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Modern Urban Forestry for Modern Cities: Technology Challenges and Opportunities for the Remote Sensing of Urban Forests

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Abstract. Background: As human populations urbanize, urban forests in many areas are decreasing in canopy extent due to disruptions on several fronts, including novel pests and diseases, climate change, and changing land uses. Methods: A review of the remote sensing, computing, and environmental literature was performed to provide an overview of current technology capabilities and to detail an agenda for a modern approach to urban forestry challenges. How to prepare current and future professionals to collect and analyze "Big Data," how to implement results, and what communication skills are needed in a modern world to provide resilient urban forests in the connected future were also reviewed. Results: This paper outlines an agenda for how the urban forestry professions can identify, analyze, and manage emergent disruptions to continue to provide urban forest benefits to residents in its shade. Current remote-sensing systems, the paradigm of Big Data, and collection and analysis platforms are discussed, and relevant scenarios are provided to guide insight into managing forests with a rejuvenated perspective using remote-sensing hardware and software. Conclusions: Modern cities will require modern digital urban forestry management, and current and future professionals must be able to access and utilize technology, sensors, and Big Data to effectively perform vegetation management and communication tasks. This paper details the framework for a new era of modern urban forest management in highly connected, resilient cities.

Keywords. Computing; Sensors; Smart Cities; Urban Forest Management.

INTRODUCTION

Artificial Intelligence, Big Data, and Remote Sensing Overview

There is a data and computing revolution occurring across the modern world (Hey 2010; United Nations Data Revolution Group 2014), which is often called the Fourth Industrial Revolution (Schwab 2016; Ndung'u and Signé 2020) and encompasses artificial intelligence (AI) and "Big Data." AI is a nebulous term but generally is defined as actions to make machines intelligent and able to learn and plan (Stone et al. 2016). Big Data is generally considered to mean data sets so large and/or complex that traditional queries and methods of storage are inadequate with traditional languages and which grow larger at increasing rates (IBM Corporation 2020). Rapid advances in AI are driving advances in disciplines such as medicine (Onukwugha 2016), agriculture (Bronson and Knezevic 2016; Kamilaris et al. 2017), and engineering (Agrawal and Choudhary 2016) and are taking advantage of this revolution due to rapidly declining costs of memory and computing power (Mühleisen 2018). Big Data and AI work together: the enormous amounts of data stored cannot be efficiently accessed and utilized without AI, and AI requires enormous amounts of data to build learning models (Ferrucci et al. 2013).

Earth observation data is most often collected by remote sensing (RS), defined here as obtaining information about objects without contacting the observed objects. "Spectral imaging" is defined here as collecting discrete bands of reflected light in the electromagnetic spectrum. Spectral imaging of woody plants is useful because plant adaptations and reactions to their environment are observable and measurable by analyzing their optical properties in selected appropriate wavelengths (Kattenborn and Schmidtlein 2019). The most common types of RS data for urban forestry are in the visible wavelengths between 400 and

700 nanometers and in the near-ultraviolet to shortwave infrared portion of the electromagnetic spectrum between 380 and 2,500 nanometers (Jones and Vaughan 2010); a more complete description of types of RS data is found below. Today, satellites, aircraft, unpiloted vehicles, ground-based sensors, and even handheld sensors carried in pockets (de With 2020) annually collect terabytes of earth observation data (Hansen et al. 2013; Hohn et al. 2021). Platforms to compile and analyze earth observation data are proliferating (Mauri et al. 2017). Courses on computing languages used to operate these platforms are some of the most requested in universities and online across the world (Dierbach 2014). The urban forestry professions can take advantage of RS and the Big Data revolution in computing to vastly improve forest assessment, monitoring, and management.

Threats to Urban Forests

Urban forests provide many benefits to humans who live, work, and play in their shade (Dwyer et al. 2000; McPherson et al. 2016). Nonetheless, urban forest canopy cover is decreasing across much of the developed world due to several current and emerging threats (Kaspar et al. 2017; Doick et al. 2020; Nowak and Greenfield 2020). Examples of current and emerging biotic threats to urban forests include emerald ash borer (*Agrilus planipennis*)(Poland and McCullough 2006), spotted lanternfly (*Lycorma delicatula*)(Urban 2020), and ash dieback (*Hymenoscyphus fraxineus*) (Díaz-Yáñez et al. 2020). Abiotic threats include anthropogenic climate change (Nowak et al. 2014; Ordóñez and Duinker 2014), which is increasing urban heat (Akbari et al. 2016) and changing weather patterns (Melillo et al. 2014; Masson et al. 2020). Densification of the built environment (Chun and Guldmann 2018; Næss et al. 2019) may result in both tree removal (Martino et al. 2021) and reduced area for new large-statured trees (McPherson et al. 2002; Haaland and Konijnendijk van den Bosch 2015). An emergent phenomenon that could create both significant challenge and opportunity is an evolution in driverless vehicles, discussed below.

How can the urban forestry professions take advantage of RS, AI, and Big Data to improve urban forest health? This paper will discuss the current capabilities and likely future directions of RS and computing, then suggest a technology path forward for the urban forestry professions to ensure future generations will enjoy the many benefits of urban forests.

MATERIALS AND METHODS

A scoping review was performed of the relevant literature in the unpiloted aerial systems (UAS), artificial intelligence, and remote sensing disciplines to bring together a disparate set of systems soon to be important to the arboricultural disciplines.

In addition, a scoping review was performed of current online analytical and data-compilation platforms, and the trade literature for the arboricultural and UAS disciplines. Due to the rapidly changing nature of the current technological environment, a thorough analysis also was performed of recent past and current news articles and press releases for the AI and UAS disciplines to get a sense of likely development directions in these respective fields.

