overall tree growth? Urban Forestry and Urban Greening 13, 295-303.

Saxton, K.E., Rawls, W., Romberger, J.S., Papendick, R.I., 1986. Estimating generalized soil-water characteristics from texture. Soil Science Society of America Journal 50, 1031-1036.

Scharenbroch, B.C., Catania, M., 2012. Soil quality attributes as indicators of urban tree performance. Arboriculture and Urban Forestry 38, 214-228.

Scharenbroch, B.C., Watson, G.W., 2014. Wood chips and compost improve soil quality and increase growth of *Acer rubrum* and *Betula nigra* in compacted urban soil. Arboriculture and Urban Forestry 40, 319-331.

Scharenbroch, B.C., Carter, D., Bialecki, M., Fahey, R., Scheberl, L., Catania, M., Roman, L.A., Bassuk, N., Harper, R.W., Werner, L., Siewert A., 2017. A rapid urban site index for assessing the quality of street tree planting sites. Urban Forestry and Urban Greening 27, 279-286.

Schoenholtz, S.H., Miegroet, H. Van, Burger, J.A., 2000. A review of chemical and physical properties as indicators of forest soil quality: Challenges and opportunities. Forest Ecology and Management 138, 335-356.

Schwarz, P.A., Fahey, T.J., Dawson, T.E., 1997. Seasonal air and soil temperature effects on photosynthesis in red spruce (*Picea rubens*) saplings. Tree physiology 17, 187-94.

Shigo, A.L., 1986. A new tree biology: Facts, photos, and philosophies on trees and their problems and proper care. Shigo and Trees, Associates pp. 259.

Sikora, L.J., Stott, D.E., 1996. Soil organic carbon and nitrogen. Methods for assessing soil quality. Soil Science Society of America, pp. 157-168.

Siewert, A., Miller, S., 2011. Urban tree growth and longevity conference at The Morton Arboretum (http://www.masslaboratory.org/urban-tree-growth--longevity.html). Accessed 12/19/2016.

Sjöman, H., Busse Nielsen, A., 2010. Selecting trees for urban paved sites in Scandinavia- A review of information on stress tolerance and its relation to the requirements of tree planters. Urban Forestry and Urban Greening 4, 281-293.

Smiley, E.T., Calfee, L., Fraedrich, B.R., Smiley, E.J., 2006. Comparison of structural and noncompacted soils for trees surrounded by pavement. Arboriculture and Urban Forestry 32, 164-169.

Smith, J.A., Miller, A.J., Baeck, M.L., Nelson, P.A., Fisher, G.T., Meierdiercks, K.L., 2005. Extraordinary flood response of a small urban watershed to short-duration convective rainfall. Journal of Hydrometeorology 6, 599-617.

Smith, J.L., Doran, J.W., Jones, A.J., 1996. Measurement and use of pH and electrical conductivity for soil quality analysis. Methods for assessing soil quality. Soil Science Society of America, pp. 169-185.

Stark, J.M., Firestone, M.K., 1995. Mechanisms for soil moisture effects on activity of nitrifying bacteria. Applied and environmental microbiology 1, 218-221.

Subburayalu, S., Sydnor, T.D., 2012. Assessing street tree diversity in four Ohio communities using the weighted Simpson index. Landscape and Urban Planning 106, 44-50.

Thompson, I., Mackey, B., McNulty, S., Mosseler, A., 2009. Forest resilience, biodiversity, and climate change. A synthesis of the biodiversity/resilience/ stability relationship in forest ecosystems. Secretariat of the Convention on Biological Diversity, Montreal. Technical series no. 43.

Thomas, G.W., 1996. Soil pH and soil acidity. Methods of soil analysis. Part 3-Chemical methods. Soil Science Society of America, pp. 475-490.

Watson, G.W., Hewitt, A.M., Custic, M., Lo, M., 2014. The management of tree root systems in urban and suburban settings: A review of soil influence on root growth. Arboriculture and Urban Forestry 40, 193-217.

Wear, D.N., Greis, J.G., 2013. The southern forest futures project: Technical report. USDA-Forest Service, Southern Research Station 178, 1-542.

Whittaker, R.J., Willis, K.J., Field, R., 2001. Scale and species richness: Towards a general, hierarchical theory of species diversity. Journal of Biogeography 28, 453-470.

TOWARD AN IMPROVED RAPID URBAN SITE INDEX

2.1 ABSTRACT

Arborists and urban foresters need an accurate and efficient tool to assess soil conditions and observe the efficacy of soil management actions. To address this need, the Rapid Urban Site Index (RUSI) model was developed and found to significantly correlate to urban tree health (P = <0.0001; R^2 = 0.18-0.40). This study was conducted to further investigate these correlations and evaluate the RUSI model in three cities in Wisconsin, USA. In this current study, the RUSI model was found to significantly correlate to tree health (P = <0.01; R^2 = 0.09-0.10). To increase correlation strength, weighting schemes on RUSI parameters were investigated. However, weighted models showed no significant correlation with tree health (P = 0.3-0.8; R^2 = <0.01). This research also tested the RUSI model's sensitivity to soil management actions intended to improve site quality. After the addition of individual labile organic carbon parameters, only the RUSI + permanganate oxidizable carbon model showed a significant mean change as a result of a soil amendment application (P = 0.04; F = 3.47). Future research should continue to expand the geographic extent of the RUSI models' evaluation as well as investigate other potential parameters, such as plant available water, to aid in identifying site quality.

2.2 INTRODUCTION

2.2.1 Urban site assessments

Urban soils are highly variable and influence tree species selection and performance, which includes both tree health and growth. An urban site index would allow arborists and urban foresters to address soil heterogeneity, which may increase tree longevity, species diversity, and reduce tree loss (Scharenbroch et al., 2017). Different tree species have a range of tolerance to urban site conditions (Sjöman and Nielsen, 2010) such as limited growing space and reduced soil quality including poor soil structure, high bulk densities, and elevated soil pH (Day and Bassuk, 1994). By planting trees that are less tolerant to these urban site conditions on high-quality sites, new tree species may be successfully introduced to the urban environment. Urban site tolerant trees can then be planted on low-quality sites to maintain and improve forest canopy. An accurate and field-based site index may allow arborists and urban foresters to increase the health and benefit of urban forests.

An urban site index would also aid in the management of urban soils for individual tree performance. Due to the often degraded nature of urban soils, amendments have been shown to enhance urban tree performance (Scharenbroch and Watson, 2014). Industry standards recommend, but do not require, soil testing before and after management actions (ANSI, 2011). However, current assessment tools are limited in their ability to measure the efficacy of urban soil management actions (Scharenbroch et al., 2014). Improving these assessment tools will allow for improved urban tree site management by allowing for site specific soil management programs that maximize tree performance and longevity.

2.2.2 Rapid urban site index

Recent efforts to create an urban site index include the Ohio urban site index (Siewert and Miller, 2011), the soil quality minimum data set (Scharenbroch and Catania, 2012), and the rapid urban site index (RUSI) (Scharenbroch et al., 2017). The RUSI model was based on these previous urban and several non-urban site indices (e.g. agronomic and timber) (Doran and Parkin, 1994; Amacher et al., 2007). The model consists of five factors and fifteen parameters. Factors include climate, urban, soil physical, soil chemical, and soil biological. Climate parameters include precipitation, growing degree-days, and exposure. Urban parameters include traffic, infrastructure, and penetration. Soil physical parameters include texture, structure, and penetration. Soil chemical parameters include pH, electrical conductivity, and organic matter. Soil biological parameters include estimated rooting area, depth of the A horizon, and wet aggregate stability. Each parameter is evaluated in the field and scored from 0 to 3 with three being ideal conditions (Appendix A).

After development, the model was tested in seven cities to determine its ability to predict urban tree performance. Initial testing was performed in Boston, MA; Chicago, IL; Cleveland, OH; Springfield, MA; Toledo, OH; Ithaca, NY; and New York City, NY. This research showed a significant correlation between the RUSI model and urban tree performance across all cities and species tested (P = <0.0001; R^2 = 0.18–0.40). The initial testing showed the need for continued model development to include expanded geographic range, parameter weighting, and identifying additional parameters to improve correlation to urban tree performance.

2.2.3 Geographic extent

An ideal site index for urban trees would be accurate across a range of geographical scales. The geographic scale is important as urban forests are often developed at different times creating a patchwork of site quality based on time since development and methods used (De Kimpe and Morel, 2000). The geographic location may also influence soil properties through differences such as parent material and climate (Jenny, 1941). Regional changes in climate have been shown to heavily influence tree species range throughout urban forests (Millar et al., 2007). These are just a few of the many spatial factors influencing site quality and an urban site index must be able to address them.

2.2.4 Parameter weighting

The current RUSI model assigns equal weights for all fifteen parameters, but initial testing identified several parameters that appear to be better predictors of urban tree performance. These parameters include those associated with soil volume and compaction, such as estimated rooting area, soil structure, and wet aggregate stability. The importance of these parameters was not surprising, as many urban tree health issues result from limited soil volume and compaction (Jim, 1998). Numerous soil quality indices address unequal parameter importance using weighting schemes (Andrews et al., 2002). These schemes have been developed using expert opinion (Karlen et al., 1998) or ordination analyses (Sharma et al., 2005). Assigning higher weights to RUSI parameters with greater influence on tree performance may improve the models’ ability to assess site quality.

2.2.5 Additional labile carbon parameter

Labile organic carbon (LOC) is the portion of total soil organic carbon that is readily available for decomposition by soil organisms. This carbon provides the energy that drives microbial activity, which in turn influences plant available nutrients and soil structure (Van Der Heijden et al., 2008). This relationship may link plant productivity to the amount of LOC present, making it a potential indicator of site quality (Sharifi et al., 2008). Determining LOC content may provide arborists and urban foresters a method to make informed decisions related to site quality and management.

Methods for determining LOC include direct measurement of the physical organic matter (Marriot and Wander, 2006) or indirect measurement of microbial activity (Zou et al., 2005). Direct measurements include physically separating different size classes (e.g. 0.05-2.0 mm) after which particulate organic matter content is determined for each fraction (Cambardella and Elliot, 1992). Other direct measurements use chemical methods in which oxidizing agents are used to calculate the amount of reactive LOC (Tirol-Padre and Ladha, 2004). Biological measurements include quantifying microbial respiration defined as the CO_2 production of soil organisms in a sealed container (Alvarez and Alvarez, 2000). These CO_2 levels are often measured by observing a color change using chemical indicators. Measuring a more sensitive indicator, such as LOC, may increase the accuracy of the RUSI model, and allow it to be used to assess soil management actions and site quality.

2.2.6 Objectives

This study investigated three knowledge gaps of the current RUSI model. First, does the model correlate to tree performance outside of the current geographical range? Second, can customizing the model for a specific management area through weighting of parameters increase its correlation to tree growth and health? Third, is the current model sensitive to soil management actions and does the addition of a LOC parameter increase this sensitivity? To address these knowledge gaps three specific hypotheses were developed:

1. The RUSI model will significantly correlate to tree performance in three Wisconsin cities.
2. Adjusting the weight of individual parameters will improve the correlation between RUSI and tree performance.
3. The addition of a LOC parameter will increase the RUSI models' ability to detect the application of an organic soil amendment.

2.3 METHODS AND MATERIALS

2.3.1 Description of study cities and plots

Cities selected for this study include Stevens Point, Green Bay, and Milwaukee, WI USA (Appendix A). These cities were chosen due to their willingness to participate, the presence of tree inventories, and geographical distribution within the state. Thirty sample plots were selected in each city using tree inventories to identify the most common species planted from 2005-2012, when planting data was available. This planting period was selected in an attempt to avoid any transplant stress while also attempting to get a single season growth response from the trees. In Green Bay, planting data was not always available and sample plots were chosen from the available tree inventory. *Tilia spp.* was found to be the most suitable tree species in all three communities.

Sample plots were defined as a single tree and the surrounding 9.3 m^2 circular or rectangular planting area. In Stevens Point and Green Bay, fifteen plots were rectangular shaped between the street and the sidewalk with the other fifteen plots circular shaped and not bound by a sidewalk. In Milwaukee, all of the study sites were rectangular shaped between the street and sidewalk. After all possible plots were identified, thirty sample and ten backup plots were randomly selected in each city. Backup plots were selected in case field verification found that the location did not meet the required criteria. Several backup plots were used in each community, most often due to the removal of the *Tilia spp.* and replanting of a different species.

2.3.2 Field assessments

Site quality was assessed at each sample plot using the RUSI model in the spring and fall of 2017. The RUSI model uses climatic, urban, soil physical, soil chemical, and soil biological factors to provide an index (0-100) of urban site quality (Scharenbroch et al., 2017). Embedded in each of these main factors are three parameters. Individual parameters were assessed in the field and scored on a 0-3 scale using the scoring functions described in Appendix A (Scharenbroch et al., 2017). Observed scores were summed, divided by the maximum possible score, and then multiplied by 100 to compute the RUSI score. The primary investigator performed all assessments to limit bias.

During these visits, urban tree performance was also assessed using urban tree growth and health metrics. The urban tree health metrics included tree condition (TC), tree condition index (TCI), and urban tree health (UTH) as used by Scharenbroch et al. 2017 (Appendix A). Tree health was also assessed by measuring the relative leaf chlorophyll content of twelve leaves per tree using a SPAD meter (SPAD-502, Konica Minolta, Tokyo, Japan) (Percival et al., 2008). These twelve leaves were collected on four sides of the tree from equally distributed branch tips throughout the bottom, middle, and top of the crown. Growth metrics included total tree height (m) measured with a height pole and diameter at breast height (DBH; cm), which was measured at 1.37 m and marked to ensure accurate follow-up readings. Crown volume was calculated by measuring the crown base radius in each of the four cardinal directions and then calculated following Moser et al. (2015).

2.3.3 Soil collection, treatment, and analyses

During each site visit, twenty 2.5 cm wide x 15 cm deep soil cores were randomly collected throughout each sample plot. Cores were composited by plot, placed in individually labeled plastic bags, and kept on ice in a cooler until being transported to the laboratory where they were then stored at 5 °C until analyses were performed.

In the laboratory, each soil sample was sieved through a 6 mm screen for homogenization and removal of coarse material. Soil particle-size analysis was performed using the hydrometer method (Gee and Or, 2002). The total organic matter was determined using the loss on ignition method at 360 °C for 6 hours (Nelson et al., 1996). The particulate organic matter (POM; g kg^{-1}) was determined following particle size fractionation (Gregorich et al., 2008). Potassium permanganate oxidizable carbon (POX-C; g kg^{-1}) was determined colorimetrically (Weil et al., 2003). Potentially mineralizable carbon (PMC; mg CO_2 kg^{-1} d^{-1}) was measured as the amount of CO_2 in 0.25*M* NaOH traps following a seven-day soil incubation, which was then titrated to a phenolphthalein endpoint using 0.25 *N* HCl (Parkin et al., 1996). Soil respiration was determined using the Solvita® CO_2 burst test (Solvita; mg CO_2 kg^{-1} d^{-1}) (Kearney, NE, USA) which incubates a color gel paddle in a container with a field moist soil sample for 24 hours, after which the paddle color indicates the quantity of CO_2 present (Haney et al., 2008). Microbial biomass carbon (g kg^{-1}) and nitrogen (g kg^{-1}) were determined using a chloroform fumigation and extraction (Vance et al., 1987), assigning efficiency factors of k_N = 0.54 (Joergensen and Mueller, 1996) and k_C = 0.45 (Beck et al., 1997). After fumigation, samples were extracted using 0.5*M* K_2SO_4 and analyzed for microbial biomass nitrogen and carbon on a PerkinElmer C:N analyzer (PerkinElmer Inc., Waltham, MA, USA).

