The Digital Forest: Mapping a Decade of Knowledge on Technological Applications for Forest Ecosystems

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Abstract Forest ecosystem resilience is of considerable interest worldwide, particularly given the climate crisis, biodiversity loss, and recent instances of zoonotic diseases linked to deforestation and forest loss. Novel, digital-based technologies are also increasingly ubiquitous. We provide a more comprehensive understanding of how these new technologies are being used for forest management in different sectors and contexts, and discuss potential implications and future research needs for forestry researchers, managers, and policymakers. We carried out a literature database search and scoping review to collect peer-reviewed articles from 2010 to 2020, and developed a forest-technology classification to identify hardware and/or software technologies and techniques, methodology used, forest management application(s), spatial and temporal context, subsequent challenges and limitations, and opportunities. A qualitative analysis revealed a strong emphasis on remote sensing-based innovations for forest monitoring, planning, and management, where machine-learning techniques also play an important role in data collection, processing, and analysis. Data fusion approaches are also becoming more common, enabled by open-source data sets and data sharing practices. More emerging technologies and applications include virtual/augmented environments for understanding human-nature relationships and behavior patterns, automated workflows for forestry operations, and urban green infrastructure mapping and ecosystem services assessments via social media and mobile tracking applications. The continued adoption of digital-based tools will likely bring about new research questions about forest ecosystems as dynamic social, ecological, and technological landscapes, and future work should more closely examine how forestry researchers, managers, and stakeholders can anticipate and adapt to both environmental and technological uncertainty change in a forest-ecosystem context.

Plain Language Summary There is global recognition that healthy forests are key to ensuring a sustainable future, yet they are threatened by climate change and various human activities and impacts. Meanwhile, our world is becoming increasingly digital. Yet little research has fully identified and discussed the uses and implications of these new tools, devices, and techniques, which is a gap that we aim to fill. Where are these technologies being used, how, and for what purpose? We searched for existing research on technology and forests over the last 10 years, and categorized different types of technologies and tools, methods, and uses in forestry. We found that sensors, including satellites and lasers, are widely used in forest management through remote data collection and analysis. Novel technologies being used in recent years include virtual reality to understand human responses to forest environments, sophisticated computer programs to make forest planning more efficient, and social media to track how people move around urban parks. Exploring uses of technology in forestry is important because we will need to understand how these will impact the forests that many forms of life depend on. We should also identify ways in which these technologies can help sustain forests into the future.

1. Introduction

As the Anthropocene epoch progresses, there is global interest in ensuring that forest ecosystems worldwide manifest resilience in the face of anthropogenic pressures (Reyer et al., 2015). Recent instances of zoonotic diseases linked to deforestation and forest loss have highlighted the vulnerability of and interconnections between forests and people (Branclilion et al., 2020). Furthermore, as urbanization continues to expand worldwide (Aronson et al., 2014), there is a need to mitigate negative impacts on forest habitat...
and biodiversity, as well as find ways to retain, restore, and design forest ecosystems in and around cities to support all forms of urban life (Endreny, 2018).

We are also living in a digital age. Literature in earth sciences, ecology, and conservation have highlighted shifts towards more ubiquitous digital practices in recent years to support environmental data collection, monitoring, and management practices (Arts et al., 2015; Bakker & Ritts, 2018; D’Urban Jackson et al., 2020). Evidence also points towards forestry as a laggard when it comes to innovation (Choudhry & O’Kelly, 2018; Weiss, 2013). Nevertheless, the literature suggests that digital tools are being increasingly studied and used in forest management contexts (Avdeeva et al., 2020; Salam, 2020; Zou et al., 2019). In Weiss et al.’s (2020) review of trends in innovation research in forest-based industries over several decades, digital-based concepts and technologies (such as digital disruption platforms) feature in more recent years. The growing digital economy and landscape create opportunities to consider the varied roles and applications for digital and “smarter” technologies in forest systems, yet there appears to be no comprehensive understanding to date about how these technologies are being used for forest management in different sectors, contexts, and at varying scales. This knowledge gap may act as a barrier for innovation in forest management and, more broadly, the sustainable management of forests.