A challenging aspect of any review conducted for a set of rapidly changing disciplines is choosing what is relevant information. Guiding these choices is the author's experience in the field interacting with a disparate set of partners, from growers, pilots, UAS and sensor manufacturers, researchers, and software developers. Working backwards from an assumed endpoint—what industries and businesses expect to be the most likely futures toward which they are striving—is the main driver of the methodology of this review. Although it is by no means certain, a future where the arboricultural disciplines use modern and future technology to assist in the analysis and typical work of the profession is very likely, therefore the aim of this paper is to prepare the arboricultural professions for a presumed high-tech future.

RESULTS

What follows is an outline of the findings important to the arboricultural disciplines: what types of data are or will be relevant in a high-tech future, and how they are or will be collected, analyzed, and applied. Then discussed will be how management can approach the coming disruption in the profession, as well as a discussion of how current or future workers can prepare themselves for the future. Lastly, a set of scenarios illustrate how the results can be applied to real-world problems that exist now or likely will exist soon.

Data Collection

Collecting data on urban forests is traditionally performed by visiting a site and physically measuring parameters such as species, location, diameter at breast height (DBH), and health condition (Gordon and Templeton 2015). Today, these data points require collection in the field, then entry of the collected data into a centralized database. A street tree inventory for a city of 100,000 people may take 4 to 5 weeks using a typical crew of 6 people working 40 hours a week, depending upon how many parameters are measured (TJ Wood, personal communication, 2021 May 4).

Today, a tremendous amount of urban forest data is already being incidentally collected by third-party RS platforms (Liu 2015; Mohney 2020). For example, traditional large satellites such as the European Space Agency's Sentinel 2 and 3 platforms (Phiri et al. 2020), Worldview 3 platform (Ozkan et al. 2020), or constellations of small satellites such as "Doves" manufactured by Planet Labs (Werner 2019) collect RS data at sufficient resolution to be used for some urban forestry applications (Alonzo et al. 2013; Schlemmer et al. 2013; Segarra et al. 2020; PlanIT Geo 2021). Some platforms image a specific area several times a week or better, weather permitting (Bradshaw 2020). Aircraft can be tasked to fly over cities to collect data that can be utilized for urban forest assessments, for example, the Denver Regional Council of Governments in Colorado, USA (DRCOG 2018) regularly collects leaf-on and leaf-off data for built environment purposes that also contain data usable for urban forestry analyses. Google Earth has information across much of the developed world at sufficient resolution to estimate DBH class, tree genus, and location (Berland and Lange 2017). Remotely Piloted Aircraft (RPA) are also beginning to collect very high-resolution urban forest data (see examples in Figures 1 and 2) that researchers are using to begin to decipher plant reflectance and identify health and key pests (Staley et al. 2019). Much more RPA data will be available soon as aviation governing bodies in countries across the planet approve operations for flying RPA over cities and beyond line of sight (Jones 2017).

A description of the types of data currently relevant at urban forest vegetation scales and how they are collected follows:

- Visible and spectral imagery: These data are collected from satellites, aircraft, RPA, and ground-mounted sensors such as Google Street View vehicles and handheld smartphones. These data can be used to determine tree canopy health, disease, canopy extent, pest presence, and—depending on the sensor—tree species (Thenkabail et al. 2018).
- Thermal data: These data are collected from aircraft, RPA, and some satellites. These data can be used to detect heat islands, plant water stress, and indicators of moisture such as irrigation leaks (Stankevich et al. 2019).
- LiDAR data: LiDAR (light detection and ranging) is similar to radar, but utilizes light instead of radio waves. These data are collected from aircraft, RPA, ground-mounted sensors, handheld sensors, and even smartphones (de With 2020). These data can display high-resolution 3D surface and elevation models of canopy, individual trees, or structures. LiDAR can also assist in calculations for wood volume or carbon sequestration (Tigges and Lakes 2017).
- Digital surface models (DSMs): Constructed using data and photogrammetry from satellites, aircraft, and RPA (Escobar Villanueva et al. 2019). These data can depict urban forest and built environment structure across scales. DSMs can be derived from sources such as visual imagery, LiDAR, spectral imagery, or Synthetic Aperture Radar mounted on satellites or aerial platforms.
- 3D models: Derived from photogrammetry or other processes using sensors mounted on aerial or ground platforms and constructed from visible, spectral, or LiDAR data using specialized software.
- Traditional environmental monitoring data: Here defined as instruments that collect parameters, including soil moisture, temperature, and pan evaporation.

If current trends continue, soon a vast amount of data for urban forest trees, both public and private, will routinely be collected for use in urban forestry and curated somewhere for later discovery and analysis.

Data Analysis

Today, most urban forest inventory data are analyzed on purpose-built inventory software created by third-party entities, stored in the software system, and accessed via simple queries within the software interface. Where are all the data on urban forests described above stored and analyzed?

Discovering, accessing, and analyzing urban forest data curated on third-party platforms is not straightforward today. Data must be found across a growing number of sites. Once data are located, computer languages such as Python (Bogdanchikov et al. 2013) or

R (R Foundation 2021) are generally used to query the data sets and parameterize output. Accessing some data may require paying a fee (Satellite Imaging Corporation 2021). Nonetheless, terabytes of earth observation data, including urban forest data across scales, are available now on platforms such as the European Space Agency's Copernicus platform (ESA 2021), Google Earth Engine (Anchang et al. 2020), Arlula (Arlula 2021), and open-source platforms such as GitHub (GitHub 2021) and Orfeo (Grizonnet et al. 2017). Governments may make data collected for various purposes available, often for free (Baines et al. 2020; Galle et al. 2021). Examples of publicly available urban forest data sets include Denver, Colorado, USA (City and County of Denver 2021) and Melbourne, Victoria, Australia (City of Melbourne 2020).