Immediately after the first soil sampling, a top dressing of organic biosolids (Milorganite, Milwaukee, WI, USA) was applied by hand at three rates. Application rates based on nitrogen (N) content were chosen in accordance with industry standards for urban tree fertilization (ANSI, 2011). Accordingly, ten sites per city received the maximum recommended rate of 2.92 kg N 100 m^{-2}, ten sites received the standard rate of 1.46 kg N 100 m^{-2}, and the remaining ten sites received no soil amendment and served as the control.

2.3.4 Statistical Analysis

To answer the first research question, statistics were computed to summarize the relationship between RUSI scores and tree performance. First, linear regression analyses were performed to examine whether the RUSI model correlated with tree performance across all cities as well as within each city.

To answer the second research question, different weighting schemes were developed for each of the fifteen parameters based on a principal component analysis (PCA), relative variance, or relative correlation strength to tree metrics. Weights were developed using the data collected during the second sampling period and were tested on data collected during the first sampling period. Following Sharma et al. (2005), a PCA was performed and weights were calculated based on the percentage of the variation each parameter explained. An individual parameter's variation percentage was divided by the total variation explained by all the PCs providing a weighting coefficient based on the relative percentage of variation explained (Equation 1) ($RUSI_{PCA}$).

Equation 1. $P_w = \frac{P_{VP}\ variation\ \%}{T_{VP}\ variation\ \%}$, where P_w is the RUSI parameter weight, P_{VP} is the parameter variation percentage, and T_{VP} is the total variation percentage.

Parameter weights were also calculated based on their proportional variance ($RUSI_{VAR}$) and proportional correlation strength ($RUSI_{R^2}$). The final set of weights were also based on variance and correlation strength, but used a binning system to determine the final weight. For these weights, the proportional variance or correlation strength were ranked and the top five parameters with the highest variance or correlation strength were given five times the weight, the five middle parameters were given three times the weight, and the five lowest parameters were left unweighted ($RUSI_{VARbin}$ and $RUSI_{R^2 bin}$).

For the third research question, ANOVA tests were used to examine differences in the LOC parameters as a result of the soil amendment application. Prior to running the ANOVA's, the normality of the data distributions was check using the Shapiro-Wilk test and mean separations were assessed using Tukey's HSD test. These parameters were then scored and added to RUSI as a 16th parameter. The ANOVA tests were again used to examine differences in the $RUSI_{LOC}$ as a result of the soil amendment application. Linear regressions analyses were performed to examine each $RUSI_{LOC}$ models correlation with tree performance. These models included parameters based on POM ($RUSI_{POM}$), POX-C ($RUSI_{POX\text{-}C}$), PMC ($RUSI_{PMC}$) and Solvita ($RUSI_{Solvita}$).

All tests were conducted using SAS JMP 13.2.1 software (SAS Institute Inc., Cary, North Carolina, U.S.) with significance determined at a 95% confidence level.

2.4 RESULTS AND DISCUSSION

2.4.1 RUSI significantly correlates with urban tree performance in Wisconsin

Across all three cities, RUSI scores significantly correlated with the tree health metrics (P = <0.01; R^2 = 0.09-0.10) (Table 2.1). The RUSI scores were not significantly correlated with DBH, SPAD, tree height, or crown volume (P = >0.05; R^2 = 0.00-0.01; data not shown). This lack of significance mirrors that of the original RUSI study and suggest that the model is a better predictor of the more important metric, tree health compared to tree growth. Within each community, the TC and TCI scores were not significantly correlated to RUSI scores (P = >0.01; R^2 = 0.02-0.13), and only in Milwaukee were UTH scores found to be significant (P = <0.0057; R^2 = 0.24). These results show that RUSI scores were significantly, but weakly, correlated to urban tree performance at a regional scale, but this significance was most often nonexistent within each community. The correlation between RUSI scores and tree performance was much weaker than in the previous study on the RUSI model (Scharenbroch et al., 2017). This finding raises the question of why was there such a difference in the observed performance of the model. Three possible explanations for the overall performance of the RUSI model are explored in a later section.

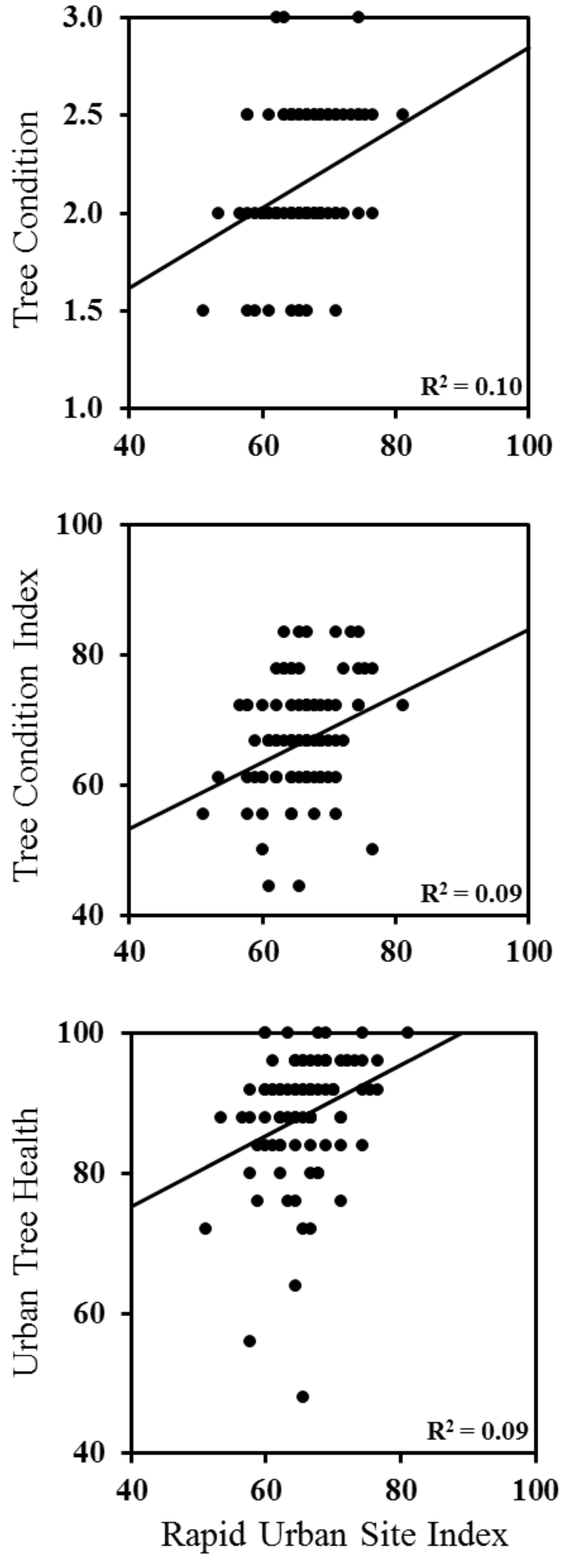


Fig. 2.1. Significant linear regressions (*P* <0.01) between the rapid urban site index and tree condition, tree condition index, and urban tree health. Data from Stevens Point, Green Bay, and Milwaukee, WI collected spring 2017 (N = 90**).**

Table 2.1. R^2 and *P*-values for linear regression models for RUSI, weighted RUSI models[x] including $RUSI_{PCA}$, $RUSI_{VAR}$, $RUSI_{R^2}$, $RUSI_{VARbin}$, $RUSI_{R^2 Bin}$, and labile organic carbon (LOC) RUSI models[y] including $RUSI_{POM}$, $RUSI_{POX\text{-}C}$, $RUSI_{PMC}$, $RUSI_{Solvita}$ and tree health metrics[z]. Data from Stevens Point, Green Bay, and Milwaukee, WI collected spring 2017 (N = 90).

2.4.2 Weighting RUSI parameters does not improve model fit

Weighting parameters resulted in no significant correlation between RUSI scores and urban tree health metrics (Table 2.1). Five weighting schemes were included in this study based on a principal component analysis, variation levels, and significant correlation of each parameter to tree health metrics. The failure of these methods to improve the correlation between RUSI scores and tree health metrics is not surprising given the initial low correlation before weighting. It appears that weighting alone is not the ideal method to adapt the model to specific locations.

Model		TC (0-3)	TCI (0-100)	UTH (0-100)
RUSI	Fit y by x	TC = 0.80 + 0.02*RUSI	TCI = 36.06 + 0.47*RUSI	UTH = 55.11 + 0.01*RUSI
	P value	0.003	0.005	0.005
	R^2	0.10	0.09	0.09
$RUSI_{PCA}$	Fit y by x	Not significant	Not significant	Not significant
	P value	0.593	0.568	0.344
	R^2	<0.01	<0.01	0.01
$RUSI_{VAR}$	Fit y by x	Not significant	Not significant	Not significant
	P value	0.631	0.430	0.406
	R^2	<0.01	<0.01	<0.01
$RUSI_{R^2}$	Fit y by x	Not significant	Not significant	Not significant
	P value	0.511	0.748	0.694
	R^2	<0.01	<0.01	<0.01
$RUSI_{VARbin}$	Fit y by x	Not significant	Not significant	Not significant
	P value	0.675	0.469	0.535
	R^2	<0.01	<0.01	<0.01
$RUSI_{R2bin}$	Fit y by x	Not significant	Not significant	Not significant
	P value	0.521	0.848	0.568
	R^2	<0.01	<0.01	<0.01
$RUSI_{POM}$	Fit y by x	Not significant	Not significant	Not significant
	P value	0.979	0.476	0.968
	R^2	<0.01	0.01	<0.01
$RUSI_{POX-C}$	Fit y by x	Not significant	Not significant	Not significant
	P value	0.549	0.775	0.157
	R^2	<0.01	<0.01	0.04
$RUSI_{PMC}$	Fit y by x	Not significant	Not significant	Not significant
	P value	0.727	0.732	0.810
	R^2	<0.01	<0.01	<0.01
$RUSI_{Solvita}$	Fit y by x	Not significant	TCI = 30.97 + 0.58*$RUSI_{Solvita}$	Not significant
	P value	0.059	0.034	0.107
	R^2	0.08	0.10	0.06

[x] Principle Component Analysis (PCA), Variation (VAR), Correlation (R^2), Variation binned (VARbin), Correlation binned (R^2bin)

[y] Particulate organic matter (POM), Permanganate oxidizable carbon (POX-C), Particulate organic matter (POM)

[z] Tree condition (TC), Tree condition index (TCI), Urban tree health (UTH)

2.4.3 RUSI and RUSI$_{LOC}$ are minimally sensitive to soil amendments

RUSI score means did not fluctuate as a result of the soil amendment application (P = 0.33; F = 1.1). This finding was expected, as most soil parameters within the RUSI model are not dynamic enough to be impacted by the application of biosolids. For example, texture and estimated rooting area were found to be important properties in the initial study but would be unaffected by the addition of organic material. The limitations of the current RUSI model may be improved with the addition of a more sensitive soil parameter such as LOC.

Soil LOC was measured in an attempt to increase the sensitivity of the RUSI model. Four LOC parameters were measured with only POX-C showing significant mean changes between treatment rates (P = 0.05, F = 3.20) and Solvita showing significant mean increases on treated vs non-treated sites (P = 0.02, F = 5.43) (Table 2.2). Marginally significant mean increases were also observed in POX-C on untreated sites (P = 0.08, F = 3.05) and in Solvita between treatment rates (P = 0.08, F = 2.66).

The POX-C test measures the amount of active carbon present in the soil (Weil et al., 2003). The biosolids application increased this amount of active carbon as well as providing a source of nitrogen, both of which may have primed the biological communities and increased decomposition on the treated sites (Sullivan et al., 2006). Sites treated at the lower biosolid rate saw an increase in microbial activity, which may have decomposed the applied biosolids as well as preexisting organics, resulting in a net loss of LOC (Table 2.2). The biological activity explanation is also supported by the significant increase in microbial respiration rates measured by the Solvita test (Table 2.2). Sites with the highest amendment rate would also experience an increase in microbial respiration; however, the additional biosolids appear to have maintained a LOC level similar to the control.

Each LOC assessment was scored and added to the RUSI model as a sixteenth parameter. The $RUSI_{POX\text{-}C}$ ANOVA test indicated a significant mean difference (P = 0.04) however, the follow-up Tukey's HSD test did not identify any differences between the treatment rate means. No other $RUSI_{LOC}$ models showed significant mean changes related to treatment rates or between treated and non-treated sites (Table 2.2). The LOC measurements lack of initial significance, as well as the noise introduced in scoring these parameters, may be responsible for the limited $RUSI_{LOC}$ differences.

This study hypothesized that $RUSI_{LOC}$ models would be significantly correlated to the addition of an organic soil amendment. However, high initial site quality levels may have limited any impact of this amendment. The first site visits showed RUSI scores ranging from 51.0-81.1 and an average of 65.7 across all cities. Total organic matter levels also indicated high site quality with an average content of 6.4% and a range of 2.6-12.7%. Existing organic matter and microbial communities may have already been providing tree nutrients and water holding capacity to the point they were no longer the limiting site factors (Knoepp et al., 2000). The high site quality and organic matter levels present in this study would negate most of the anticipated site improvement effects of the biosolid amendment.

Soil LOC parameters should continue to be evaluated for their sensitivity to site management. In this study, the limited number of sites per city per treatment may not have been fully representative of the natural variability throughout each community. These unanticipated levels of variability, along with the high initial site quality may have caused the low average test power (0.1) in the LOC and $RUSI_{LOC}$ analyses, which decreases the ability of the statistical test to indicate a difference if one does exist for research question three (Stiedl et al., 1997). Continued research specifically on POX-C and Solvita is warranted as they have shown significant correlations to soil amendment.

Table 2.2. Analysis of variance (ANOVA)[x] ± the standard error for labile organic carbon (LOC) properties[y] and $RUSI_{LOC}$ models at second sampling. Letter indicate significant mean differences using Tukey's HSD test. Data from Stevens Point, Green Bay, and Milwaukee, WI collected fall 2017 (N = 90).

	Treatment Mean ± SE			F Ratio	*P*-value	Treatment Mean ± SE		F Ratio	*P*-value
	Maximum	Standard	Control			Treated	Non-treated		
Total POM (g/kg)	8.83 ±0.8 a	9.42 ±0.8 a	8.99 ±0.8 a	0.14	0.87	9.12 ±0.6 a	8.99 ±0.8 a	0.02	0.89
POX-C (g/kg)	9.91 ±55.7 ab	8.50 ±55.7 b	10.42 ±55.7 a	3.20	0.05	92.0 ±40.4 a	10.4 ±57.1 a	3.05	0.08
PMC (mg CO_2 kg^{-1} d^{-1})	86.35 ±6.9 a	91.59 ±6.9 a	80.51 ±6.9 a	0.00	0.99	88.97 ±4.8 a	80.51 ±6.8 a	1.01	0.32
Solvita (mg CO_2 kg^{-1} d^{-1})	84.73 ±1.1 a	84.51 ±1.1 a	81.49 ±1.1 a	2.66	0.08	84.62 ±0.8 a	81.49 ±1.1 b	5.43	0.02
$RUSI_{POM}$	69.2 ±1.35 a	66.32 ±1.35 a	69.03 ±1.35 a	1.41	0.26	67.74 ±1.0 a	69.03 ±1.4 a	0.59	0.45
$RUSI_{POX-C}$	69.86 ±1.36 a	65.35 ±1.36 a	66.84 ±1.36 a	3.47	0.04	67.60 ±1.0 a	69.58 ±1.4 a	1.28	0.26
$RUSI_{PMC}$	69.03 ±1.30 a	66.60 ±1.30 a	69.03 ±1.30 a	1.17	0.32	67.81 ±0.9 a	69.03 ±1.3 a	0.57	0.45
$RUSI_{Solvita}$	70.69 ±1.30 a	66.88 ±1.30 a	68.61 ±1.30 a	2.09	0.14	68.78 ±0.9 a	68.61 ±1.4 a	0.01	0.92

[x] Values within rows not followed by the same letter are significantly different at the 0.05 probability level using Tukey's HSD test.
[y] Particulate organic matter (POM), Permanganate oxidizable carbon (POX-C), Particulate organic matter (POM)

2.4.5 *RUSI performance assessment*

Compared to the previous RUSI research, this study found the model to be weakly correlated to tree health and that model additions often resulted in no significant correlation. Three reasons are presented to explain the greater correlation in the past study.