Framed as a knowledge synthesis, the objective of this review is to map knowledge, over the last 10 years, on applications for digital-based and smart technologies and techniques for forest ecosystem monitoring and management. Our intent is also to identify emerging trends that may shape the future of forest ecosystems and/or their management. We purposefully consider both urban and rural areas in this review to capture the full spectrum of forest ecosystems and management practices. We searched for publications in both English and French, the two official languages of Canada (given the project and funding context).

2. Materials and Methods

2.1. Scoping Review Protocol

We used a modified PRISMA scoping review framework (Arksey & O’Malley, 2005) to collect relevant literature (Figure 1). Due to the scope of the literature and the large number of results from the database search, eligibility for full-text review was based on impact (e.g., number of citations as of 2020).

2.2. Database Search and Data Collection

Keywords were developed by the research team, based on other scoping reviews on digital technologies (Andrachuk et al., 2019; Granheim et al., 2020; Lapierre et al., 2018) and further refined after an initial database search (Table 2). This was to ensure that key papers identified beforehand as meeting the criteria appeared in the search. During initial database searches, the research team also identified key terms that resulted in a significantly larger number of irrelevant results (e.g., “random forest”). These were explicitly removed from the search query. We specifically included forest-related keywords applicable to both rural and urban contexts, to capture the full spectrum of forest ecosystems and management practices. We searched for publications in both English and French, the two official languages of Canada (given the project and funding context).
From July to August 2020, we used the search query outlined above in three different databases: Scopus, GEOBASE, and Web of Science. Articles (with all metadata available) were downloaded in raw form to CSV format and uploaded to Covidence (https://www.covidence.org), a web platform for managing literature reviews, for group titles/abstracts screening purposes. Due to the scope of the literature, each paper was screened by a single group member. To ensure consistency among screeners, an online training document was created outlining proposed criteria and specific inclusion/exclusion examples. Each screener also virtually met one-on-one with the research lead to corroborate inclusion/exclusion decisions and discuss more difficult cases that arose, refining the criteria as needed in the process (Table S1).

We carried out keyword trend analyses based on author-defined keywords from the screened articles. We first identified the most commonly occurring keywords for each year, and subsequently grouped keywords thematically. For example, the “Light Detecting and Ranging (LiDAR)” thematic group comprises all words synonymous or sufficiently similar to the technology, including “terrestrial laser scanner” and “aerial laser scanning.” We then plotted, over the last 10 years, the most common thematic groupings that emerged representing both technologies/tools and forest management applications. Thematic groupings that were relatively scarce in earlier years, but experienced jumps in later years without necessarily illustrating a clear upwards trend (suggesting some degree of uncertainty in terms of impact and adoption), were classified as “emerging” and also plotted over the last 10 years.

### 2.3. Full-Text Review

Once articles were screened based on title and abstract, articles were ranked and selected for full-text review based on impact (e.g., number of times cited) for the years 2010–2020 (30 top-ranked articles total), as well as separately for 2017, 2018, 2019, and 2020 (15 top-ranked articles for each year). This particular time series was chosen for two reasons: (a) To assess more current trends that have taken shape over the last 10 years; and (b) To identify emerging phenomena in more recent years (2017 onwards), to account for potentially