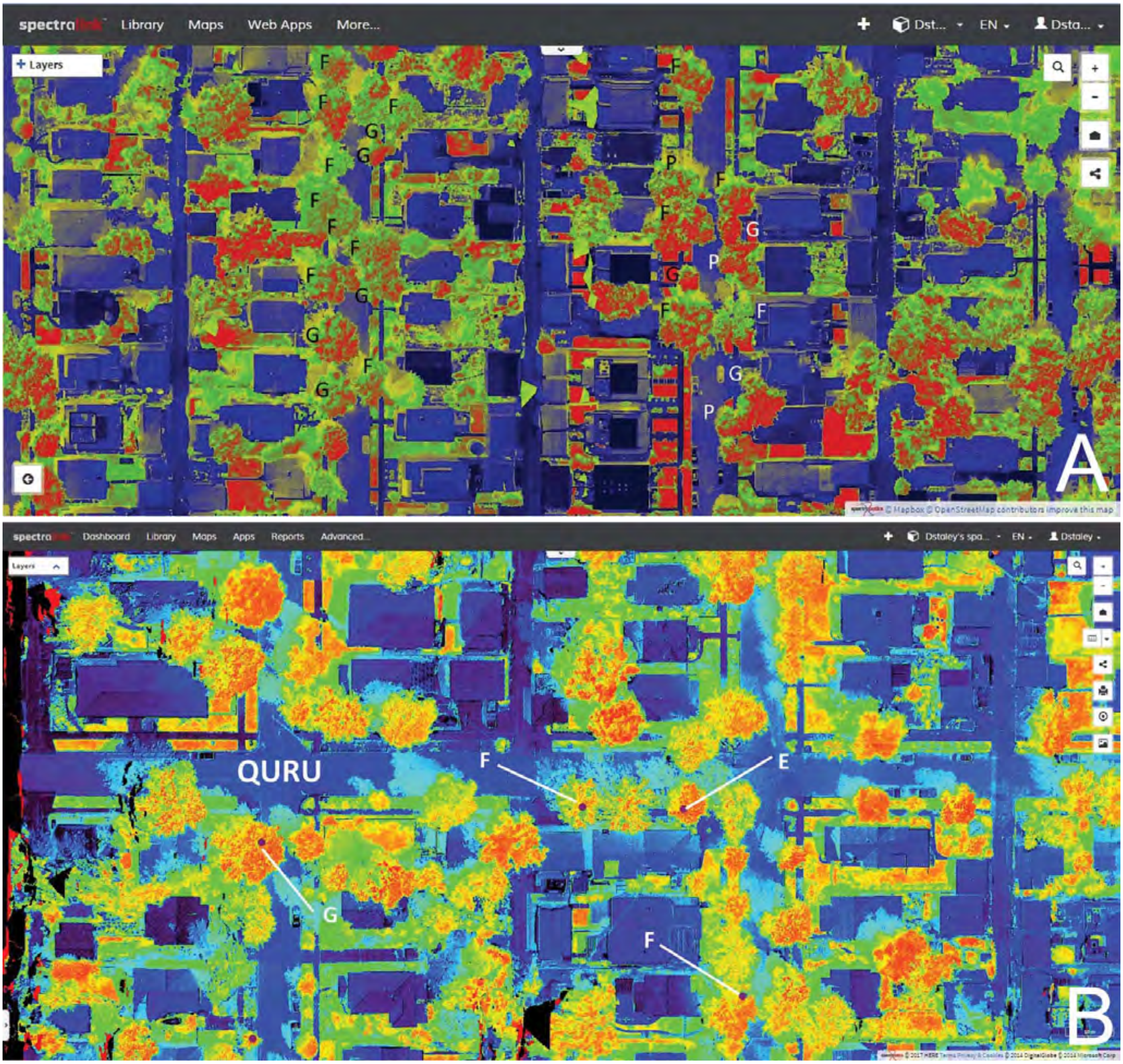

Figure 1. Reflectance signals to identify plant health and pests. (A) Use of spectral algorithms derived from reflectance values to determine overall plant health and compare ground-based inventory (inventory year: 2015), with proprietary health indicators (collection year: 2018). Red denotes healthy vegetation. E = Excellent, G = Good, F = Fair, P = Poor. Derived health indicators match well with ground-based inventory. Location: Denver, Colorado, USA. (B) Detail of 1A but comparing *Quercus rubra* with known stress (QURU). E = Excellent, G = Good, F = Fair. Spectrally derived health indicators match well with ground-based inventory.

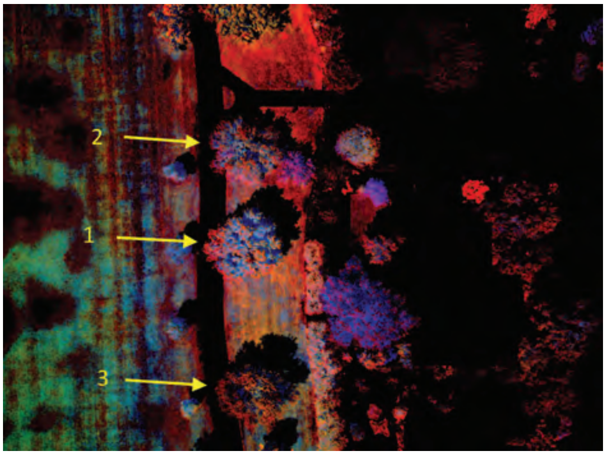

Figure 2. Pest detection using spectral reflectance algorithms. Proprietary plant health algorithm developed specifically to detect emerald ash borer (EAB). Three *Fraxinus pennsylvanica* attacked by EAB and in various stages of early stress are denoted by yellow arrows. 1 = best condition and 3 = worst condition. In this image, colors are only relevant for *Fraxinus*: blue is healthy foliage, and orange is thinning foliage due to EAB attack. At the time of imaging, only crown thinning was evident visually, and no other indicators of attack were visible. Woodpeckers were found in these trees several months after this imaging mission. Location: Boulder, Colorado, USA.