The first reason why there was a reduced correlation between RUSI and tree health is related to the study sites. In this study, each site contained a single tree that may have not shown the effects of the sites quality given the high urban tolerance of the species selected (*Tilia*) and young age of the trees (5-12 years post planting). Scharenbroch et al. (2017) found that RUSI correlations with tree health where greater with larger trees (> 30 cm DBH) compared to smaller trees (< 30 cm DBH), all trees in this study were < 22 cm DBH. Additionally, the previous study sites contained at least three trees per site and covered a wider range of tree ages allowing site quality to have a greater influence on tree performance. In this study, the single genus and narrow tree age range were selected in an attempt to assess the model across three communities, negate any nursery effect, and observe a growth response to a soil amendment within a single growing season.

The second reason may be the decreased climate variability related to the limited geographic extent and seasonality of assessment. Initial study sites occurred in four states across 1500 km (Google Maps, 2018), had a mean annual temperature range from 6.7 to 12.9 °C (US Climate Data, 2018), a mean annual precipitation range from 830 to 1,219 mm yr^{-1} (US Climate Data, 2018), and a growing degree days range from 2,808 to 3,948 (Growing Degree Days, 2014). Sites in this study occurred in one state across 250 km (Google Maps, 2018), had a mean annual temperature range from 6.7 to 8.8 °C (US Climate Data, 2018), a mean annual precipitation range from 830 to 876 mm yr^{-1} (US Climate Data, 2018), and a growing degree days range from 2,378 to 2,696 (Growing Degree Days, 2014). Changes in the seasonality of sampling may also influence RUSI's performance. During the previous study, site and tree assessments occurred throughout the growing season. In this study, assessments occurred during a single week in spring and in fall. This reduction in seasonal variability may have altered both site and tree scoring, limiting the accuracy of the models site quality prediction.

The third reason the RUSI model was weakly correlated to tree health may be that the site and tree assessments are missing key parameters or are currently poorly assessed. Additional key site parameters related to tree performance may include rooting volume and soil compaction. Negative alterations to these parameters reduces PAW (Mullaney et al., 2015), nutrient uptake (Franco et al., 2011), and ultimately reduces the long-term success of street trees (Sanders and Grabosky, 2014). Field methods for determining PAW are currently being researched and may provide an additional parameter to assess urban site quality (Appendix B). Existing parameters may have shown low correlation to tree performance due to the coarseness of measuring and scoring. A specific example would be soil organic matter readings, which showed no significant correlation to tree health. This lack of correlation may be due to the colorimetric field assessment using a color chart that was developed on soils outside the geographic extent of this study. Future research should continue to investigate new field methods for measuring parameters as well as adjustments to current scoring functions.

2.5 CONCLUSION

Urban site assessments need to be practical and accurate to aid in the management of urban trees and forests. While RUSI has been introduced as a model for predicting tree performance, the results of this study suggest it should be used more as an approach. Rather than taking the model as is and using it, new users should alter parameter inclusion, assessment, and scoring to fit their unique area of interest. With this in mind, the geographical range of the model should continue to be expanded as well as a much-needed expansion of the urban tree species evaluated. These continued efforts are indicative of the challenge in creating an urban site index; however, the importance of such an approach should not be overlooked. Increasing the understanding of site quality may allow arborists and urban foresters to improve individual tree care as well as expand tree species selection thereby increasing the health and benefit of urban forests.

ACKNOWLEDGMENTS

This study was funded by a Hyland R. Johns Grant (No. 16-HJ-01) from the Tree Research and Education Endowment (TREE) Fund, Naperville, Illinois, as well as funding from the Wisconsin Arborist Association, the College of Natural Resources at University of Wisconsin – Stevens Point, Stevens Point, Wisconsin, and The Morton Arboretum, Lisle, Illinois. Field data was collected by Luke Scheberl and was assisted by Alyssa Gunderson. Laboratory work was performed by Joel Gebhard and Luke Scheberl and was assisted by Alyssa Gunderson at the University of Wisconsin – Stevens Point.

2.6 REFERENCES

Alvarez, R., Alvarez, C.R., 2000. Soil organic matter pools and their associations with carbon mineralization kinetics. Soil Science Society of America Journal 64, 184-189.

Amacher, M.C., O'Neill, K.P., Perry, C.H., 2007. Soil vital signs: a new soil quality index (SQI) for assessing forest soil health. US Department of Agriculture, Forest Service, Rocky Mountain Research Station.

American National Standards Institute (ANSI), 2011. American national standard for tree care operations - Tree, shrub, and other woody plant maintenance - Standard practices (Soil management a. Modification, b. Fertilization, and c. Drainage) (ANSI A300, Part 2). Tree Care Industry Association Inc., Londonderry, NH.

Andrews, S.S., Karlen, D.L., Mitchell, J.P., 2002. A comparison of soil quality indexing methods for vegetable production systems in Northern California. Agriculture, Ecosystems and Environment 90, 25-45.

Beck, T., Joergensen, R.G., Kandeler, E., Makeschin, F., Nuss, E., Oberholzer, H.R., Scheu, S., 1997. An inter-laboratory comparison of ten different ways of measuring soil microbial biomass C. Soil Biology and Biochemistry 29, 1023-1032.

Cambardella, C.A., Elliott, E.T., 1992. Particulate soil organic-matter changes across a grassland cultivation sequence. Soil Science Society of America Journal 56, 777-783.

Day, S.D., Bassuk, N.L., 1994. A review of the effects of soil compaction and amelioration treatments on landscape trees. Journal of Arboriculture, 20, 9-17.

De Kimpe, C.R., Morel, J.L., 2000. Urban soil management: A growing concern. Soil Science 165, 31-40.

Doran, J.W. and Parkin, T.B., 1994. Defining and assessing soil quality. Defining soil quality for a sustainable environment, Soil Science Society of America, pp.1-21.

Franco, J.A., Bañón, S., Vicente, M.J., Miralles, J., Martínez-Sánchez, J.J., 2011. Root development in horticultural plants grown under abiotic stress conditions- A review. The Journal of Horticultural Science and Biotechnology 86, 543-56.

Gee, G.W., Or, D., 2002. Particle-size analysis. Methods of soil analysis. Part-4 Physical methods. Soil Science Society of America, pp. 255-293.

Gregorich, E.G., Beare, M.H., McKim, U.F., Skjemstad, J.O., 2008. Chemical and biological characteristics of physically uncomplexed organic matter. Soil Science Society of America Journal 70, 975-985.

Growing Degree Days, 2014. Application. iNet Solutions Group. https://itunes.apple.com/us/app/growing-degree-days/id386655475?mt=8. Accessed 06/06/2017.

Google Maps, 2018. https://www.google.com/maps. Accessed 04/10/2018.

Haney, R.L., Brinton, W.F., Evans, E., 2008. Soil CO2 respiration: Comparison of chemical titration, CO2 IRGA analysis and the Solvita gel system. Renewable Agriculture and Food Systems 23, 171-176.

Jenny, H., 1941. Factors of soil formation: A system of quantitative pedology. Macgraw Hill. New York, NY.

Jim, C.Y., 1998. Urban soil characteristics and limitations for landscape planting in Hong Kong. Landscape and Urban Planning 40, 235-249.

Joergensen, R.G., Mueller, T., 1996. The fumigation-extraction method to estimate soil microbial biomass: Calibration of the k_{EN} value. Soil Biology and Biochemistry 28, 33-37.

Karlen, D.L., Gardner, J.C., Rosek, M.J., 1998. A soil quality framework for evaluating the impact of CRP. Journal of Production Agriculture 11, 56-60.

Knoepp, J.D., Coleman, D.C., Crossley Jr, D.A., Clark, J.S., 2000. Biological indices of soil quality: An ecosystem case study of their use. Forest Ecology and Management 138, 357-368.

Marriott, E.E., Wander, M.M., 2006. Total and labile soil organic matter in organic and conventional farming systems. Soil Science Society of America Journal 70, 950-959.

Millar, C.I., Stephenson, N.L., Stephens, S.L., 2007. Climate change and forests of the future: managing in the face of uncertainty. Ecological Applications 17, 2145-2151.

Moser, A., Rötzer, T., Pauleit, S., Pretzsch, H., 2015. Structure and ecosystem services of small-leaved lime (*Tilia cordata* Mill.) and black locust (*Robinia pseudoacacia* L.) in urban environments. Urban Forestry and Urban Greening 14, 1110-1121.

Mullaney, J., Lucke, T., Trueman, S.J., 2015. A review of benefits and challenges in growing street trees in paved urban environments. Landscape and Urban Planning 134, 157-166.

Nelson, D.W., Sommers, L.E., 1996. Total carbon, organic carbon, and organic matter. Methods of soil analysis. Part-3 Physical methods. Soil Science Society of America, pp. 961-1010.

Parkin, T.B., Doran, J.W., Franco-Vizcaino, E., 1996 Field and laboratory tests of soil respiration. Methods for assessing soil quality. Soil Science Society of America, pp. 231-244.

Percival, G.C., Keary, I.P., Noviss, K., 2008. The potential of a chlorophyll content SPAD meter to quantify nutrient stress in foliar tissue of sycamore (*Acer pseudoplatanus*), English oak (*Quercus robur*), and european beech (*Fagus sylvatica*). Arboriculture and Urban Forestry 34, 89-100.

Sanders, J.R., Grabosky, J.C., 2014. 20 years later: Does reduced soil area change overall tree growth? Urban Forestry and Urban Greening 13, 295-303.

Scharenbroch, B.C., Catania, M., 2012. Soil quality attributes as indicators of urban tree performance. Arboriculture and Urban Forestry 38, 214-228.

Scharenbroch, B.C., Watson, G.W., 2014. Wood chips and compost improve soil quality and increase growth of *Acer rubrum* and *Betula nigra* in compacted urban soil. Arboriculture and Urban Forestry 40, 319-331.

Scharenborch, B.C., Smiley, E.T., Kocher, W., 2014. Soil management for urban trees. Best management practices - Soil management. International Society of Arboriculture. Champaign, IL.

Scharenbroch, B.C., Carter, D., Bialecki, M., Fahey, R., Scheberl, L., Catania, M., Roman, L.A., Bassuk, N., Harper, R.W., Werner, L., Siewert A., 2017. A rapid urban site index for assessing the quality of street tree planting sites. Urban Forestry and Urban Greening 27, 279-286.

Sharifi, M., Zebarth, B.J., Burton, D.L., Grant, C.A., Bittman, S., Drury, C.F., McConkey, B.G., Ziadi, N., 2008. Response of potentially mineralizable soil nitrogen and indices of nitrogen availability to tillage system. Soil Science Society of America Journal 72, 1124-1131.

Sharma, K.L., Mandal, U.K., Srinivas, K., Vittal, K.P., Mandal, B., Grace, J.K., Ramesh, V., 2005. Long-term soil management effects on crop yields and soil quality in a dryland Alfisol. Soil and Tillage Research 83, 246-259.

Shigo, A.L., 1986. A new tree biology: Facts, photos, and philosophies on trees and their problems and proper care. Shigo and Trees, Associates pp. 259.

Siewert, A., Miller, S., 2011. Urban tree growth and longevity conference at The Morton Arboretum. http://www.masslaboratory.org/urban-tree-growth--longevity.html. Accessed 12/19/2016.

Sjöman, H., Busse Nielsen, A., 2010. Selecting trees for urban paved sites in Scandinavia - A review of information on stress tolerance and its relation to the requirements of tree planters. Urban Forestry and Urban Greening 4, 281-293.

Steidl, R.J., Hayes, J.P., Schauber, E., 1997. Statistical power analysis in wildlife research. The Journal of Wildlife Management 61, 270-279.

Sullivan, T.S., Stromberger, M.E., Paschke, M.W., Ippolito, J.A., 2006. Long-term impacts of infrequent biosolids applications on chemical and microbial properties of a semi-arid rangeland soil. Biology and Fertility of Soils 42, 258-266.

Tirol-Padre, A., Ladha, J.K., 2004. Assessing the reliability of permanganate-oxidizable carbon as an index of soil labile carbon. Soil Science Society of America Journal 68, 969-978.

US Climate Data, 2018. http://www.usclimatedata.com/. Accessed 04/10/2018.

Van Der Heijden, M.G.A., Bardgett, R.D., Van Straalen, N.M., 2008. The unseen majority: Soil microbes as drivers of plant diversity and productivity in terrestrial ecosystems. Ecology Letters 11, 296-310.

Vance, E.D., Brookes, P.C., Jenkinson, D.S., 1987. An extraction method for measuring soil microbial biomass C. Soil Biology and Biochemistry 19, 703-707.

Weil, R.R., Islam, K.R., Stine, M.A., Gruver, J.B., Samson-Liebig, S.E., 2003. Estimating active carbon for soil quality assessment: A simplified method for laboratory and field use. American Journal of Alternative Agriculture 18, 3-17.

Zou, X.M., Ruan, H.H., Fu, Y., Yang, X.D., Sha, L.Q., 2005. Estimating soil labile organic carbon and potential turnover rates using a sequential fumigation-incubation procedure. Soil Biology and Biochemistry 37, 1923-1928.

Appendix A. Description of study areas, and tree and site indices

Description of Wisconsin study areas

Stevens Point (44.5236 °N, 89.5746 °W) has a total population of 26,670 people with an elevation of 331.9 m, average precipitation of 830 mm, and an average temperature of 6.7 ^{o}C. Native soils in Stevens Point are described as a Plainfield-Friendship association, which is moderate to excessively well drained and formed in deep sandy glacial deposits (USDA, 1978). Stevens Point has approximately 7,230 city trees distributed among 47 species with dominate genera of *Acer* 25%, *Fraxinus* 15%, *Malus* 7%, *Tilia* 6%, and *Pinus* 6% (Davey, 2010).

Green Bay (44.5192 °N, 88.0198 °W) has a total population of 104,779 people with an elevation of 177.0 m, average precipitation of 749 mm, and an average temperature of 6.7 ^{o}C. The native soils in Green Bay are described as Oshkosh-Manawa association. These soils are well-drained to somewhat poorly drained with sand and loamy subsoil (USDA, 1974). Green Bay has approximately 35,000 city trees with dominate genera of *Acer* 31%, *Fraxinus* 21%, *Tilia* 19%, and *Gleditsia* 9% (Freberg, 2016).

Milwaukee (43.0389 °N, 87.9065 °W) has a total population of 599,164 people with an elevation of 188 m, average precipitation of 874 mm, and an average temperature of 8.7 ^{o}C. The native soils in Milwaukee are described as Ozaukee-Marley-Mequon association. These soils are well drained to somewhat poorly drained with clay subsoils (USDA, 1971). Milwaukee's total tree population is approximately 3,377,000 trees with dominate genera of *Rhamnus* 23%, *Acer* 20%, *Fraxinus* 17%, *Ulmus* 6%, and *Gleditsia* 6% (USDA-FS, 2008). It should be noted that native soils in all three cities may have been significantly altered by urbanization.

Tree performance metrics

Qualitative tree health was assessed using three metrics: tree condition (TC), tree condition index (TCI) and urban tree health (UTH). These metrics were developed from discussions with experts as well as from literature (Webster, 1979; Bond, 2012: Scharenbroch and Catania, 2012). Equations and scoring functions for these metrics are as follows.