### Table 1

| Key terms               | Definitions                                                                                                                                 |
|-------------------------|-------------------------------------------------------------------------------------------------------------------------------------------|
| Digital technology     | Digital: “Digital systems record or transmit information in the form of thousands of very small signals.” (Collins Dictionary, 2021a)          |
|                         | Technology: “refers to methods, systems, and devices which are the result of scientific knowledge being used for practical purposes.” (Collins Dictionary, 2021b) |
|                         | Digital technologies refer to tools, systems, devices, and resources that homogenize data and are reprogrammable, allowing for storage, processing, and transmission across devices with computing capabilities (Hukal & Henfridsson, 2017) |
| Smart technology/device| “A smart device is a context-aware electronic device capable of performing autonomous computing and connecting to other devices wire or wirelessly for data exchange.” (Silverio-Fernández et al., 2018, p. 8) |
| Digital forest          | “A digital representation of forestry information” (Zhao et al., 2005, p. 48)                                                               |
|                         | Digital forestry as “the science, technology, and art of systematically acquiring, integrating, analyzing, and applying digital information to support sustainable forests.” (Zhao et al., 2005, p. 47–48) |
| Smart forest            | “emerging digital infrastructures that are materializing [...] transforming into technologies [...] to manage and mitigate environmental change” (Gabrys, 2020, p. 1) |
| Emerging technology     | Characterized by five digital practices: (1) observation, (2) automation and optimization, (3) datafication, (4) participation, and (5) regulation and transformation (Gabrys, 2020) |
|                         | A technology characterized by “...(i) radical novelty, (ii) relatively fast growth, (iii) coherence, (iv) prominent impact, and (v) uncertainty and ambiguity” (Rotolo et al., 2015, p. 1840) |
|                         | Emerging technologies are understood to exert influence over 10- to 15-year horizons (Porter et al., 2002; Stahl, 2011) |
fast-paced technological change and innovation. There are limitations to this approach, as citations tend to accrue over time and may skew the findings towards earlier publications. For future reviews, researchers might consider other frameworks and metrics beyond citation count, such as network analyses to assess interactions between researchers and stakeholders for social impact (Spaapen & Drooge, 2011), or socio-economic dimensions such as spread (e.g., community impact) and depth (e.g., transformational impact) of research output (Penfield et al., 2014; Scoble et al., 2010).

Finally, we developed a classification framework based on our research questions. For each full-text review, we identified the hardware and/or software-based technologies and techniques, methodology used, the forest management application(s), the spatial and temporal context, partners and funding sources, and subsequent challenges, opportunities, and research needs identified by the study author(s).

3. Results: Scope of the Research and Key Trends

3.1. Overview of Published Research

In total, 1,169 records were included in the title and abstract review. A general growth trend in publications was observed over the last 10 years, with a considerable jump occurring between 2017 and 2018, suggesting very recent momentum in research interest and output (Figure 2). This growth trend will most likely continue into the future, particularly when taking into account most recent output (Figure 2). The majority

Figure 1. Scoping review protocol flow chart.
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of research at the intersection of forestry and digital technologies takes place in Annex I countries (United Nations Framework Convention on Climate Change, 2021); North America, Northern and Western Europe, and Oceania are especially well represented. The country with the highest research output from 2010 to 2020 is the United States (205 publications), followed by China (155), Finland (66), Italy (54), Spain (54), and Canada (51). Out of the top 10 countries in terms of output, eight are Annex I countries (Figure 3). Much of the research from the non-Annex I countries has emerged from Brazil, China, and India.

To identify the disciplines represented in this review, and to assess how these might be changing over time, we plotted the output of the most popular journals, based on number of publications per year (Figure 4). The journal Remote Sensing dominates for the majority of years (i.e., 6/10) examined based on research output. Along the same vein, the most common thematic groupings associated with technologies/tools were remote sensing-based, and include the use of aerial and terrestrial unmanned vehicles and LiDAR. Other popular journals include Sensors and Forests, also illustrating the growing popularity of open-accessing publishing in these domains.