Collecting or accessing remotely sensed data, analyzing on software platforms, integrating new information into action, and communicating results to users and clients will soon be a standard task for the urban forestry professions. Urban forestry routinely using RS data and acting on it will be an important inflection point in the direction and history of urban forestry. "Digital urban foresters" collecting, harvesting, curating, and analyzing data will be a new specialty, because current and emergent threats to urban ecosystems—and the citizens who depend on urban forests—require utilization of all available data in an increasingly complex world. Now is the time to begin the transition to the era of Big Data-driven urban forestry.

The coming era of urban forest technology can be characterized as a "Big Data Urban Forestry" information environment. This new era will require new ways of organizing some traditional tasks and developing new tasks arising from the proliferation of data.

The CACI Model

The CACI model in this paper refers to the process of urban forest RS data **C**ollection, **A**nalysis, **C**ommunication, and **I**mplementation. Key to this process is a specialized branch of artificial intelligence computing called machine learning (ML), discussed below.

Collection is finding relevant existing data ("discovery"), and/or physically collecting needed RS data. RS data discovered or collected may be from any platform and curated in the public or private sphere (open-source or fee-based data).

Analysis requires an understanding of both the *applicability* and *relevance* of remote sensing outputs, such as vegetation indices, LiDAR point clouds, Digital Evaluation Models (DEMs), 3D models, and digital orthophotos. Applicability and relevance of sensor outputs are key considerations for choosing a particular sensor for urban forest analysis. Spectral imagery can be processed into vegetation indices to indicate tree health and help determine canopy extent (Jensen et al. 2012; Alonzo et al. 2016), as well as attempt to determine genus and species. It is important to understand that, currently, analysis of spectral data using existing commercial agriculture software platforms on the internet does not sufficiently analyze trees for accurate pest and disease tracking (Staley et al. 2019) and requires human intervention using a platform such as ENVI (Harris Geospatial Solutions Inc. 2021), ArcGIS (ESRI 2009), or QGIS (QGIS 2021). Choosing data types will be an important analysis and budget consideration in the future: just because data exist, does not mean those data are relevant to a particular analysis (Li et al. 2019). For example: dense point clouds of LiDAR data are excellent for three-dimensional representations of tree crowns (Gülçin and Konijnendijk van den Bosch 2021) but currently struggle to resolve parameters such as leaf chlorophyll content or presence of pests or disease (Fahey et al. 2021). Paying for the right data and analysis will be an important discussion in many urban forests soon.

Communication, for purposes of this paper, includes written, spoken, and digital communication. Examples of communication types relevant to urban forestry include tasks such as explaining to decision makers the merits of a project or a proposal, advising third-party contractors on the validity of an output or conclusion, notifying citizens of the findings of a project, writing urban forest plans based on RS data and analysis, asking for money to act on a proposal or analysis, explaining to a contractor the scope of project requirements and expectations, and answering questions or relaying findings to the public via social media and web pages. Communication skills and coalition building will be even more important in an information-rich environment with multiple communication platforms used by diverse publics. Communicating effectively to many different audiences will soon be an important skill in an information-rich world.

Implementation in this paper is defined as action resulting from results of analysis. This action results in outcomes such as publishing and enforcing a management plan, requesting for a budget to address findings, submitting a bid encompassing work for a Request for Proposal, or issuing work orders.

Machine learning will be a key component of the future CACI process and is a sub-discipline of artificial intelligence. ML uses data and algorithms to make predictions, models, and decisions, without being explicitly programmed to make predictions and decisions, then learns and improves with experience (Malone et al. 2020). ML is a rapidly growing field, is quickly becoming ubiquitous across many fields of human endeavor, and includes plant species identification applications on smartphones and plant disease identification algorithms for handheld sensors (Mohanty et al. 2016; Buja et al. 2021).

It is likely at the current pace of ML development that within 10 years, ML algorithms will be available for many urban forest needs, using data from numerous places to perform both user-based and machine-based queries and actions, ranging from canopy health assessments across scales, to amount and timing of irrigation or nutrient delivery in constructed landscapes.

DISCUSSION

Considerations for Management

In the future, organizations, departments, and companies will need to decide between: (1) hiring digital forestry staff to perform most or all of the CACI process; (2) hiring third parties to do most or all of the CACI process; or (3) some combination of the two. These options will require a new set of knowledge and skills to ensure a positive outcome from the project. Whatever option is chosen, each choice requires that digital forestry staff have knowledge of RS and data analysis. Option (1) is a cost the organization must bear; option (2) is a cost the market will bear; for option (3) both bear the costs.

Hiring a specialized team consisting of staff competent in both plant knowledge and computer science may be reserved for only a few of the largest organizations with the budget to fund skilled specialty teams and necessary office equipment. Conversely, relying on outside contractors to do most of the work will require that an organization has project management staff who can ensure third parties perform work per contracts and that the output makes sense. Balancing these two considerations will be an important task for urban forest managers and require discipline to keep everyone on track.

Key questions for operations will be how much capacity, resources, and competency the organization will keep in house versus how much will be acquired via third-party contractors. Other questions include: Who curates the data? Who handles cybersecurity protocols and responsibilities? Who purchases physical infrastructure such as office space, computers, servers, data purchase, data security, and software licenses? Who writes the technical reports and management plans arising from data analysis? Who creates, presents, and shares the visual representations of data and results to the client or the public? These questions will be relevant in many organizations in the future.