Tree condition (TC) was scored and calculated using Table and Equation A1. This method is a quick assessment of the relative growth (branch elongation) and signs/symptoms of stress. It provides a 0-3 rating based on an ocular estimation of the presence of leaves and their condition, bark condition, and growth rate. The tree condition is considered dead when more than ½ of the crown is dead and bark is sloughing off. Trees are in poor condition when less than half the crown is dead and there are signs of severely stunted growth. Trees are in fair condition if they have reduced growth, minor dieback, and/or are chlorotic. Trees are in good condition when there are no signs of stress present and high growth rates.

Equation A1. Tree condition (TC) = n

Table A1. Parameters and scoring function for the tree condition (TC) model.

Tree Condition	**Score**
Dead (>1/2 of the crown dead, sloughing bark)	0
Poor (<1/2 of the crown dead, growth severely stunted)	1
Fair (reduced growth, chlorotic, minor dieback)	2
Good (no stress present, high growth rates)	3

Tree condition index (TCI) scores were calculated using the modified Webster (1979) method first used by Scharenbroch and Catania, 2012 (Equation A2; Table A2). This method provides a rating on a 1-5 scale on the trees trunk, crown, roots. The trunk factor rates how sound the tree is and the presence of damage or decay and its extent. Crown is the trees canopy density and balance or evenness. The roots factor is the presence of proper rooting habits represented by a large evenly spaced structural root flare around the entire trunk.

Equation A2. Tree Condition Index (TCI) = $(\sum s/3n) * 100$,

where s = parameter scores and n = the number of TCI parameters assessed

Table A2. Parameters and scoring function for the tree condition index (TCI) model. Adapted from Webster (1979).

TCI	**5**	**4**	**3**	**2**	**1**
Trunk	Sound and solid throughout	Minor damage	Early decay signs	Extensive decay, hollowness, cambium damage	Same as two, but cross-section is a half circle
Crown	Dense, evenly balanced crown	Dense, slightly unbalanced crown	Thin or severely imbalanced crown	Thing and slightly imbalanced crown	Thin and severely imbalanced crown
Roots	Three or more visible and evenly balanced root flares (<2 cm deep)	Three or more visible and slightly unbalanced root flares (<2 cm deep)	Less than three visible or severely unbalanced root flares (<2 cm deep)	No visible root flares and structural roots (2 to 15 cm deep)	Structural roots (>15 cm deep)

Urban tree health (UTH) scores were calculated using the modified Jerry Bond (2012) first used by Scharenbroch et al. (2017) (Equation A3; Table A3). This method provides a 0-5 rating on the tree's live crown ratio, opacity, vitality, growth, and quality. The live crown ratio is the percent live crown height to the total live tree height. Opacity is the percent of light visibly blocked by branches, foliage, and reproductive structures of the actual live crown. Vitality is the percent of the upper crown that is free from recent mortality. Growth is the three-year average terminal shoot extension on three random branches with the same sun exposure that have not been pruned or damaged. Quality is defined as the percent of the upper crown that is free from necrotic, chlorotic, or undersized foliage.

Equation A3. Urban Tree Health (UTH) = $(\sum s/5n) * 100$

where s = parameter scores and n = the number of TCI parameters assessed

Table A3. Parameters and scoring function for the urban tree health (UTH) model. Adapted from Bond (2012).

UTH	0	1	2	3	4	5
Crown Ratio	No live crown	1-20%	21-40	41-60	61-80	81-100
Opacity	No live crown	1-20%	21-40	41-60	61-80	81-100
Vitality	No live crown	1-20%	21-40	41-60	61-80	81-100
Growth	No live crown	<5 cm	5-10	10-15	15-20	>20
Quality	No live crown	1-20%	21-40	41-60	61-80	81-100

Rapid urban site index

Rapid urban site index (RUSI) scores were calculated following Scharenbroch et al., 2017 (Equation A4; Table A4). A description of each of the 15 RUSI parameters is as follows.

The climate factors of the RUSI model include precipitation (PPT), growing degree days (GDD), and exposure (EXP). For PPT and GDD scores, it is suggested to use the most recent, practical, and accurate local data available. The PPT score was calculated using data acquired from U.S. Climate Data (2014). If irrigation was present on the site, then the PPT score was increased one point to a maximum score of three. The GDD score is a measure of heat accumulation. The GDD units are calculated by mean daily temperature (maximum plus minimum divided by two) minus base temperature (10°C). The GDD units are summed for the year for annual GDD. The Growing Degree Days smartphone application was used to determine the GDD score for each location (Growing Degree Days, 2014). The start date was 01/01/16 and the end date was 12/31/16 and the GDD50 was selected as the base temperature. The free application returns the GDD for the most recent two years and a mean of this value was used to score GDD. The EXP score was assessed in the field based on the number of faces of the tree that are exposed to full sun.

The urban factors in the RUSI model are traffic (TRAF), infrastructure (INFR), and surface (SURF). The TRAF score was based on the number of lanes and amount of parking available on the street. More lanes and less parking indicate more traffic, likely faster-moving automobiles, and more of an “urban” impact (e.g., road salts, recent soil disturbance) on the site. The INFR score was based on the distance to the nearest hard-space or building from the main stem of the tree. The SURF score is based on the type of ground covering for the majority (>50%) of the rooting area for the tree.

Soil physical factors include texture (TEXT), structure (STRC), and penetration (PEN). Texture reflects the relative particle size distribution and is determined by the feel method. Structure is the shape of the soil aggregates present. Methods for assessing soil texture by the feel method and structure shape are described in Schoenberger et al., (2012) and Scharenbroch et al., (2014). Penetration was assessed by recording the depth and ease that the core sampler went into the soil when collecting samples.

The soil chemical factors were pH (pH), electrical conductivity (EC), and soil organic matter (SOM). Soil pH and EC were measured on homogenized subsamples at each site using a handheld combination pH/EC meter. For this research, the Oakton PCTestr 35 (OAKTON Instruments Vernon Hills, IL, USA) was used. Soil organic matter was estimated using the Color Chart for Estimating Organic Matter in Mineral Soils of Illinois (University of Illinois Extension, Champaign, IL USA).

The soil biological factors were estimated rooting area (ERA), depth of the A horizon or topsoil (AHOR), and wet aggregate stability (WAS). Estimated root area was an evaluation of the surface permeable space for root growth. The ERA score was increased by one to a maximum of three if a breakout area of at least 50 m^2 was present within 2 m of the tree. The AHOR was the depth of the A horizon or topsoil via visual inspection. The A horizon was distinguished by darker color, a more well-developed structure, and a greater abundance of fine roots compared to the underlying horizon. Wet-aggregate stability is an estimate of the strength of the aggregates to resist degradation (Nimmo and Perkins, 2002). A modified field-method was used to assess WAS. Five aggregates 2 to 5 mm in diameter were placed on a 1 mm screen. The aggregates are soaked in water for 30 s. After 30 s the screen was agitated (i.e., a vigorous swirl) for another 30 s. The number and amount of aggregates left after the soak and swirl were volumetrically estimated and scored.

Equation A4. Rapid Urban Site Index (RUSI) = $(\sum s/3n) * 100$

where s = parameter scores and n = the number of TCI parameters assessed

Table A4. Parameters and scoring functions for the rapid urban site index (RUSI) model.

RUSI	units	0	1	2	3
PPT[1]	mm yr^{-1}	<500	500-750	751-1,000	>1,000
GDD	d	<1,000	1,001-2,500	2,501-4,000	>4,000
EXP	#	0	1-2	3-4	5
TRAF	n/a	>4 lanes	2-4; no parking	2-4; parking	<2 lanes
INFR	m	<1	1-5	6-10	>10
SURF	n/a	non-permeable or bare	patchy vegetation	thick vegetation	organic mulch
TEXT	n/a	no soil; CF>75%	S, SI, C; CF=50-75%	LS, SCL, SICL, CL, SC, SIC; CF=25-49%	SL, SIL, L; CF<25%
STRC	n/a	M, SG, PL	ABK	SBK	GR
PEN	Cm	<5	5-20	20 with max effort	20 with min effort
AHOR	Cm	<1	1-5	6-15	>15
ERA[2]	m^2	<5	5-25	26-50	>50
WAS	%	no aggregates	<50% post soak	<50% post swirl	>50% post swirl
SOM	IL SOM chart	gray	chip 1	chip 2-3	chip 4-5
EC	µS cm^{-1}	<50 or >3,000	50-100 or 2,001-3,000	101-300 or 1,001-2,000	301 to 1,000
pH	n/a	<4 or >9	4-4.9 or 8.1-9	5-5.9 or 6.6-8	6-6.5

Footnotes: [1]Add 1 to the PPT if irrigation is present within 3 m of the tree. [2]Add 1 to the ERA score if break-out a zone of at 50 m^2 is present within 3 meters of the main stem of the tree.

References

Davey Resource Group. 2010. Urban forest management plan, Stevens Point, WI. Davey Resource Group.

Freberg, M., 2016. City of Green Bay Tree Inventory. Accessed 12/05/16.

Growing Degree Days., 2014. Application. iNet Solutions Group. https://itunes.apple.com/us/app/growing-degree-days/id386655475?mt=8. Accessed 06/05/17.

United States Census Bureau., 2017. Population. http://www.census.gov/topics/population.html. Accessed 01/14/17.

US Climate Data. 2014. http://www.usclimatedata.com. Accessed 01/06/14.

USDA-FS., 2008. i-Tree Ecosystem Analysis of Milwaukee, WI.

USDA-NRCS., 1917. Soil survey of Portage County, Wisconsin. United States Department of Agriculture – Natural Resources Conservation Service.

USDA-NRCS., 1974. Soil survey of Brown County. United States Department of Agriculture – Natural Resources Conservation Service.

USDA-NRCS., 1971. Soil survey of Milwaukee County. United States Department of Agriculture – Natural Resources Conservation Service.

Appendix B. Toward field determination of plant available water

Introduction

Proper urban tree management requires quick and accurate field determination of site conditions. This information may be used to maximize plant health while also increasing species diversity in the urban forest (Scharenbroch et al., 2017). Soil moisture plays a critical role in root growth with elongation decreasing rapidly under moisture stress in most plant species (Lyr and Hoffmann, 1976). This stress can impact many physiological processes including tree photosynthesis (Hsiao et al., 1976), tree growth (Hasiao, 1973), and tree defense (McDowell et al., 2008). Specific responses to soil moisture levels vary amongst plant species (McDowell et al., 2008), but often result in increased mortality rates during both flooding and drought conditions (Allen et al., 2010). These conditions alter the amount of plant available water (PAW); defined as the amount of soil moisture between field capacity and permanent wilting point. Soil moisture varies spatially and temporally requiring repeated evaluation throughout the growing season and site (Famiglietti et al., 2008). To maintain optimal PAW and maximize tree performance, arborists and urban foresters need a quick, accurate, and affordable method to monitor soil moisture levels.

The purpose of this study was to evaluate a field method of estimating PAW. Specifically, can PAW be estimated from a soil volumetric moisture content (VMC) reading at simulated field capacity?

Study sites and field data collection

Fifteen research sites were randomly selected from thirty street tree planting sites previously identified throughout Stevens Point, WI. Soils on these sites are described as a Plainfield-Friendship association with a texture class of loamy sand to sandy loam, a pH range of 6.3-7.8, and organic matter contents ranging from 1.5-8.5% (Scheberl et al., in preparation). At each research site, two sample plots were selected 1.2 m from opposite sides of the tree, parallel with the street. The first plot was sampled under current field conditions. Soil VMC was measured using five different soil moisture sensors (Table B1), and a 15 cm deep by 5.4 cm wide core was collected, placed in a plastic bag, and transported to the laboratory for analysis. Separate cores, 6 cm x 5.4 cm, were also collected to determine soil bulk density and gravimetric moisture content. The second plots were then saturated by adding 5.6 L deionized water to a 0.92 m^2 area, simulating a 7.62 cm rain event. These sites were then allowed to drain 24 hr after which it was assumed they were at field capacity. Soil VMC was then measured and cores were collected following the same procedure as the first sampling.

Table B1. Soil sensors used for field evaluation of volumetric moisture content.

Sensor	**Method**†	**Prong length (cm)**	**Range**	**Accuracy (%)**	**Manufacturer**
General Moisture Meter	EC	21.0	0-50%	±5	General Tools and Instruments, Secaucus, NJ, USA
EXTECH Moisture Meter	EC	21.0	0-50%	±5	FLIR Commercial Systems Inc., Nashua, NH, USA
5TE	FDR	5.0	0-50%	±3	Decagon Devices Inc., Pullman, WA, USA
Hydrosense I	TDR	12.0	0-50%	±3	Campbell Scientific Inc., Logan, UT, USA
Hydrosense II	TDR	20.0	0-50%	±3	Campbell Scientific Inc., Logan, UT, USA

† EC (electrical conductivity); FDR (frequency domain reflectometry); TDR (time domain reflectometry)

Laboratory analysis

The separate soil cores were used to determine bulk density and gravimetric moisture content (24 hr at 105 °C) which was then used to determine VMC (Ferré and Topp, 2002). Field capacity and permanent wilting point moisture contents were measured using a pressure plate extraction method (Dane and Hopmans, 2002). Field capacity moisture content was determined on intact saturated cores at -33 kPa. Soils were then sieved at 2 mm to homogenize the sample and isolate the soil fraction. Permanent wilting point moisture content was then measured on a sieved subsample at -1500 kPa.

Findings and future implications

Initial results show significant correlation between soil VMC measured with the EC sensors and PAW (P = 0.029, 0.041; R^2 = 0.32, 0.28). The significance and strength of this relation support further research on this important topic as well the exploration of the addition of a PAW parameter to the rapid urban site index model. The lack of correlation between the other sensors and field conditions was surprising given that these sensors performed well in a laboratory study (Scheberl et al., in preparation). Future research should continue to evaluate limitations of these sensors when used within an urban landscape.

References

Allen, C.D., Macalady, A.K., Chenchouni, H., Bachelet, D., McDowell, N., Vennetier, M., Kitzberger, T., Rigling, A., Breshears, D.D., Hogg, E.H., Gonzalez, P., Fensham, R., Zhang, Z., Castro, J., Demidova, N., Lim, J.H., Allard, G., Running, S.W., Semerci, A., Cobb, N., 2010. A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. Forest Ecology and Management 259, 660-684.

Dane J.H., Hopmans, J.W., 2002. Pressure Plate Extractor. Methods of soil analysis Part 4-Physical methods. Soil Science Society of America, 688-690.

Famiglietti J.S., Ryu D., Berg A.A., Rodell M., Jackson T.J., 2008. Field observations of soil moisture variability across scales. Water Resources Research 44, 1-16.

Ferré, P.A., Topp, G.C., 2002. Time domain reflectometry. Methods of soil analysis. Part 4-Physical methods. Soil Science Society of America, 434-446.

Hsiao, T.C., 1973. Plant responses to water stress. Annual Review of Plant Physiology 24, 519-570.

Hsiao, T.C., Acevedo, E., Fereres, E., Henderson, D.W., 1976. Water stress, growth, and osmotic adjustment. Philosophical Transactions of the Royal Society B: Biological Sciences 273, 479-500.

Lyr, H., Hoffmann, G., 1967. Growth rates and growth periodicity of tree roots. International review of forestry research. Vol 2. Academic Press, 181-236.

McDowell, N., Pockman, W.T., Allen, C.D., Breshears, D.D., Cobb, N., Kolb, T., Plaut, J., Sperry, J., West, A., Williams, D.G., Yepez, E.A., 2008. Mechanisms of plant survival and mortality during drought: Why do some plants survive while others succumb to drought? New Phytologist 178, 719-739.

Scharenbroch, B.C., Carter, D., Bialecki, M., Fahey, R., Scheberl, L., Catania, M., Roman, L.A., Bassuk, N., Harper, R.W., Werner, L., Siewert, A., Miller, S., Hutyra, L., Raciti, S., 2017. A rapid urban site index for assessing the quality of street tree planting sites. Urban Forestry and Urban Greening 27, 279-286.