| Keywords related to “forest ecosystem” | Keywords related to “technology” |
|----------------------------------------|----------------------------------|
| Forest, forests, forester              | Smart technology(ies)            |
| Green space(s)                         | Digital technology(ies)          |
| Woodland(s)                            | Information technology(ies)      |
| Urban park(s), urban parkland(s)       | Information and communication technology(ies) |
| National park(s), national parkland(s) | Data science                     |
| Regional park(s), regional parkland(s) | Online, on-line                 |
| Local park(s), local parkland(s)       | Virtual                          |
| Parkland                               | Automate, automation, automaton  |
| Silviculture, silvicultural            | Autonomous(ly)                   |
| Arboriculture, arboricultural          | Mobile application(s), app(s)    |
| Community forest(s), community forester| Smart phone(s), smartphone(s)    |
| Forest ecology, forest ecologist       | Cellphone(s), cell phone(s)      |
| Forest ecosystem(s)                    | Social media                     |
| Green infrastructure(s)                | Mobile device(s), smart device(s)|
| Forest conservation                    | Artificial intelligence          |
| Forest resource(s)                     | Machine learning                 |

**Database search query**

Topic (Web of Science), Title/Abstract/Keywords (Scopus), Subject/Title/Abstract (Geobase) = (forest* OR “green space*” OR woodl* OR “urban park*” OR “national park*” OR “regional park*” OR “local park*” OR “parkland” OR silvicultur* OR arboricultur* OR “community forest*” OR “forest ecolog*” OR “forest ecosystem*” OR “green infrastructur*” OR “forest conservation” OR “forest resource*”)

AND

(“smart technolog*” OR “digital technolog*” OR “information technolog*” OR “information and communication technolog*” OR “data science” OR online OR on-line OR virtual OR automat* OR autonomous* OR “mobile application*” OR app OR apps OR “smart phone*” OR smartphone* OR cellphone* OR “cell phone*” OR “mobile device*” OR “smart device*” OR “social media” OR “artificial intelligence” OR “machine learning”)

NOT (“random forest*” OR “random forest algorithm” OR “forestall”)

**Database search inclusion criteria:**

- Language: English and French
- Temporal limit: 2010–2020
- All countries/institutions (e.g., no geographic limitation)
- Types of articles: peer-reviewed journal articles (including research and review articles)

**Database search exclusion criteria:**

- Articles where abstract and full text is not accessible
- Articles that do not include search terms in title, abstract, or associated keywords
- Articles where metadata is not available for download
Artificial intelligence and machine learning technologies appear to be gaining significant traction in the last 3 years (Figure 5); many of these apply to the collection, processing, and analysis of remotely sensed data, including a range of techniques from classification and segmentation algorithms, to convolutional neural networks. The unmanned vehicle group, which consists primarily of aircraft but also includes autonomous terrestrial vehicles such as tractors, has experienced a steady rise in interest since 2015. The thematic grouping comprising LiDAR-associated keywords exhibits a pattern that highlights more consistency in terms of...
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The number of keywords related to urban ecosystems and urban planning is trending upwards in recent times. In comparison, papers discussing forest inventories and forest fire management are only rising slightly in number over time (Figure 6).
Out of the thematic groupings classified as “emerging,” virtual/augmented environments, although almost non-existent until 2014, seem to be gaining momentum in forest-related research (Figure 7). Keywords associated with automation (e.g., autonomous vehicles, automatic measurement) and smartness (e.g., smartphone, smart city) show somewhat similar trends, with large jumps in 2018 and 2019. While in
comparison, robotics and Internet of Things technologies trail behind, it is worth noting that the number of robotics-based keywords rose in the last 2 years.

Where funding was disclosed, the vast majority of studies (~90%) that underwent full-text review were supported by governmental organizations, ranging from forestry departments (e.g., Canadian Forest Service, South Australian Forestry Corporation), to remote sensing and space research organizations (e.g., NASA, European Space Agency), to scientific research funding agencies (e.g., National Natural Science Foundation of China, Natural Environment Research Council). Of these studies, just over 15% were also funded by either industry (e.g., NVIDIA, Microsoft) or other non-governmental, non-profit organizations (e.g., National Geographic Society). Academic funding sources contributed to ~20% of research output.