Career Paths and Other Opportunities to Address Modern Technology Challenges

As the demand for Big Data grows, one can envision the existing industry of environment-specific companies such as those providing field technology services for wetland delineation, surveying, construction management, and engineering expanding their offerings to provide urban forestry services (Schewe 2020). Similarly, existing analytics and technology-focused office firms that are lacking field experience or botanical education may need individuals from the urban forestry professions to assist in product development, testing, or deployment. Lastly, a market may evolve for firms that specifically offer RS and/or Big Data services tailored for the urban forestry professions or other professions in built or wild landscapes. Organizations may forego investment in maintaining physical resources and staff and instead decide to contract services to provide and curate data, provide analysis, and manage software licensing, data security, and physical infrastructure for smaller organizations or companies. Similarly, a niche may arise for a career consultant who bills time by specializing in interpreting data or analyses and writes highly technical data reports for diverse environmental clients.

Individuals already in the traditional urban forestry professions looking for a change due to age, injury, or life event may want to have an option like those discussed above for a new career path in digital urban forestry. New blood interested in trees will soon have another entry point via technology in addition to the traditional labor path. The proliferation of telework means that digitally focused urban forestry professionals may not have to move to continue a career path, or they can move and continue their career. Analysis work on software platforms can be done from anywhere with a good computer and reliable internet connection, and reports can be written anywhere.

Another labor consideration for changes in the digital future: development of data collection options may soon reduce staff field visits and will create flexible methods to verify conditions on the ground. Not only will data collection have more options and be faster with the proliferation of devices to collect data, but soon people with minimal training will be able to visit a site and collect data with a smartphone (Trimble Geospatial 2020; EcoBot Inc. 2021) or handheld device (Buja et al. 2021) and upload the data to the cloud for inclusion in the CACI process. Consider these digital field tasks being performed by staff wishing to cut hours, by staff recovering from injury, by summer interns, by temporary staff, by staff on loan, or by volunteer tree stewardship groups looking to expand their services (The Park People 2021). Or consider the implications of the current "citizen scientist" trend (Nitoslawski et al. 2019) being directed or expanded in multiple productive directions by citizens assisting in RS data collection or validation. This sort of flexibility in work allows more people—new blood—to enter the urban forestry professions. Is an organization looking for avenues for inclusion, equity, and opportunity? Perhaps one solution is creating digital urban forestry options to attract people who love trees but may not want to start out on the ground behind a chipper.

EXAMPLES OF TECHNOLOGY APPLICATIONS: FIELD SCENARIOS

How might the technology described above be applied in the future? The following scenarios are either familiar situations occurring today that will benefit from RS and Big Data in the future, or scenarios that will likely occur soon in an information-rich world. These scenarios describe use of RS technology and Big Data using the CACI process. Some scenarios are presumed to require third-party input for all but the largest organizations, for example, data collection by aircraft is presumed to be by a third-party, but no such presumption exists for RPA deployment. Cost, legal constraints, and privacy are not discussed due to space limitations.

Disease Front Progression

With increasing global trade of goods and services, the opportunities for tree pests and diseases to be introduced and spread is increasing (Roy et al. 2014). For example, recent high-profile introduced pests such as emerald ash borer and ash dieback threaten to eliminate significant fractions of *Fraxinus* from the urban forest canopy on several continents if no control is found soon.

Monitoring and managing the movement of urban tree pests and disease can be significantly improved by collecting and analyzing near-time RS data to make intervention decisions that can result in timely and responsive actions (Shojanoori and Shafri 2016). Current commercial satellite technology does not have the resolution to accurately identify individual pests and diseases, but airborne piloted and remotely piloted aircraft can carry sensor payloads that can resolve a small, individual tree's health. Although it is not possible at this time to have a universal vegetation index or health index to identify stress or disease across species or scales (Thenkabail et al. 2018), the early stages of identifying specific pests and disease via RS analytics has begun (Näsi et al. 2018; Staley et al. 2019).

Today, tracking disease fronts by collecting near-time RS data of public and private trees can be performed by contracting piloted or remotely piloted aircraft to carry a payload spectral sensor and visual camera. Some models of multispectral camera may be sufficient for some analyses, depending upon the pest and which bands are collected. Hyperspectral imagery can indicate tree health and help determine canopy extent (Jensen et al. 2012; Alonzo et al. 2016), as well as attempt to determine genus and often species; several software platforms such as ENVI can process hyperspectral data. Large areas require piloted aircraft for technological and legal reasons; for less than a few square kilometers, RPAs are sufficient. Utilizing geographical information systems (GIS) land cover data layers will be necessary to obtain property data for accurate location and tracking.

In the near future, it likely will be possible for constellations of satellites or high-altitude RPAs to image the earth's surface with sufficient resolution to collect high-resolution, near-time spectral and visual data on

Figure 3. RPA image resolution and plant health. Proprietary early machine learning–derived plant health algorithm at neighborhood scale overlaid with visual imagery. Flight level: 120 m above ground level. The resolution of tree crowns less than 1-m diameter is detectable. Location: Denver, Colorado, USA.

urban tree canopy. Piloted aircraft and low-altitude RPAs will likely carry sensor payloads that collect plant health–specific spectra for targeted data collection and analyses (Figure 3). ML routines will exist to determine RS data collection tasking, taking weather, solar angles, and airspace restrictions into account. ML plug-ins to software analysis platforms (Agisoft 2021) will likely be developed to run plant-specific sets of algorithms that will take spectral and visual data and identify key signatures of pest and disease outbreaks within and across urban tree species. Algorithms will also assess an area's degree days to predict insect emergence. ML routines will also likely exist to scrape data on cooperating individuals' smartphone applications looking for tree images—these ML routines will automatically assist in pest and disease identification and tracking.

Urban forest professionals and managers will use these data and analytics outputs to task work crews, notify the public of impending conflicts with machinery and property, and use outputs to notify stakeholders, decision makers, and citizens of findings, implications, and plans to address pest and disease impacts across multiple communication platforms.