EVALUATION OF SOIL pH AND SOIL MOISTURE FIELD SENSORS TOWARD USE IN AN URBAN SITE ASSESSMENT

3.1 ABSTRACT

Soil moisture and pH levels directly affect urban tree performance. An accurate sensor to assess these soil conditions would allow arborists and urban foresters to make and evaluate management actions. These actions may then be used to improve tree species diversity and site quality. Toward this goal, twenty-two soil pH and moisture sensors were tested for their ability to accurately and precisely measure soil pH, volumetric soil moisture content (VMC), or both. This research was conducted on four different soil texture classes (loamy sand, sandy loam, clay loam, and clay) at three different moisture levels (air dry, ≈ 0.5 field capacity, and ≈ field capacity). Soil pH sensors using a glass-electrode in a 1:2 (soil:deionized water) solution were found to accurately and precisely measure soil pH (P = <0.0001; ρ_c = >0.95). However, sensors using metal electrodes inserted into the soil had no significant correlation to soil pH levels (P = >0.1; ρ_c = <0.2). When selecting a soil pH sensor, measurement method may be the most important consideration. Soil VMC sensors using time domain reflectometry and frequency domain reflectometry methods performed best (P = <0.0001; ρ_c = >0.76). Sensors using the electrical conductivity method were highly variable in cost, accuracy, and precision. When selecting a soil VMC sensor, measurement method and cost are both important variables. With accurate soil assessments, arborists and urban foresters can better select tree species and improve soil management decisions.

3.2 INTRODUCTION

3.2.1 Urban site conditions

Field knowledge of site conditions is crucial for managers seeking to maximize tree health while adding diversity to the urban forest. Factors influencing site quality include urban development (Greinert, 2015), time since disturbance (Scharenbroch et al., 2005), surface vegetation (Salvucci, 1998), and weather (Bolan et al., 2003). These elements create a patchwork of soil physical, chemical, and biological properties across a single community. Management of urban trees in this heterogeneous and changing landscape may be improved with the use of an urban site index (Scharenbroch et al., 2017). Two important variables of a site index are soil pH and soil moisture (Shukla et al., 2006). Soil moisture and pH levels fluctuate spatially and temporally (Wuest, 2015) requiring repeated evaluation throughout the growing season and site. A site index that uses quick and accurate field assessments may aid arborists and urban foresters in estimating site quality.

3.2.2 Soil pH

Soil pH impacts tree performance by influencing the availability of essential plant nutrients with an ideal pH range of 5.5-7.2 (Watson et al., 2014). This ideal range is often not observed in urban soils as a result of increased pH levels from deicing compounds, high pH irrigation water, and the weathering of concrete surfaces (Ware, 1990). Soil pH may also play an important role in tree species selection with ideal pH ranges varying by species. Due to the importance and variability of soil pH, arborists and urban foresters need a method to quickly and accurately measure it in the field

Two methods commonly used for determining pH are colorimetric and electrometric. The colorimetric method uses weak acids and bases as indicators whose color is based on the concentration of hydrogen ions in solution (Thomas, 1996). This method benefits from its low-cost and portability but is subject to human interpretation, resulting in errors > 0.3 pH units (Peech, 1965) and was therefore not included in this study. Electrometric methods determine pH by measuring the flow of ions between two electrodes made of either metal or glass (Table 3.1). Metal electrode sensors determine total soil electrical conductivity (EC) between two metal surfaces that are separated by an insulator. These sensors do not require a sample to be removed from the site as they are inserted directly into the soil. They also cost less than glass electrode sensors, but may not be sensitive enough to accurately measure soil pH for assessing site quality.

Table 3.1. Comparison of different methods used for measuring soil pH.

Sensor type	Cost ($)	Flexibility	Response time	Principle[†]	Remarks
Metal electrode sensor	10-300	Field	<3 min	EC	Noninvasive, immediate results, highly dependent on soil moisture and salt content
Glass electrode sensor	135-225	Field/Lab	<30 sec	HC	Mildly invasive, instantaneous, fails in highly saline soils

[†] EC (electrical conductivity; HC (hydrogen ion conductivity)

Glass electrode sensors use two different electrodes to determine soil pH. A hydrogen sensitive glass electrode measures the level of hydrogen ion conductivity while a metal reference electrode measures total EC. These two conductivity values are then analyzed by the sensor to provide pH readings that are accurate to within 0.01 pH units (Thomas, 1996). This method requires destructive sampling and mixing the soil with deionized water or a salt solution (e.g. $CaCl_2$). Despite these limitations, glass electrode sensors are the preferred method of field evaluation of soil pH due to their high accuracy (Thomas, 1996).

3.2.3 Soil moisture

Soil moisture plays a critical role in photosynthetic rates (Hsiao et al., 1976), root growth (Lyr and Hoffmann, 1967), tree growth (Hsiao, 1973), and tree defense (McDowell et al., 2008). Moisture level response varies amongst species (McDowell et al., 2008); with most trees experiencing increased levels of mortality during both flooding and drought conditions (Allen et al., 2010). Saturated soils limit oxygen availability resulting in root loss and ultimately tree mortality. Drought conditions reduce soil moisture levels, limiting tree uptake of water and essential elements increasing tree mortality. Two important theoretical moisture levels are field capacity and permanent wilting point. Field capacity is the soil moisture content after it has been freely drained by gravity. Permanent wilting point is the soil moisture content after which plants wilt and fail to regain turgor upon rewetting, resulting in plant death. Soil moisture between field capacity and permanent wilting point is known as plant available water. By maintaining soil moisture within the range of plant available water, managers can decrease tree stress and improve performance. To do this, urban managers need a quick, accurate, and affordable method to monitor soil moisture content.

Soil moisture has long been determined using the thermogravimetric technique, which determines soil moisture by recording the loss of mass in response to heating the sample (Ferré and Topp, 2002). This method is accurate and cost-effective, however, it cannot be used for repetitive sampling as the sample is removed from the site and requires long dry times (≥ 24 h) before providing soil moisture contents. These shortcomings have led to the development of many different field methods of moisture estimation (Table 3.2) including measuring EC or dielectric permittivity.

Table 3.2. Comparison of different methods used for measuring soil moisture.

Method[†]	Cost ($)	Flexibility	Response time	Principle[ʔ]	Output[‡]	Remarks
TG	500	Lab	24 hr	EVAP	GMC	Destructive, time consuming, no salt limitations
TDR	545	Field/Lab	<30 sec	DC	VMC	Noninvasive, instantaneous, fails in highly saline soils
FDR	755	Field/Lab	<30 sec	DC	VMC	Noninvasive, instantaneous, fails in highly saline soils
EC	10-375	Field/Lab	1-5 min	EC	VMC	Noninvasive, immediate, highly dependent on salt content

[†] TG (thermogravimetric); TDR (time domain reflectometry); FDR (frequency domain reflectometry); EC (electrical conductivity), [ʔ] EVAP (evaporation); DC (dielectric constant); EC (electrical conductivity), [‡] GMC (gravimetric moisture content); VMC (volumetric moisture content)

Soil EC sensors estimate volumetric moisture content (VMC) by measuring the rate of conductance through the soil between two metal electrodes. While affordable, these sensors vary in their accuracy due to interference associated with soil texture and salinity. Soil dielectric permittivity sensors use time domain reflectometry (TDR) or frequency domain reflectometry (FDR) to estimate soil moisture using the large contrast between the permittivity of water ($\varepsilon \approx 80$), soil solids ($\varepsilon \approx 2$-9), and air ($\varepsilon \approx 1$). The TDR method sends an electromagnetic wave along waveguides and measures the signal's return velocity which is then used to calculate soil VMC (Topp et al., 1980). The FDR method works similarly to TDR but measures the variation in the signal frequency as opposed to its return velocity (Robock et al., 2000). Benefits of dielectric permittivity sensors include portability, and quicker readings than the gravimetric method (Dobriyal et al., 2012). These sensors have the same limitations as EC sensors, but dielectric permittivity sensors can be calibrated to produce accurate readings in most soils. Quick and affordable sensors allow for multiple readings enabling arborists and urban foresters to better evaluate a site and the efficacy of management actions.

3.2.4 Field sensors for urban site assessments

The purpose of this study was to compare field methods of measuring soil pH and VMC and identify the most accurate and precise method of determination for use in an urban site assessment. In order to evaluate these relationships, sensors were tested across a range of soil moisture contents and textures commonly found in the urban setting. This studies specific objectives were to:

1. Compare soil pH values determined with metal electrode and glass electrode sensors to a laboratory standard.
2. Compare soil VMC values determined through TDR, FDR, and EC to a laboratory standard.
3. Discuss mechanisms influencing accuracy and precision of different evaluated

sensor methods.

4. Identify key attributes to consider for sensor selection.

3.3 MATERIALS AND METHODS

3.3.1 Study soils and preparation

Sensors were evaluated in four soil texture classes (loamy sand, sandy loam, clay loam, and clay) from a Wyocena loamy sand in Portage County, WI (Typic Hapludalf; USDA-NRCS, 1978) and a Kewaunee silt loam in Fond du Lac County, WI (Typic Hapludalf; USDA-NRCS, 1973) (Table 3.3). Sand, silt, and clay contents were determined using the hydrometer method (Gee and Or, 2002). Loss on ignition was used to determine soil organic matter content (Nelson and Sommers, 1996) and EC was determined using a glass-electrode sensor (PCTestr 35; Oakton Instruments, Vernon Hills, IL, USA) in a 1:2 (soil:deionized water) solution.

Table 3.3. Descriptions and properties of investigated soils including soil series, subgroup, texture, organic matter content by loss on ignition (OM), soil bulk electrical conductivity (EC) and soil bulk density (ρb).

Soil Series	Subgroup	Soil Texture	Horizon	Sand (%)	Silt (%)	Clay (%)	OM (%)	EC (µS m^{-1})	ρ_b (Mg m^{-3})
Kewaunee	Typic Hapludalfs	Clay Loam	Ap	33	32	35	4.56	20500	1.21
		Clay	Bt	10	32	58	3.64	23600	1.19
Wyocena	Typic Hapludalfs	Sandy Loam	Ap	67	24	9	2.67	12400	1.38
		Loamy Sand	BC	83	8	9	0.51	5500	1.44

In preparation, soils were by sieved at field moisture content through a 6 mm sieve to homogenize the samples and remove any large materials that may have interfered with sensor readings. Soils were then air-dried in plastic trays for a minimum of 96 hours. After air drying, deionized water was added by volume to the soil until target VMC's (0-30%) were reached (Ferré and Topp, 2002). These levels were achieved by repetitious misting and mixing of the soils, which were then covered and allowed to equilibrate for a minimum of 12 hours. Soils were then packed into PVC containers (10 cm inside diameter, 24.5 cm inside height) to target bulk densities (Table 3.3). To maintain a consistent bulk density, the soil was compacted in three sections of 5 cm to a total soil depth of 15 cm. Seven replicates were prepared for each moisture content and texture type (n = 84).

3.3.2 Laboratory sensor analyses

Soil pH was evaluated using two glass electrode and five metal electrode sensors. The glass electrode sensors were tested in a 1:2 (soil:deionized water) solution, while the metal electrode sensors were inserted directly into each soil container. Soil VMC contents were evaluated using one FDR, one TDR, and eight EC sensors inserted directly into each soil container. Soil pH and VMC were also evaluated using four metal EC sensors that measured both variables. A full list of sensors and manufacturer information can be found in Appendix C.

Manufacturer instructions for sensor preparation and calibration were followed to limit user bias. Accordingly, only the Lincoln Moisture Meter (8000; Lincoln Irrigation, Lincoln, NE, USA) was calibrated in a container of saturated soil for each texture. To avoid artifacts resulting from soil disturbance, the sensors were carefully inserted in order of probe size from smallest to largest, avoiding locations of previous insertion. All testing was done with soils at ambient laboratory temperature (20 °C ± 1 °C). Soil pH standards were determined for each container using a benchtop glass electrode sensor (Sension+ PH3, Hach Co., Loveland, CO, USA) (Thomas, 1996). Soil VMC standards of each container were determined on three subsamples collected at 5 cm depth increments. These subsamples were analyzed using the gravimetric method (24 hr at 105 °C) which was then converted to volumetric content using the measured bulk density (Ferré and Topp, 2002).

During preliminary testing, the Luster Leaf 1880 (1880; Luster Leaf Inc., Woodstock, IL, USA) failed when one of the three soil probes separated from the unit, and as a result, it was not included in the study. The Dr. Meter® 4-in-1 (S20; HISGADGET Inc., Union City, CA, USA) failed after performing 10 out of the 12 experimental runs and was included in the analysis.

3.3.3 Statistical analyses

Summary statistics were computed to evaluate the sensors' ability to predict soil conditions at the 95% confidence level. Pearson's and Spearman's correlation coefficients were calculated to assess sensor precision and Lin's concordance coefficient was calculated to assess sensor accuracy and precision. Accuracy was defined as the ability of the sensor to estimate actual soil conditions. Precision was defined as the repeatability of sensor measurements. Standard error and Lin's concordance coefficient was calculated using Microsoft Excel 2016 software (Microsoft Inc., Redmond, WA USA). Pearson's and Spearman's coefficients were calculated using SAS JMP 7.0

software (SAS Inc., Cary, NC USA).

3.4 RESULTS AND DISCUSSION

3.4.1 Soil pH

The metal electrode sensors failed to significantly and accurately measure soil pH across all soil textures and moisture contents ($P = >0.1$; $\rho_c = <0.2$) (Table 3.4) and did not follow a 1:1 correlation with the standard (Fig. 3.1). In air-dry soils, these sensors fail to make a measurement with readings showing little deviation from their zeroed value of seven pH. These sensors measure the soils conductance of an electrical signal, which is dependent on soil moisture. When there is a lack of moisture, the soil cannot conduct this signal resulting in sensors failing to measure soil pH. As moisture content increases, sensors can better measure soil EC resulting in an increase in variability of the readings (Fig. 3.1). Soil texture had no observed influence on soil pH readings, although it has been shown to affect EC readings (Mandal et al., 2015). Sensors requiring the insertion of the probe are at a fundamental disadvantage when measuring soil pH, which is stated as the hydrogen ion concentration in a solution (Schofield and Taylor, 2007). By inserting the probe into the soil there may be a lack of contact between the sensor and the soil solution resulting in inaccurate readings. Another issue with metal electrode sensors is the method uses bulk soil EC to estimate the concentration of hydrogen ions. Urban soils often include many other salts, making any hydrogen ion specific determination difficult.