A full list of the thematic groupings and associated keywords can be found in the Supporting Information (Table S2).

3.2. Full-Text Review

3.2.1. Technologies and Tools

Of the 30 most impactful papers published in the last 10 years, the vast majority (23) focus on aerial and/or satellite-based remote sensing techniques. Airborne laser scanning was used in one-third of the high-impact research over this period of time, while unmanned aerial vehicles (UAVs) featured in six publications. Comparatively, UAVs were used in just under half of the 30 research outputs examined from 2019 to 2020, illustrating what seems to be a more recent uptake for forest ecosystem management. In over one-third of research outputs using UAVs, other sensors in addition to visual (e.g., RGB) cameras were used, including infrared, multispectral and hyperspectral, laser scanning systems, pressure gauges and temperature sensors, and accelerometers. Data fusion approaches and multi-source remote sensing systems were used in 32 of all reviewed papers (35%), and in just under half of papers (46%) published in the last 2 years.

Of the most impactful papers reviewed, 20 (22%) use satellite imagery for forest cover and canopy mapping, assessing landscape change over time, detecting and managing disturbances, and supporting forest inventory practices. Of these, eight (40%) were published in the last 2 years, and the majority of use cases combined multiple data inputs (e.g., UAVs, multiple satellite systems). The most commonly used satellite imagery sources over the last 10 years were Landsat (seven papers, or 35%), Sentinel (three papers, or 15%), Quickbird (15%), MODIS (two papers, or 10%), WorldView (10%) and RapidEye (10%). Artificial intelligence and machine learning-based technologies used in conjunction with remote sensing tools also featured heavily in highly cited papers, particularly in more recent years. The most common machine-learning techniques were algorithms for segmentation, classification, and regression, including random forests, k-nearest neighbors, and support vector machines. Artificial neural networks (such as convolutional neural network, deep learning network, feedforward neural network) are becoming especially popular in recent years; only three reviewed papers (3%) used neural networks prior to 2019 (Giusti et al., 2015; Khan et al., 2017; Yuan et al., 2015), while nine reviewed papers (10%) used them in the last 2 years.

One of the least common software technologies that emerged during this review is the use of street-view image gathering—in other words, images collected at the street level, often from a moving vehicle. Only two (2%) papers (Berland & Lange, 2017; Helbich et al., 2019) refer to this type of imaging, and in both cases its usage is meant to facilitate urban green infrastructure assessment and monitoring.

3.2.2. Forest Ecosystem Management Applications

Although the forest inventory thematic grouping did not feature as heavily in the overall keyword trend analysis, inventorying was identified as a common forest management application during full-text review. Just over 40% of all papers that underwent full-text review mentioned forest inventorying as a use case for technology applications, more specifically for genus/species identification and mapping, forest operations (e.g., harvest planning, cost estimation), and quantification of ecosystem services and benefits (e.g., aboveground biomass estimation for carbon stock assessment). LiDAR technologies tend to co-occur with forest inventory applications; 26/38 inventory-focused publications (68%) use either terrestrial-based (used most often for stem counting, tree and stand parameter modeling, and aboveground biomass estimations)
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or airborne-based (used most often in taxonomic identification and mapping) laser scanning methods. Out of these, only two publications (5%) use both methods together.

The vast majority of reviewed articles focused on forest ecosystems in rural contexts; only nine (10%) mentioned or featured uses in urban areas, five of which were published after 2017, suggesting more recent interest in these areas. Of those based in urban environments, 5/9 (55%) examined forest inventory applications and, related, canopy mapping, tree-species identification, and monitoring. Since 2018, three urban-focused publications (33%) explored the use of social media and two publications used virtual reality environments (22%) to elicit values and perceptions about urban green spaces, along with human health outcomes associated with urban nature exposure.