Climate Change and Urban Tree Species Distribution

Climate change has begun to be felt in many cities across the planet (Melillo et al. 2014) and is an impending and serious challenge for the urban forest professions (Roman et al. 2013; Cheng et al. 2021; Zhang and Brack 2021). Increasing heat in many areas is exacerbated by the urban heat island (UHI)(Parker 2009; Manoli et al. 2019), addressed in a separate scenario below.

Climate change may severely stress or extirpate some tree species not adapted to tolerate high urban temperatures (Brandt et al. 2016). Further causes of stress include changing precipitation patterns that may compound stress in already challenging urban environments (Safford et al. 2013; Stagge et al. 2017). In the global north, temperature patterns are already shifting northward (Woodall et al. 2010; Daly et al. 2012), and as a result, more mobile animal species are moving north (Beniston 2014), in some places faster than plant migration (Parker and Abatzoglou 2016), creating a phenological mismatch between trees and animals (Visser and Both 2005; Both et al. 2009; Scranton and Amarasekare 2017) which may affect tree pollination, pest pressure (Altermatt 2010; Lehmann et al. 2020), and disease life cycles (Kelly and Goulden 2008).

A significant hurdle for the urban forestry professions to overcome will be altering urban forest species composition to adapt to changing climates. Challenges include choosing and testing climate-ready new woody plant species, finding test planting sites in already-developed cities, and obtaining experimental planting stock from regions likely to represent future climate (Fitzpatrick and Dunn 2019). Challenges not directly related to trees include obtaining budget resources to plant out experimental trees while old trees still exist, developing methodologies and protocols to monitor field experiments, and reporting progress to professionals, decision makers, and the public.

Today, collecting RS data can be performed by contracting piloted or remotely piloted aircraft to carry a payload of a spectral sensor and visual camera; collecting spectral data to analyze baseline tree health and classify land cover; and visual data for mapping and as a visual aid for stakeholders. Utilizing existing GIS land cover data will be necessary to age the inventory and precisely locate sites for test planting (Boucher 2016). Google Earth View or Street View imagery can be accessed and analyzed externally (Meunpong et al. 2019) using basic ML algorithms (Li 2020) or analyzed in the Google Earth Enterprise (Google Earth Engine 2021) to estimate parameters such as DBH class and identify suitable planting sites (Li et al. 2015; Boucher 2016; Berland and Lange 2017), as well as obtain tree leaf imagery to assist in verifying species. An early example of this effort is Google Earth Enterprise and AI creating a Los Angeles, California, USA Tree Canopy visualization tool in 2020 for public use and engagement (Calma 2020).

In the near future, to analyze tree health and progress of species tests, ML routines and analytics will be available to run preprogrammed sets of algorithms to collect appropriate data to assist in the analysis of urban forests and climate adaptation. ML routines will take any number of data sets and determine tree or canopy health without human intervention. ML algorithms will access hyper- or multispectral data and determine the optimal bands for a particular analysis to save computing time and reduce errors. ML routines will be used in Google Earth Engine that can look for any visual tree parameters necessary for analysis: DBH, open sites, leaf shapes, flowers, even visual health assessment cues. Weather and agricultural data will be mined for trends, as will construction permits and other sources the ML algorithms deem necessary.

Urban forest professionals and managers will use these data and analysis outputs to notify stakeholders, decision makers, and citizens of findings, implications, and plans to remedy climate change impacts. New analysis outputs can be used to make compelling visual images to help stakeholders understand and act, and savvy communicators will utilize available communication platforms to disseminate information about threats to the urban forest and measures being taken to adapt to these threats.

Urban Heat Island Mitigation

The urban heat island (UHI) is a phenomenon of increased heat in urban environments due to changes in land surfaces, the heat storing properties of building materials, and waste heat of human activity (Akbari et al. 2015; Mohajerani et al. 2017). Urban heat disasters are increasing in frequency due to urbanization and increasing temperatures from climate change (Corburn 2009). Now, disaster management professionals across the world have plans for urban heat events that include urban greening strategies (Wong et al. 2021), because urban forests are recognized as an important component of mitigating the UHI. Urban heat event disaster management plans (hereafter both combined as "UHI plans") are dependent upon urban forest management plans and thus are closely aligned with UHI plans.

Today, collecting modern technology data for UHI plans is straightforward. Inventory data that comprise data that include digitized tree crowns, species, location, and condition are an excellent start for UHI managers. Having digitized data of empty and available planting spaces, growth and change over time, and species distribution change are important UHI plan components as well (Li 2020). At a minimum, having medium- to high-resolution visual satellite data (Duan et al. 2019) integrated with traditional inventory data is an excellent UHI plan component. Tools exist today to extract total canopy cover from satellite images (PlanIT Geo 2021). Collecting high-resolution spectral data from aircraft or RPAs over multiple years can assist urban foresters in predicting future urban heat event severity for UHI forecasters by having a better mortality model to predict areas of increasing heat. Creating good collaboration and sharing networks today is essential to the success of UHI plans, which are complicated logistically and are for, currently, rare events.

In the near future, ML algorithms that model canopy growth and decline based on plant health—obtained from spectral and visual data and canopy crown extent over time—will be used by UHI managers and forecasters to manage assets and resources to prepare for urban heat events. High-resolution visual and spectral satellite images used by urban forest managers will also be used by UHI managers in their short-term plans. New methods of measuring temperature (Allen et al. 2018) that benefit urban forest managers and UHI plans will produce fine-grained data that can be mined by ML algorithms tracking microclimates for tree growth (as in the climate change scenario above). Simple coordination and data sharing by forestry and disaster management agencies are easy ways to ensure both interests are served.