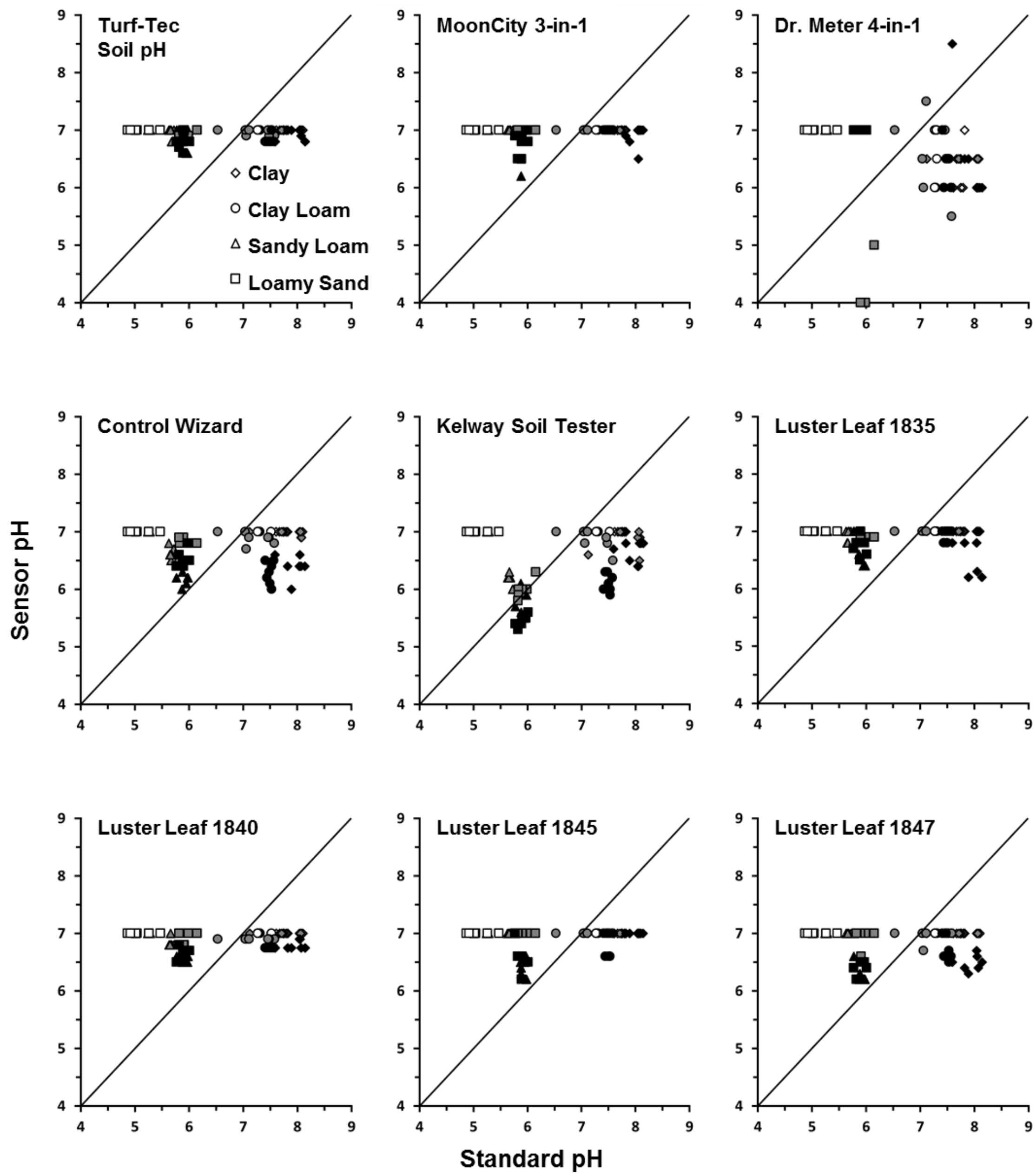


Fig. 3.1 Soil pH metal electrode sensor readings compared to laboratory standard (Hach Sension+ PH3).

The glass electrode sensors were found to significantly and accurately measure soil pH across all soil textures and moisture contents (P = <0.0001; ρ_c = >0.95) (Table 3.4). These high levels of accuracy and precision may be due to readings occurring in a soil solution, ensuring complete sensor contact and negating any issues with soil moisture or texture (Fig. 3.2). For this study, the solution was made using a 1:2 (soil:deionized water) ratio. This solution can also be made with a calcium chloride or potassium chloride solution for more accurate readings in high salt content soils (Thomas, 1996).

Table 3.4. Pearson's correlation (*r*), Spearman's correlation (*ρ*) and Lin's correlation (ρ_c) and standard error (SE) values between tested pH sensors and the laboratory standard (Hach Sension+ PH3).

Sensor	Sensor Type	r	ρ	ρ_c	SE
PCTestr 35	Glass Electrode	0.96***	0.92***	0.95	0.28
pH 5+	Glass Electrode	0.97***	0.95***	0.98	0.28
Turf-Tec Soil pH	Metal Electrode	0.01*	0.00*	0.01	0.38
Luster Leaf 1835	Metal Electrode	-0.10*	-0.04*	-0.01	0.39
Luster Leaf 1840	Metal Electrode	-0.07*	-0.04*	0.03	0.30
Luster Leaf 1845	Metal Electrode	0.11*	0.07*	0.06	1.37
Luster Leaf 1847	Metal Electrode	-0.07*	-0.12*	0.01	3.70
MoonCity 3-in-1	Metal Electrode	0.06*	0.00*	0.02	0.86
Dr. Meter® 4-in-1	Metal Electrode	-0.28**	-0.60*	0.19	1.40
Control Wizard	Metal Electrode	-0.25*	-0.10*	-0.02	1.41
Kelway® Soil Tester	Metal Electrode	0.15**	0.08*	0.22	0.29

† No p-value is calculated for ρ_c, *** denotes $P < 0.0001$, ** denotes $P < 0.05$, * denotes $P > 0.1$

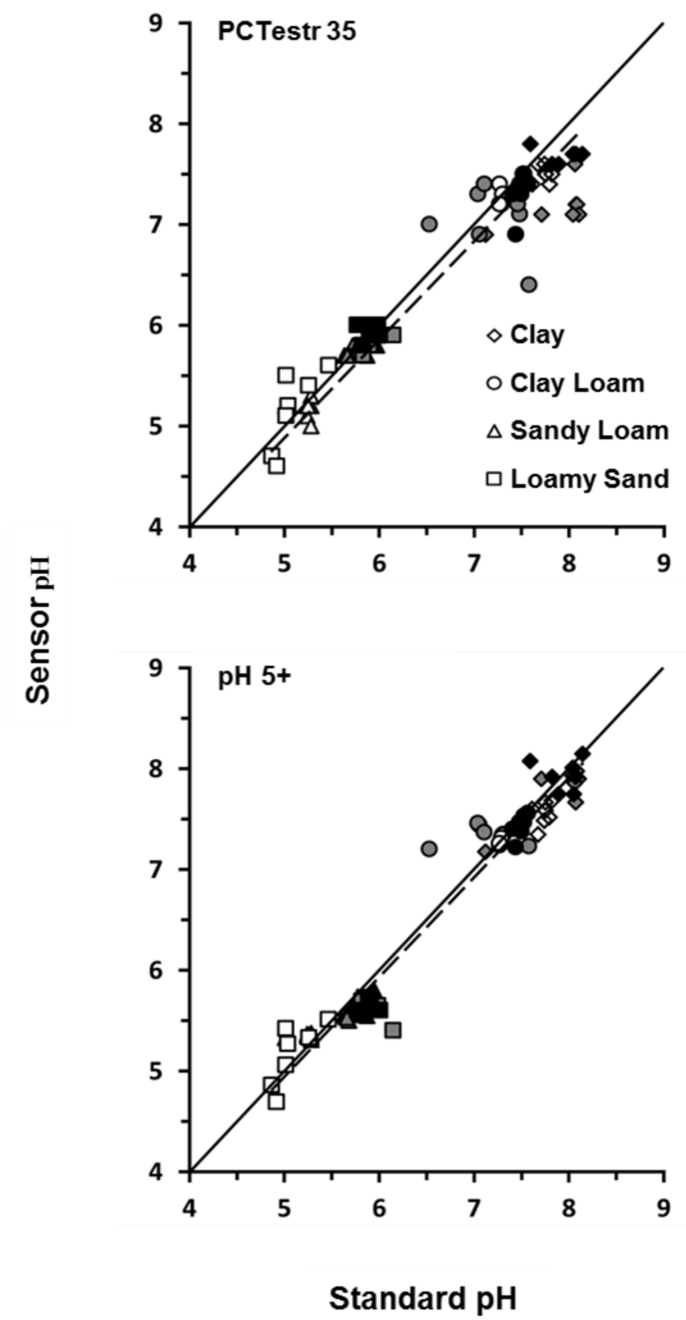


Fig. 3.2. Soil pH glass electrode sensor readings compared to laboratory standard (Hach Sension+ PH3).

3.4.2 Soil VMC

There was a strong correlation between soil VMC EC sensors and the laboratory standard across all soil moisture contents and textures ($P < 0.0001$; $r > 0.75$) (Table 3.5). However, most of these correlations failed to follow a 1:1 relationship with the standard

($\rho_c = <0.40$) (Figs. 3.3 and 3.4) with the exception of the General® (#DSMM500; General Tools and Instruments, Secaucus, NJ, USA) and Extech (MO750; FLIR Commercial Systems Inc., Nashua, NH, USA) sensors ($\rho_c = 0.71$). Electrical conductivity readings have been shown to correlate to moisture content (Zhang et al., 2004). However, due to EC and VMC's interdependence with many other soil and environmental attributes, no general model for their relationship has been proposed (Sophocleous and Atkinson, 2015). Poor performance may also be a result of low-cost manufacturing and calibration as VMC sensor cost was correlated to sensor quality ($R^2 = 0.79$) (Fig. 3.5). Of the EC sensors tested, the Turf-Tec soil moisture sensor (MS1-W; Turf-Tec International, Tallahassee, FL, USA) had the lowest cost: accuracy ratio due to its increased cost not being reflected in its accuracy.

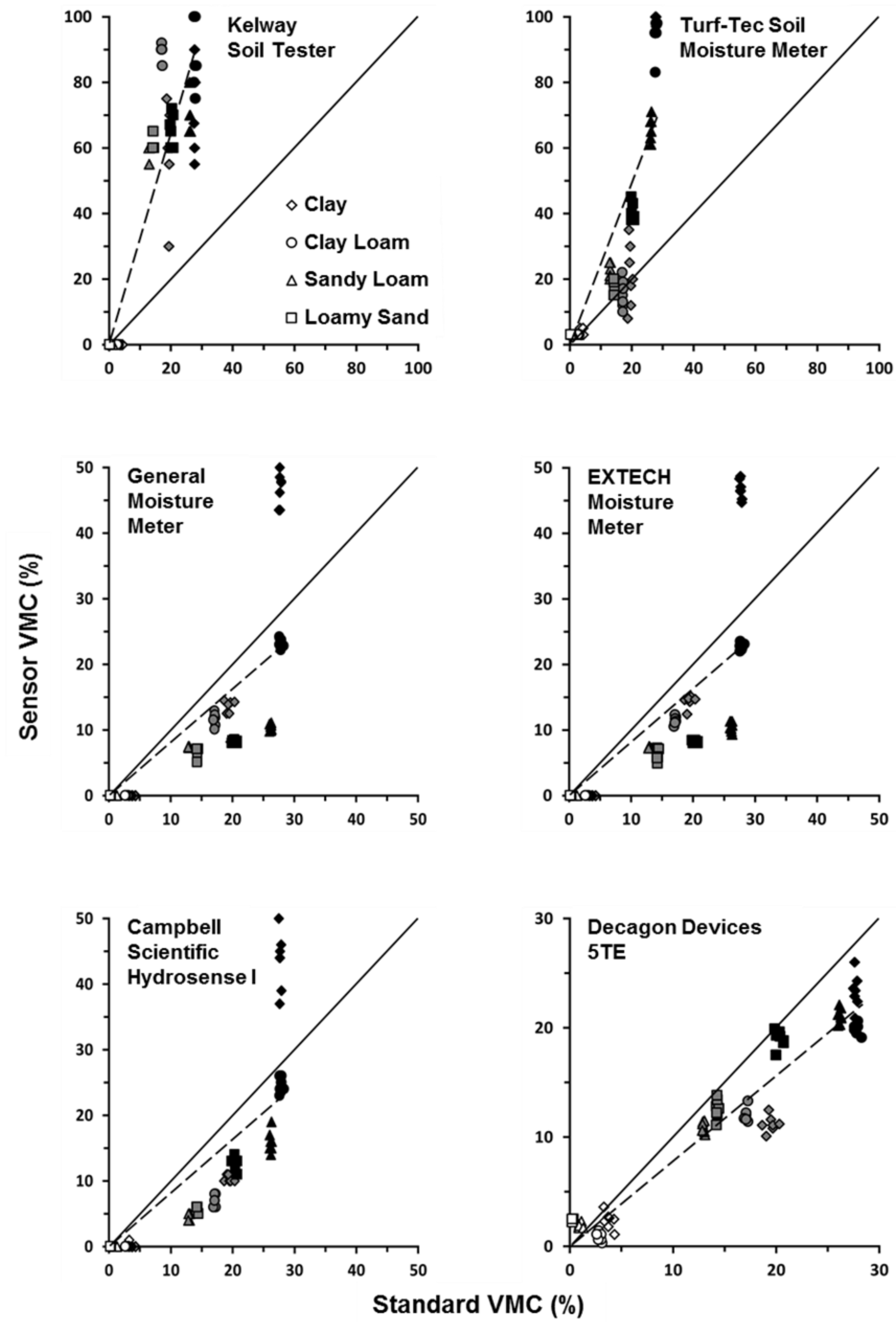
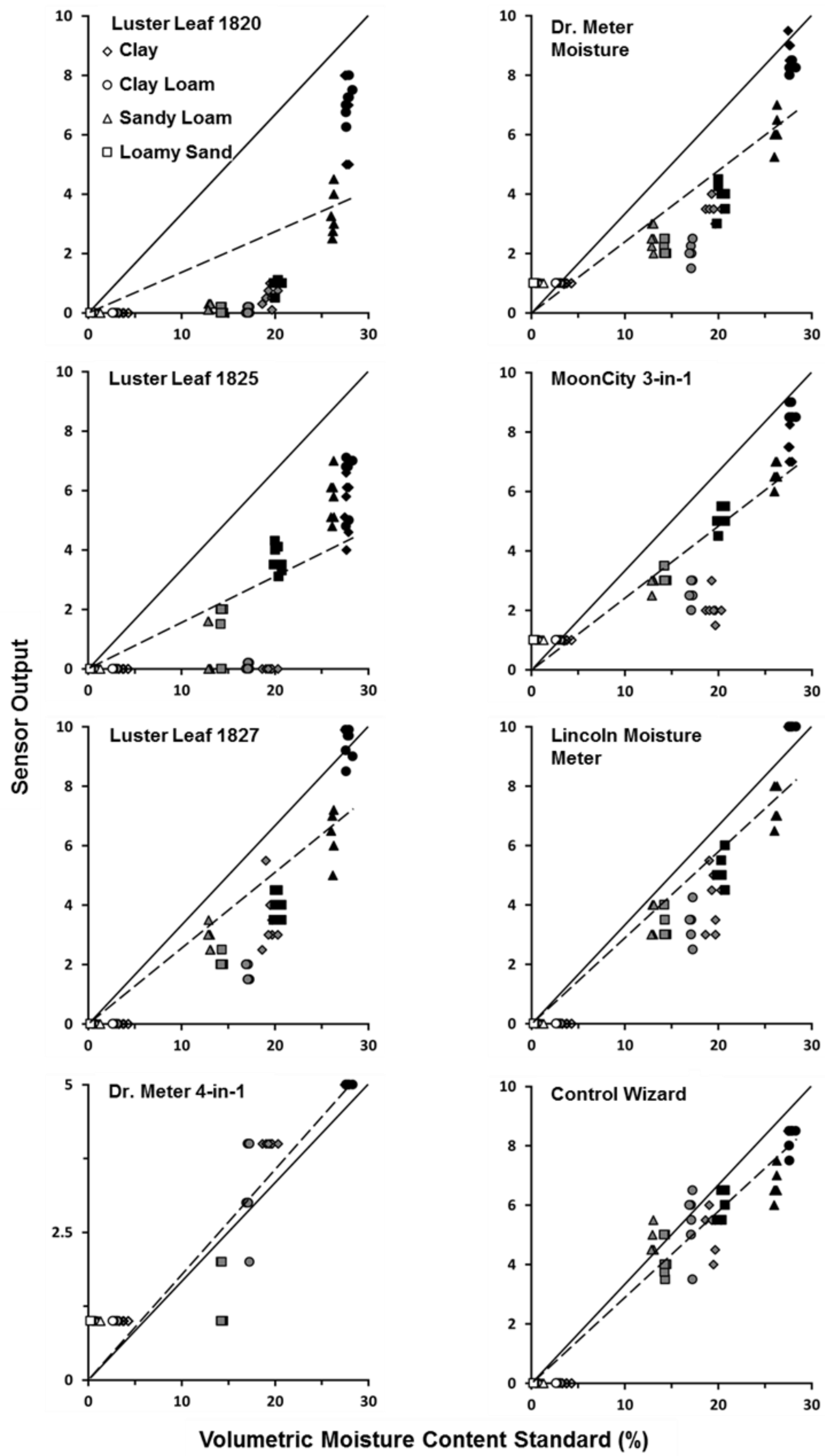


Fig. 3.3 Volumetric moisture sensors with percentage readings compared to laboratory standard (determined using gravimetric method).