A comprehensive summary of forest ecosystem applications and associated technologies, based on the full-text review, is found in Table 3.

4. Qualitative Synthesis and Discussion

4.1. Technologies

4.1.1. Broader Trends and Impacts

Our analysis revealed a strong emphasis on remote sensing-based innovations for forest monitoring, planning, and management. Machine-learning techniques also played an important role in data collection, processing, and analysis. These trends reflect broader tendencies in landscape ecology research (Crowley & Cardille, 2020), wildfire science (Jain et al., 2020), and environment and water management (Sun & Scanlon, 2019).

The rise of UAV (also known as Remotely Piloted Aircraft System, or RPAS) usage over time in forest ecosystem management research is a further indication that drones are carving out a space as the “third generation” remote sensing data platform (Milas et al., 2018). Although not an entirely novel concept, as the earliest iterations of drones began with camera-laden pigeons in the early 20th century and later, with flying hobby aircraft, modern UAVs can overcome limitations associated with other remote sensing technologies (Milas et al., 2018; Mohan et al., 2017). UAVs provide more control over the data collection process both spatially and temporally, are generally affordable and considered low-cost alternatives to other remote sensing tools and provide high-resolution imagery that may not otherwise be available, subsequently showing potential to inform forest ecosystem management and related decision making (Goodbody et al., 2018; Mohan et al., 2017; Yuan et al., 2017). The use of three-dimensional information and models obtained using drones, which can be derived from active (e.g., LiDAR) and passive (RGB cameras, multispectral, hyperspectral) sensors, has been identified as one of the “most promising” and scalable techniques for forest restoration monitoring (Almeida et al., 2020, p. 9). Given the relative ease of data collection, and what seems to be increasing demand, Mohan et al. (2017) envision a “UAV as a service” market in the foreseeable future, which could allow for forest managers limited by capacity and lack of technological expertise to access these resources.

Satellite imagery was also identified as an important remote sensing technology in this review. Many articles used data from satellite programs managed by government bodies, such as Landsat (NASA/USGS), Sentinel (ESA), and MODIS (NASA). Other commercial satellite imagery widely used in the context of forest research and management included RapidEye (now owned by Planet Labs), Quickbird, and Worldview (both owned by MDA, formerly Maxar Technologies and Digital Globe). The privatized commercial space-flight industry, which has seen a surge of interest, investment, and development over the last decade (Spector & Higham, 2019), may change how satellite imagery is collected, processed, and used for environmental applications, as well as its accessibility/cost. The availability of commercial space flights may further enable the deployment of privately managed satellites. For example, Space Exploration Technologies Corp.—better known as SpaceX and for its noteworthy founder Elon Musk—is expected to launch the new WorldView satellite legion in 2021. Smaller orbiting satellites, such as the SkySat program administered by Planet Labs that provides sub-meter resolution imagery, may also play an increasingly important role in supporting “near real time” forest monitoring needs that are already in demand (Weisse et al., 2017).
### Table 3
Summary of Forest Ecosystem Applications and Management Practices, Along With Key Tools, Technologies, and Methods Employed, Identified From Full-Text Review of Highly Cited Papers (2010–2020, in Chronological Order)