Roadside Infrastructure Design for Driverless Vehicles

Driverless vehicles likely will soon be a common feature of urban transport (Compostella et al. 2020). Driverless vehicles are highly connected and require active sensory and communication inputs to move safely (Ha et al. 2020). Near-ground urban vegetation that improves and cools urban environments but grows into driverless vehicle communication lines of sight has the potential to conflict with transport communication and risk safety; thus, near-ground urban vegetation will likely need to be more actively, cooperatively, and effectively managed in the future. Roadside designs will likely change to accommodate driverless deliveries and human transport (Freemark et al. 2019), but it is not known at this time whether tree cover will be reduced overall with these design changes (Chapin et al. 2017).

This scenario anticipates driverless network development along the current trajectory at the time of this writing. As of this writing, few firm physical urban plans have been published to guide design development, so it is difficult to anticipate specific opportunities for design intervention or improvement for this scenario, although general statements can be made.

Maintaining connectivity with vehicles and networks will be an important factor in driverless transport (Association of Metropolitan Planning Organizations 2019). Vegetation attenuating or disrupting connected vehicle communication will be viewed unfavorably, but urban greenery will be necessary for city design for human comfort, including ameliorating future urban heat, so connected networks and vegetation must coexist (Rouse et al. 2018).

Today, it is difficult to develop an autonomous transport vegetation management system using existing hardware and software technology, which does not exist at a scale that can perform the needed tasks.

In the future, both aerial and near-ground fixed and mobile spectral sensors will be utilized to assess vegetation health, because near-ground vegetation may be obscured by trees, infrastructure, and buildings, thus near-ground sensors likely will be a necessary component for monitoring and management.

There likely will be a future need for a different sensor array design than what exists today for RS data collection. To better view near-ground urban vegetation, instead of the current method of always looking down from above through layers of vegetation and urban obstructions, Sideways-Aimed Spectral Sensors (SASS) for driverless transport networks will be mounted on both fixed infrastructure and selected vehicles. SASS devices will produce output in a vertical orientation rather than the typical horizontal image. Software analytics must be developed to analyze vertical imagery at scale—and at extremely high resolution—as data will be imaged at a distance of a few meters from target vegetation instead of hundreds or thousands of meters above the surface. Combined with data from standard LiDAR and visual sensors for driverless vehicle guidance, SASS will result in a rich, high-resolution, information-dense environment near ground level that very accurately assesses urban vegetation near transport corridors. Collecting additional data from security sensors, strategically mounted environmental monitoring sensors, and handheld devices will result in a potentially immense amount of information.

Lastly, querying, analyzing, and managing vast amounts of varied types of data collected in near-ground environments will necessitate specially configured, secure, and purpose-built ML algorithms. These ML algorithms will sift through terabytes of data to analyze, monitor, and notify of any changes in near-ground plant environments. These changes will not only include plant growth, but sudden changes in plant orientation such as damage occurring from events such as accidents, vandalism, and weather events that can risk safety or signal disruption.

Other Brief Scenarios for Applied Technology Development

Other likely future scenarios for urban forests using the CACI model described above include: projects requiring the creation of very high-resolution 3D spectral and visual modeling of historic trees for preservation or construction mitigation; calculating annual changes in biomass across scales for measurement of carbon sequestration by using LiDAR payloads mounted on an RPA or an autonomous delivery vehicle; performing construction site monitoring in real or near time for permit violations or vegetation stress by using a tasked RPA or data from a small satellite tasked nearby or during a defined period; collecting RS data on tree species, health, pest presence, and volumetric data by using a smartphone or dashboard camera application developed by a graduate student in partnership with the computer science department; monitoring nutrient or toxicity concentrations of runoff with potential to harm downstream vegetation using a third-party tasked RPA carrying a hyperspectral sensor; monitoring vegetation health in near time after pollution events, such as low-level ozone formation, using a piloted aircraft carrying several sensors; assessment of turf compaction in public parks after large events using an RPA carrying a spectral sensor and a ground-based autonomous vehicle carrying a payload designed to sample soil; and monitoring fuel load and energy release potential of vegetation in the Wildland-Urban Interface by using an array of environmental monitors aloft, on the ground, and fixed in place. How many more new opportunities to better manage urban environments are possible for current urban forest professionals, future digital urban forest professionals, or those seeking to enter the fields through nontraditional avenues?

CONCLUSION

This paper reviewed the current state of technologies in remote sensing and computing relevant for urban forestry monitoring and management across scales and introduced the CACI model—Collection, Analysis, Communication, Implementation—to place the technologies and their application in relevant context for urban forestry. Then this paper provided near-future scenarios where these concepts could be applied to meet urban forestry challenges, offered avenues for future career paths related to digital urban forestry, and outlined opportunities for needed hardware and software development to improve urban forestry monitoring, management, and communication.

Examples of areas of empirical study for emerging RS technology and ML in urban forests include further refinement on what are relevant spectral data for common urban plant species. We do not know how quickly urban tree species adapt to climate change, or their potential new ranges, or how to best measure relevant parameters with emerging RS technology. Is there a need to develop new sensors that measure thermal data to study species adaptation, stress, or effectiveness of plants for building conditioning in warming urban microclimates? What are user preferences for understanding the meaning of RS outputs such as 3D models or digital surface models versus LiDAR point clouds? Similarly, what are appropriate visualizations to depict the new species and changes to the urban forest in 50 years, how the neighborhood will look with new climate-resilient species, and how using RS outputs can assist user understanding?

Lastly, explaining to the public what all these new data and analyses represent and mean for the urban forest across scales will be of increasing importance and will be a required skill for some urban foresters. Clear explanations must lead to calls for action, and action requires planning across diverse groups. How will digital foresters of the future explain what is happening or tell the stories of what is needed for the urban forest, and what tools can assist them in a Big Data world? Urban forestry professionals always have been prepared with appropriate data for the time and have always had a passion for trees that helps tell a compelling story. New data and new stories are necessary. The urban forest professions still have time and passion to get ready to lead the way forward, prepared with new digital tools for the trees.