1622 **Fig. 3.4. Volumetric moisture sensors with ordinal readings compared to laboratory**
1623 **standard (determined using gravimetric method).**

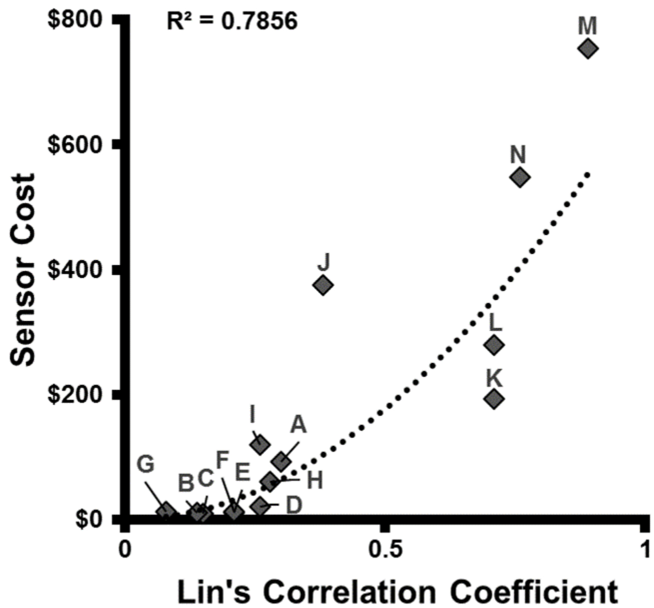


Fig. 3.5. Correlation between VMC sensor cost and Lin's correlation coefficient values by sensor including Lincoln Moisture Meter (A), Luster Leaf 1820 (B), Luster Leaf 1825 (C), Luster Leaf 1827 (D), Dr. Meter Moisture (E), MoonCity 3-in-1 (F), Dr. Meter® 4-in-1 (G), Control Wizard (H), Kelway® Soil Tester (I), Turf-Tec Soil Moisture (J), General® Moisture Meter (K), EXTECH Moisture Meter (L), Decagon Devices 5TE (M), and Campbell Scientific Hydrosense I (N).

Dielectric methods also showed significant correlation to the standard (*P* = <0.0001; *r* = >0.82) (Table 3.5) while closely following a 1:1 correlation (ρ_c = >0.76) (Fig. 3.3). These findings agree with those of other studies including Ledieu et al. (1986), Robinson et al. (2003) and Pelletier et al. (2016). While these sensors have higher costs, this is often a result of improved manufacturing and calibration research, which is reflected in their increased accuracy. These sensors also benefit from data logging capabilities and can be calibrated to unique soils, such as manufactured soils, to increase reading accuracy in a range of urban growing media.

Table 3.5. Pearson's correlation (*r*) (*P* < 0.0001), Spearman's correlation (*ρ*) (*P* < 0.0001) and Lin's correlation (ρ_c) and standard error (SE) values between tested soil moisture content (SMC) sensors and the laboratory standard (gravimetric method).

Sensor	Method[†]	r	ρ	ρ_c[‡]	SE
Lincoln Moisture Meter	EC	0.95	0.95	0.30	0.39
Luster Leaf 1820	EC	0.75	0.91	0.14	0.28
Luster Leaf 1825	EC	0.78	0.78	0.15	0.28
Luster Leaf 1827	EC	0.90	0.94	0.26	0.38
Dr. Meter Moisture	EC	0.89	0.95	0.21	0.30
MoonCity 3-in-1	EC	0.89	0.92	0.21	0.29
Dr. Meter® 4-in-1	EC	0.93	0.91	0.08	0.22
Control Wizard	EC	0.97	0.94	0.28	0.35
Kelway® Soil Tester	EC	0.90	0.82	0.26	3.87
Turf-Tec Soil Moisture	EC	0.87	0.98	0.38	3.70
General® Moisture Meter	EC	0.77	0.91	0.71	1.41
EXTECH Moisture Meter	EC	0.77	0.91	0.71	1.40
5TE	FDR	0.96	0.90	0.89	0.86
Hydrosense I	TDR	0.82	0.97	0.76	1.37

[†] EC (electrical conductivity); FDR (frequency domain reflectometry); TDR (time domain reflectometry), [‡] No p-value is calculated using ρ_c

Moisture content limitations were observed, with all tested sensors failing to accurately measure moisture contents below 10% (Figs. 3.3 and 3.4). Accuracy and precision of moisture readings may be impacted by the moisture content depending on the calibration of the unit. General factory calibrations may only be suitable for soils with moisture contents ranging from 10-50 % VMC (Weitz et al., 1997). While sensor accuracy generally improved as moisture content increased, soil texture also appears to influence accuracy. Specifically, sensors overestimated VMC and showed a decrease in precision in clay soils when moisture contents are above 25%. This overestimation is often a result of study soils having higher fine (silt and clay) particle contents than those used when developing the general factory calibration (Ganjegunte et al., 2012).

3.4.3 Management Use

All of the instruments evaluated are marketed for determination of soil pH, VMC, or both for plant management. It is important to identify sensors that use methods that are scientifically supported and provide accurate and repeatable measurements. Determining soil pH is necessary to manage plant available nutrients on a site and should be routinely measured as part of any fertilization plan. Glass electrode sensors can be used in the field or laboratory and provide accurate and instantaneous information on current soil conditions. Measuring VMC helps managers understand current moisture conditions and plant available water characteristics of a site.

Sensor durability was not tested in this study, however; the 5TE sensor (Decagon Devices Inc., Pullman, WA, USA) is not designed for repeated surface insertion and is not recommended for use in this setting. Sensor output must also be considered when making a selection. Evaluated qualitative sensors provided interpretation information for agriculture crops or houseplants, but not for tree and shrub species.

3.5 CONCLUSION

The goal of this study was to evaluate low-cost field pH and VMC sensors for use in a site assessment for urban tree management. This study used repacked soils to test the accuracy and precision of these sensors. While sensor accuracy has been shown to be consistent between natural and repacked soils, this is only true if they are of similar texture and structure (Czarnomski et al., 2005). Therefore, sensor accuracy observed here cannot be used to guarantee performance in other soil structures or textures. Soil pH and moisture are easy to determine and important soil variables that may influence tree performance and species selection. This study found cost might be an indicator of sensor quality for VMC sensors, but there was no correlation between pH sensor effectiveness and cost. In the case of soil pH, measurement method appears to the most important indicator of sensor performance. Information presented here may be used when selecting a measurement method.

ACKNOWLEDGMENTS

This study was funded, by a Hyland R. Johns Grant (No. 16-HJ-01) from the Tree Research and Education Endowment (TREE) Fund, Naperville, Illinois, as well as funding from the College of Natural Resources at University of Wisconsin – Stevens Point, Stevens Point, Wisconsin, The Morton Arboretum, Lisle, Illinois, and Bartlett Tree Experts, Charlotte, North Carolina. Laboratory assistance was provided by Alyssa Gunderson at the University of Wisconsin – Stevens Point.

3.6 REFERENCES

Allen, C.D., Macalady, A.K., Chenchouni, H., Bachelet, D., McDowell, N., Vennetier, M., Kitzberger, T., Rigling, A., Breshears, D.D., Hogg, E.H., Gonzalez, P., Fensham, R., Zhang, Z., Castro, J., Demidova, N., Lim, J.H., Allard, G., Running, S.W., Semerci, A., Cobb, N., 2010. A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. Forest Ecology and Management 259, 660-684.

Bolan, N.S., Adriano, D.C., Curtin, D., 2003. Soil acidification and liming interactions with nutrient and heavy metal transformation and bioavailability. Advances in Agronomy 78, 215-272.

Czarnomski, N.M., Moore, G.W., Pypker, T.G., Licata, J., Bond, B.J., 2005. Precision and accuracy of three alternative instruments for measuring soil water content in two forest soils of the Pacific Northwest. Canadian Journal of Forest Research 35, 1867-1876.

Dobriyal, P., Qureshi, A., Badola, R., Hussain, S.A., 2012. A review of the methods available for estimating soil moisture and its implications for water resource management. Journal of Hydrology 458, 110-117.

Ferré, P.A., Topp, G.C., 2002. Time domain reflectometry. Methods of soil analysis. Part 4-Physical methods. Soil Science Society of America, pp. 434-446.

Ganjegunte, G., Sheng, Z., Clark, J., 2012. Evaluating the accuracy of soil water sensors for irrigation scheduling to conserve freshwater. Applied Water Science 2, 119-125.

Gee, G.W., Or, D., 2003 Particle-size analysis. Methods of soil analysis. Part-4 Physical methods. Soil Science Society of America, pp. 255-293.

Greinert, A., 2015. The heterogeneity of urban soils in the light of their properties. Journal of Soils and Sediments 15, 1725-1737.

Hsiao, T.C., 1973. Plant responses to water stress. Annual Review of Plant Physiology 24, 519-570.

Hsiao, T.C., Acevedo, E., Fereres, E., Henderson, D.W., 1976. Water stress, growth, and osmotic adjustment. Philosophical Transactions of the Royal Society B: Biological Sciences 273, 479-500.

Ledieu, J., De Ridder, P., De Clerck, P., Dautrebande, S., 1986. A method of measuring soil moisture by time-domain reflectometry. Journal of Hydrology 88, 319-328.

Lyr, H., Hoffmann, G., 1967. Growth rates and growth periodicity of tree roots. International review of forestry research. Vol 2. Academic Press, 181-236.

Mandal, U.K., Burman, D., Mahanta, K.K., Sarangi, S.K., Raut, S., Mandal, S., Maji, B., Bandyopadhyay, B.K., 2015. Bulk soil electrical conductivity for coastal salt affected soils of West Bengal. Journal of the Indian Society of Coastal Agricultural Research 33, 11-18.

McDowell, N., Pockman, W.T., Allen, C.D., Breshears, D.D., Cobb, N., Kolb, T., Plaut, J., Sperry, J., West, A., Williams, D.G., Yepez, E.A., 2008. Mechanisms of plant survival and mortality during drought: Why do some plants survive while others succumb to drought? New Phytologist 178, 719-739.

Nelson, D., Sommers, L., 1996. Total carbon, organic carbon, and organic matter. Methods of soil analysis. Part 2-Chemical and microbiological properties, Soil Science Society of America, pp. 961-1010.

Peech, H.M., 1965. Hydrogen-ion activity. Methods of soil analysis. Part 2-Chemical and microbiological properties, Soil Science Society of America, pp. 1149-1178.

Pelletier, M., Schwartz, R., Holt, G., Wanjura, J., Green, T., 2016. Frequency domain probe design for high frequency sensing of soil moisture. Agriculture 6, 60.

Robinson, D.A., Jones, S.B., Wraith, J.M., Or, D., Friedman, S.P., 2003. A review of advances in dielectric and electrical conductivity measurement in soils using time domain reflectometry. Vadose Zone Journal 2, 444-475.

Robock, A., Vinnikov, K.Y., Srinivasan, G., Entin, J.K., Hollinger, S.E., Speranskaya, N.A., Liu, S., Namkhai, A., 2000. The global soil moisture data bank. Bulletin of the American Meteorological Society 81, 1281-1299.

Salvucci, G.D., 1998. Limiting relations between soil moisture and soil texture with implications for measured, modeled, and remotely sensed estimates. Geophysical Research Letters 25, 1757-1760.

Scharenbroch, B.C., Lloyd, J.E., Johnson-Maynard, J.L., 2005. Distinguishing urban soils with physical, chemical, and biological properties. Pedobiologia 49, 283-296.

Scharenbroch, B.C., Carter, D., Bialecki, M., Fahey, R., Scheberl, L., Catania, M., Roman, L.A., Bassuk, N., Harper, R.W., Werner, L., Siewert, A., Miller, S., Hutyra, L., Raciti, S., 2017. A rapid urban site index for assessing the quality of street tree planting sites. Urban Forestry and Urban Greening 27, 279-286.

Schofield, R.K., Womald Taylor, A., 1955. The measurement of soil pH. Soil Science Society of America Journal 19, 164-167.

Shukla, M.K., Lal, R., Ebinger, M., 2006. Determining soil quality indicators by factor analysis. Soil and Tillage Research 87, 194-204.

Sophocleous, M., Atkinson, J.K., 2015. A novel thick-film electrical conductivity sensor suitable for liquid and soil conductivity measurements. Sensors and Actuators, B: Chemical 213, 417-422.

Thomas, G.W., 1996. Soil pH and soil acidity. Methods of soil analysis. Part 3-Physical methods, Soil Science Society of America, pp. 475-490.

Topp, G.C., Davis, J.L., Annan, A.P., 1980. Electromagnetic determination of soil water content: Measurements in coaxial transmission lines. Water Resources Research 16, 574-582.

USDA-NRCS., 1978. Soil survey of Portage County, Wisconsin. United States Department of Agriculture - Natural Resources Conservation Service.

USDA-NRCS., 1973. Soil survey of Fond du Lac County, Wisconsin. United States Department of Agriculture - Natural Resources Conservation Service.

Ware, G., 1990. Constraints to tree growth imposed by urban soil alkalinity. Journal of Arboriculture 16, 35-38.

Watson, G.W., Hewitt, A.M., Custic, M., Lo, M., 2014. The management of tree root systems in urban and suburban settings: A review of soil influence on root growth. Arboriculture and Urban Forestry 40, 193-217.

Weitz, A.M., Grauel, W.T., Keller, M., Veldkamp, E., 1997. Calibration of time domain reflectometry technique using undisturbed soil samples from humid tropical soils of volcanic origin. Water Resources Research 33, 1241-1249.

Wuest, S.B., 2015. Seasonal variation in soil bulk density, organic nitrogen, available phosphorus, and pH. Soil Science Society of America Journal 79, 1188-1197.

Zhang, N., Fan, G., Lee, K.H., Kluitenberg, G.J., Loughin, T.M., 2004. Simultaneous measurement of soil water content and salinity using a frequency-response method. Soil Science Society of America Journal 68, 1515-1525.

Appendix C. Additional soil pH and moisture sensor information

Table C1. Commercial glass and metal electrode sensors for measuring soil pH.