| Citation            | Data collection tools & technologies | Processing & analysis methods                                                                 | Forestry application(s)                                                                 | Spatial; temporal scale(s)          |
|---------------------|--------------------------------------|------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------|-------------------------------------|
| Sano et al. (2010)  | Satellite                            | Segmentation                                                                                   | Land cover mapping; conservation                                                       | Region; short term                  |
| Ke et al. (2010)    | Satellites; multispectral sensor; airborne laser scanner (ALS) | Segmentation; classification; machine learning decision trees                                  | Forest inventory; species classification                                                | Forest; short term                  |
| Stojanova et al. (2010) | Satellite; ALS                  | Segmentation; ensemble prediction method; single-model prediction; bagging; random forests     | Forest parameters and structure; forest cover monitoring; land-use classification        | Forest; short term (2 years)        |
| Dassot et al. (2011) | ALS; terrestrial laser scanner (TLS) | 3D modeling; segmentation; fuzzy entropy approach                                             | Forest inventory; Forest parameters and structure; 3D data collection; ecological research (transpiration, habitat diversity); flood modeling | Review article                     |
| Merino et al. (2011) | Unmanned aerial system (UAS); visual and infrared cameras | Bayes filter; segmentation; classification; feature extraction; feature matching             | Forest fire monitoring                                                                  | Forest site; short term             |
| Ke and Quackenbush (2011) | Satellites                                    | Least mean fourth; watershed segmentation; valley following; region growing                   | Forest inventory; forest parameters and structure; automatic tree-crown detection         | Review article                     |
| Heinzel and Koch (2011) | ALS                                          | 3D modeling; active contour filtering                                                          | Forest inventory; species classification; vegetation studies                             | Forest site; short term             |
| Santoro et al. (2011) | Satellites                                 | BIOMASAR; k-nearest neighbors (kNN)                                                              | Forest inventory; Forest growing stock volume; resource management                        | Forest sites; short term            |
| Lovell et al. (2011) | TLS                                         | 3D modeling                                                                                     | Forest inventory; automatic stem detection                                               | Forest site; short term             |
| Lopez-Gonzalez et al. (2011) | Web application                        | Various                                                                                         | Forest inventory; forest parameters and structure; data management; research              | Global; long term (not specified)    |
| Zhao et al. (2011)   | ALS                                         | 3D modeling; kernel machine; support vector machine; Gaussian processes                           | Forest inventory; forest parameters and structure                                        | Forest site; short term             |
| Waser et al. (2011)  | Airborne digital sensor system            | Segmentation; classification; multinominal regression model                                      | Forest inventory; tree species classification and mapping                                 | Forest site; short term             |
| Townshend et al. (2012) | Satellite                                 | Change detection; support vector machine                                                          | Forest cover monitoring                                                                | Global; long term (5 years)         |
| Liang et al. (2012)  | TLS                                         | 3D modeling                                                                                     | Forest inventory; automatic stem detection and mapping                                   | Forest plot; short term             |
| Yao et al. (2012)    | ALS                                         | 3D segmentation; unsupervised classification; supervised classification; multiple linear regression | Forest inventory; forest parameters and structure; species classification                  | Forest site; short term             |
| Citation                | Data collection tools & technologies | Processing & analysis methods | Forestry application(s)                                                                 | Spatial; temporal scale(s)                        |
|-------------------------|--------------------------------------|------------------------------|----------------------------------------------------------------------------------------|-----------------------------------------------|
| Koh and Wich (2012)     | Unmanned aerial vehicle (UAV)        | Programmed autonomous flight; aerial photogrammetry | Land cover mapping; forest and wildlife monitoring; conservation                       | Forest; short term (near real time)            |