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Résumé. Contexte: À mesure que les populations humaines s’urbanisent, la canopée des forêts urbaines diminue dans de nombreuses régions en raison de multiples perturbations, notamment les nouveaux ravageurs et maladies, les changements climatiques et les modifications d’affectation des sols. Méthodes: Une revue de littérature sur la télédétection, l’informatique et l’environnement a été réalisée afin de produire un aperçu des capacités technologiques actuelles et d’élaborer un programme pour une approche moderne des enjeux de la foresterie urbaine. Les participants ont également passé en revue la manière de préparer les professionnels actuels et futurs à rassembler et à analyser les “données massives,” la manière d’appliquer les résultats et l’identification des compétences nécessaires en communication dans un monde moderne afin d’assurer la résilience des forêts urbaines dans un avenir branché. Résultats: Ce document définit un programme sur la manière dont les professionnels de la foresterie urbaine peuvent identifier, analyser et gérer les perturbations émergentes afin de continuer à fournir les bénéfices de la forêt urbaine aux résidents de la canopée. Les systèmes actuels de télédétection, le paradigme des données massives et les plateformes de collecte et d’analyse sont examinés et des scénarios pertinents sont proposés afin de générer un aperçu de la gestion des forêts dans une perspective rajeunie en utilisant le matériel et les logiciels de télédétection. Conclusions: Les villes modernes vont nécessiter une gestion de la foresterie urbaine qui soit numérique et moderne et les professionnels actuels et futurs doivent être en mesure d’avoir accès et d’utiliser la technologie, les capteurs et les données massives afin d’effectuer efficacement les tâches de gestion de la végétation et de communication. Cet article détaille le cadre d’une nouvelle ère de gestion moderne des forêts urbaines dans des villes hautement connectées et résilientes.

Zusammenfassung. Hintergrund: Mit der zunehmenden Verstädterung der Bevölkerung nimmt die Ausdehnung der städtischen Wälder in vielen Gebieten ab, was auf verschiedene Ursachen zurückzuführen ist, darunter neue Schädlinge und Krankheiten, der Klimawandel und eine veränderte Landnutzung. Methoden: Es wurde ein Überblick über die Fernerkundungs-, Computer- und Umweltliteratur erstellt, um einen Überblick über die aktuellen technologischen Möglichkeiten zu geben und eine Agenda für eine moderne Herangehensweise an die Herausforderungen der städtischen Forstwirtschaft aufzustellen. Außerdem wurde untersucht, wie heutige und künftige Fachleute auf die Erfassung und Analyse von “Big Data” vorbereitet werden können, wie die Ergebnisse umgesetzt werden können und welche Kommunikationsfähigkeiten in einer modernen Welt erforderlich sind, um belastbare städtische Wälder in einer vernetzten Zukunft zu schaffen. Ergebnisse: Dieses Papier skizziert eine Agenda dafür, wie die Berufsgruppe der städtischen Forstwirtschaft aufkommende Störungen erkennen, analysieren und bewältigen kann, um den Bewohnern in ihrem Umfeld weiterhin die Vorteile des städtischen Waldes bieten zu können. Es werden aktuelle Fernerkundungssysteme, das Paradigma von Big Data sowie Erfassungs- und Analyseplattformen diskutiert und relevante Szenarien vorgestellt, die einen Einblick in die Bewirtschaftung von Wäldern mit einer verjüngten Perspektive unter Verwendung von Fernerkundungshardware und -software ermöglichen. Schlussfolgerungen: Moderne Städte erfordern ein modernes digitales urbanes Forstmanagement, und heutige und künftige Fachleute müssen in der Lage sein, auf Technologie, Sensoren und Big Data zuzugreifen und diese zu nutzen, um Vegetationsmanagement- und Kommunikationsaufgaben effektiv durchzuführen. Dieser Artikel beschreibt den Rahmen für eine neue Ära des modernen städtischen Forstmanagements in hochgradig vernetzten, widerstandsfähigen Städten.

Resumen. Antecedentes: A medida que las poblaciones humanas se urbanizan, los bosques urbanos en muchas áreas están disminuyendo en extensión del dosel debido a las interrupciones en varios frentes, incluidas las nuevas plagas y enfermedades, el cambio climático y los cambios en los usos de la tierra. Métodos: Se realizó una revisión de la literatura de teledetección, computación y medio ambiente para proporcionar una visión general de las capacidades tecnológicas actuales y detallar una agenda para un enfoque moderno de los desafíos de la silvicultura urbana. También se revisó cómo preparar a los profesionales actuales y futuros para recopilar y analizar “Big Data”, cómo implementar resultados y qué habilidades de comunicación se necesitan en un mundo moderno para proporcionar bosques urbanos resilientes conectado en el futuro. Resultados: Este documento describe una agenda sobre cómo los profesionales forestales urbanos pueden identificar, analizar y manejar las interrupciones emergentes para continuar brindando beneficios forestales urbanos a los residentes en su sombra. Se discuten los sistemas actuales de teledetección, el paradigma de Big Data y las plataformas de recopilación y análisis y se proporcionan escenarios relevantes para guiar la comprensión de la gestión de los bosques con una perspectiva rejuvenecida utilizando hardware y software de teledetección. Conclusiones: Las ciudades modernas requerirán una gestión forestal urbana digital moderna y los profesionales actuales y futuros deben poder acceder y utilizar tecnología, sensores y Big Data para realizar de manera efectiva tareas de gestión de la vegetación y comunicación. Este documento detalla el marco para una nueva era de gestión forestal urbana moderna en ciudades altamente conectadas y resilientes.

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CEU quiz by Eric North, Minnesota Society of Arboriculture, Minneapolis, MN, USA