Sensor	Sensor Type	Sampling medium	Sampling Range (pH units)	Accuracy[†] (pH units)	Cost ($)	Manufacturer
PCTestr 35	Glass Electrode	Soil:DI Water	0.0-14.0	±0.1	135	OAKTON Instruments Vernon Hills, IL, USA
pH 5+	Glass Electrode	Soil:DI Water	0.0-14.0	±0.01	225	OAKTON Instruments Vernon Hills, IL, USA
Turf-Tec Soil pH	Metal Electrode	Soil	3.5-9.0	—	299	Turf-Tec International, Tallahassee, FL, USA
Luster Leaf 1835	Metal Electrode	Soil	1-10	—	26	Luster Leaf Inc., Woodstock, IL, USA
Luster Leaf 1840	Metal Electrode	Soil	1-10	—	14	Luster Leaf Inc., Woodstock, IL, USA
Luster Leaf 1845	Metal Electrode	Soil	1-10	—	11	Luster Leaf Inc., Woodstock, IL, USA
Luster Leaf 1847	Metal Electrode	Soil	1-10	—	21	Luster Leaf Inc., Woodstock, IL, USA
MoonCity 3-in-1[ˀ]	Metal Electrode	Soil	3.5-8.0	—	13	Moon City Shenzhen City, Guangdong Province, China
Dr. Meter® 4-in-1[ˀ]	Metal Electrode	Soil	3.5-9.0	—	13	HISGADGET Inc., Union City, CA, USA
Control Wizard[ˀ]	Metal Electrode	Soil	3.0-8.0	±0.2	60	American Agriculture, Portland, OR, USA
Kelway® Soil Tester[ˀ]	Metal Electrode	Soil	3.5-8.0	±0.2	120	Kel Instruments Co., Teaneck, NJ, USA

[†] When reported by manufacturer, [ˀ] Combination meter measuring pH and VMC

Table C2. Commercial electrical conductivity (EC), time domain reflectometry (TDR), and frequency domain reflectometry (FDR) sensors for use in the determination of soil volumetric moisture content (VMC).

Sensor	Method[†]	Prong length (cm)	Output type	Range	Cost ($)	Manufacturer
Lincoln Moisture Meter	EC	21.5	Qualitative	0-10	93	Lincoln Irrigation, Lincoln, NE, USA
Luster Leaf 1820	EC	10.5	Qualitative	1-10	12	Luster Leaf Inc., Woodstock, IL, USA
Luster Leaf 1825	EC	14.5	Qualitative	1-10	10	Luster Leaf Inc., Woodstock, IL, USA
Luster Leaf 1827	EC	16.5	Qualitative	0-9.9	21	Luster Leaf Inc., Woodstock, IL, USA
Dr. Meter® Moisture	EC	19.5	Qualitative	1-10	11	HISGADGET Inc., Union City, CA,USA
MoonCity 3-in-1[‡]	EC	17.0	Qualitative	1-10	13	Moon City Shenzhen City, Guangdong Province, China
Dr. Meter® 4-in-1[‡]	EC	19.5	Qualitative	1-5	13	HISGADGET Inc., Union City, CA, USA
Control Wizard[‡]	EC	29.5	Qualitative	1-10	60	American Agriculture, Portland, OR, USA
Kelway® Soil Tester[‡]	EC	10.0	Quantitative	0-100%	120	Kel Instruments Co., Teaneck, NJ, USA
Turf-Tec Soil Moisture	EC	10.5	Quantitative	0-100%	375	Turf-Tec International, Tallahassee, FL, USA
General® Moisture Meter	EC	21.0	Quantitative	0-50%	194	General Tools and Instruments, Secaucus, NJ, USA
EXTECH Moisture Meter	EC	21.0	Quantitative	0-50%	280	FLIR Commercial Systems Inc., Nashua, NH, USA
5TE	FDR	5.0	Quantitative	0-50%	754[+]	Decagon Devices Inc., Pullman, WA, USA
Hydrosense I	TDR	12.0	Quantitative	0-50%	545	Campbell Scientific Inc., Logan, UT, USA

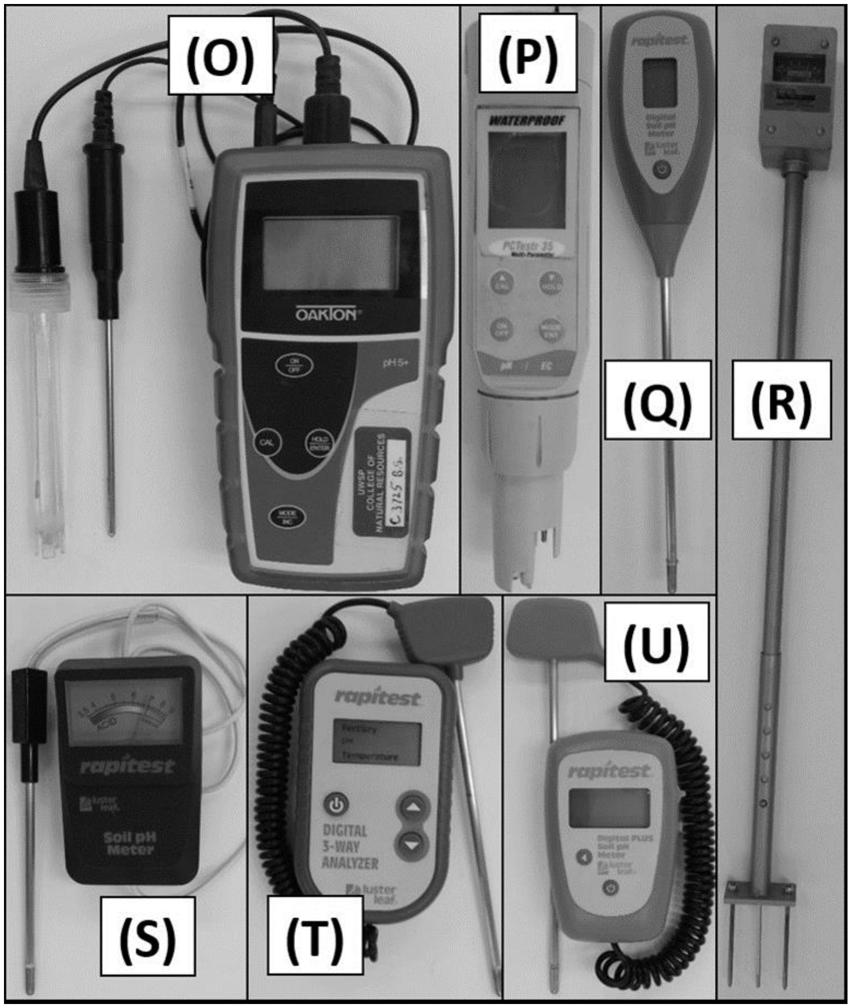


Fig. C1. Evaluated pH sensors including the Oakton pH 5+ (O), Oakton PCTestr 35 (P), Luster Leaf 1845 (Q), Turf-Tec Soil pH Meter (R), Luster Leaf 1840 (S), Luster Leaf 1835 (T), and Luster Leaf 1847 (U).

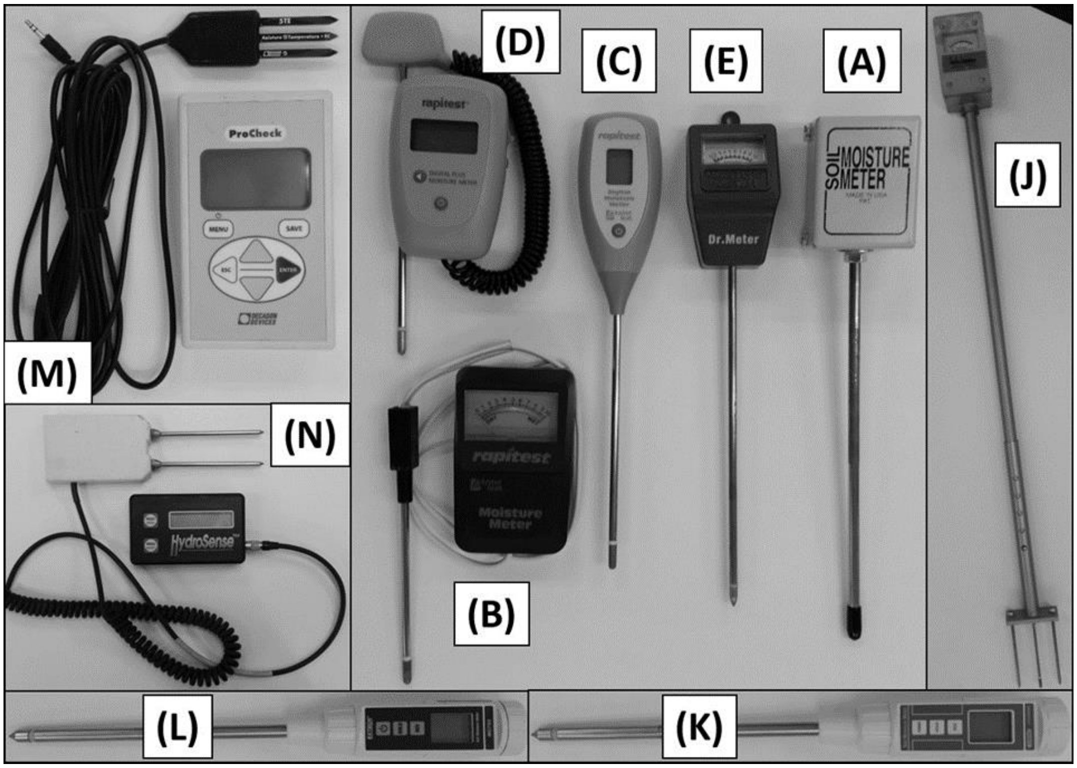


Fig. C2. Evaluated VMC sensors including the Lincoln Moisture Meter (A), Luster Leaf 1820 (B), Luster Leaf 1825 (C), Luster Leaf 1827 (D), Dr. Meter Moisture (E), Turf-Tec Soil Moisture (J), General® Moisture Meter (K), EXTECH Moisture Meter (L), Decagon Devices 5TE (M), and Campbell Scientific Hydrosense I (N).

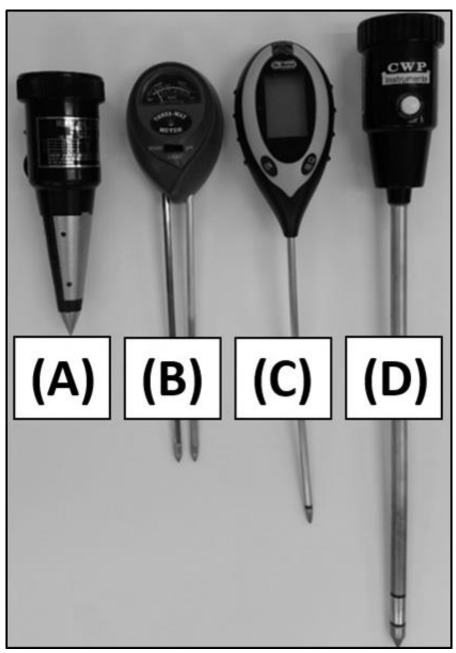


Fig. C3. Evaluated combination sensors including the MoonCity 3-in-1 (F), Dr. Meter® 4-in-1 (G), Control Wizard (H), and Kelway® Soil Tester (I).

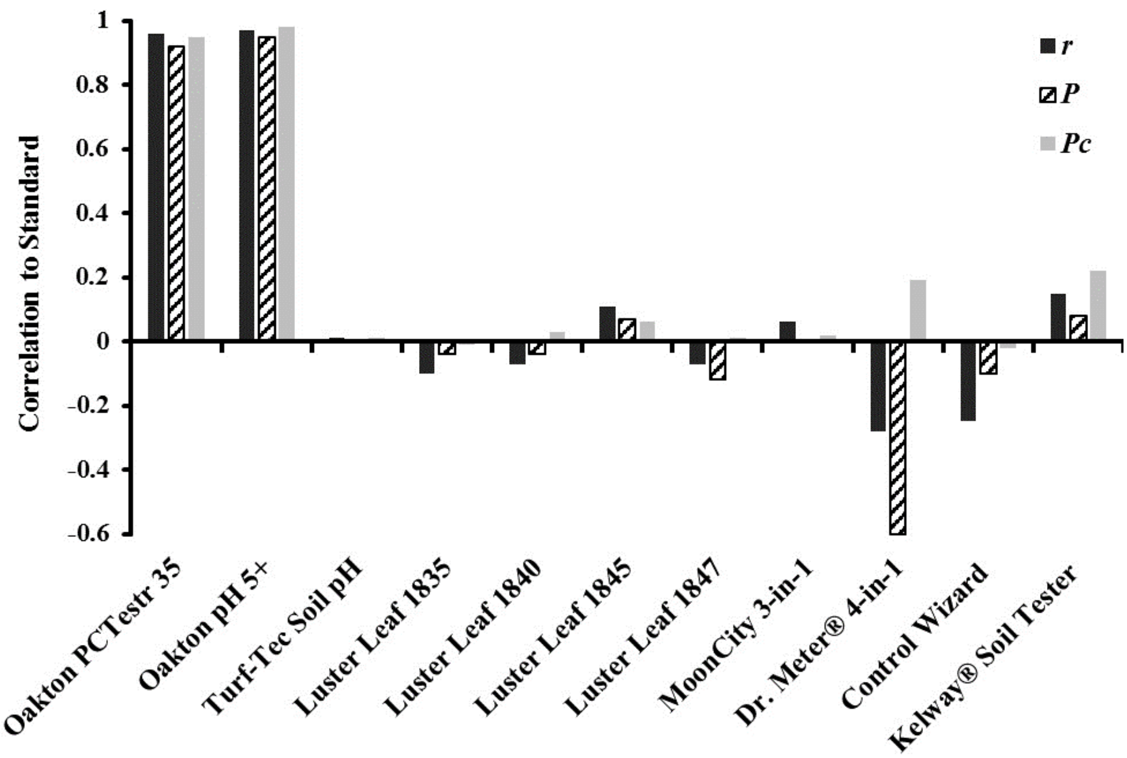


Fig. C4. Pearson's correlation (r), Spearman's correlation (P) and Lin's correlation (Pc) values between tested pH sensors and the laboratory standard (Hach Sension+ PH3).

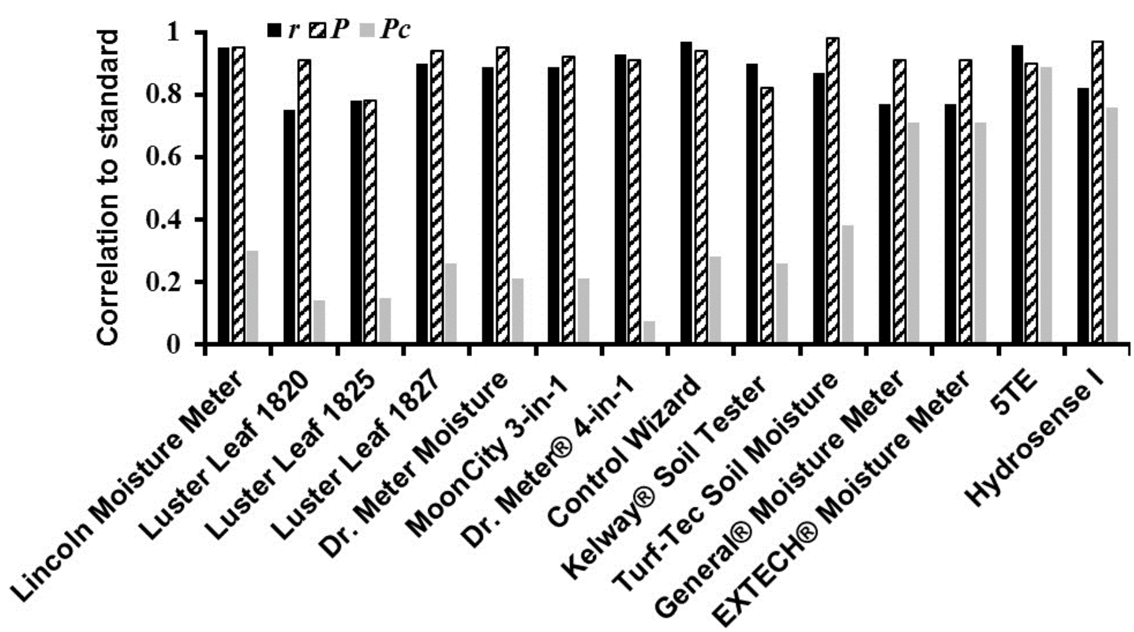


Fig. C5. Pearson's correlation (r), Spearman's correlation (*P*) and Lin's correlation (P_c) values between tested soil volumetric moisture content (VMC) sensors and the laboratory standard (determined using the gravimetric method).

1782