| Kaartinen et al. (2012) | ALS                                  | 3D modeling; local maxima (LM); Multi-scale Laplacian of Gaussian; Minimum curvature-based tree detection; tree cluster approach; Method Definiens (eCognition) | Forest inventory; tree crown delineation; forest parameters and structure               | Forest site; short term                        |
| Raumonen et al. (2013)  | TLS                                  | 3D modeling; segmentation   | Forest inventory; pre-harvest measurement; automatic models; biomass and carbon cycling estimations (ecosystem services) | Trees; short term                              |
| Annerstedt et al. (2013)| Virtual reality (VR)                 | Stress test; passive stereoscopy; surround sound | Assessing relationships between humans and nature; health response to forests          | N/A (simulated environment)                   |
| Jakubowski et al. (2013)| ALS                                  | 3D modeling; support vector regression; Gaussian processes; multiple regression | Forest inventory; forest parameters and structure                                      | Forest; short term                             |
| Wu et al. (2013)        | Mobile laser scanner (MLS)           | 3D modeling; voxel-based Marked Neighborhood Searching (VMNS) | Urban forest inventory; species classification and mapping                            | Urban forest site (road); short term           |
| Tigges et al. (2013)    | Satellite; multispectral sensor; ALS | 3D modeling; support vector machine; classification | Urban forest inventory; species classification and mapping; vegetation analysis; urban ecosystem services assessment | Urban forest (city); short term                |
| Confalonieri et al. (2013)| Smartphone; mobile application   | Gap fraction estimation; segmentation; visual jackknife method | Leaf area index (LAI) estimation; vegetation condition analysis                      | Field plot; short term                         |
| Alonzo et al. (2014)    | ALS; hyperspectral sensor            | 3D modeling; watershed segmentation; classification; canonical discriminant analysis | Urban forest inventory; species classification and mapping; urban ecosystem services assessment | Urban forest site (neighborhood); short term   |
| Dalponte et al. (2014)  | ALS; hyperspectral sensor            | 3D modeling; support vector machine; classification | Forest inventory; forest parameters and structure; species classification and mapping | Forest plot; short term                        |
| Liang et al. (2014)     | TLS                                  | 3D modeling                 | Forest inventory; profit prediction; automatic models; calibration of allometric equations | Forest plot; short term                        |
| Zarco-Tejada et al. (2014)| UAS; color and infrared camera      | 3D modeling; photo-reconstruction | Forest inventory; agriculture monitoring; forest parameters and structure               | Forest plot (orchard); short term             |
| Citation          | Data collection tools & technologies | Processing & analysis methods | Forestry application(s)                                      | Spatial; temporal scale(s) |
|-------------------|--------------------------------------|------------------------------|--------------------------------------------------------------|---------------------------|
| Giusti et al. (2015) | Micro Aerial Vehicle (MAV); smartphone | Deep neural networks (DNNs)  | Wilderness mapping; search and rescue; forest monitoring | Forest trail; short term |
| Yuan et al. (2015)  | UAV; visual, infrared, near-infrared, thermal cameras | Vision-based techniques (e.g., statistical data fusion, genetic algorithm); offline detection (e.g., neural networks, computer vision, support vector machine) | Forest fire monitoring, detection, fighting; fire early detection; telemetry; automatic geolocation | Review article |
| Beuchle et al. (2015) | Satellites | Segmentation; object-based classification | Land cover change; forest cover monitoring | Region; long term (20 years) |
| Mohan et al. (2017)  | UAV; low consumer grade cameras | 3D modeling; structure-from-motion (SFM) algorithm; local-maxima based algorithm | Forest inventory; forest parameters and structure; automatic individual tree detection (ITD) | Forest plot; short term |
| Pádua et al. (2017)  | UAS; visual and infrared cameras; multispectral and hyperspectral; LiDAR | 3D modeling; segmentation; 3D reconstruction | Agroforestry; forest cover mapping and monitoring; forest inventory; forest parameters and structure; forest fire detection and monitoring; land-use classification; wildlife detection; vegetation assessment | Review article |
| Trochta et al. (2017) | TLS; open-source software application | 3D modeling; automatic segmentation; Randomized Hough Transform algorithm | Forest inventory; Forest parameters and structure; automated workflow | N/A |
| Jaakkola et al. (2017) | UAV; ALS | Autonomous driving; Gaussian filtering; classification; principal component analysis; circle fitting | Forest inventory; forest parameters and structure; automated field measurements | Forest site; short term |
| Yuan et al. (2017)  | UAV | Fire detection algorithm; optical flow algorithms; color and motion vision-based system | Forest fire detection and monitoring | Forest; short term (near real time) |
| Abegg et al. (2017)  | TLS | 3D modeling; virtual scenes | Forest inventory; forest parameters and structure | Forest plot; short term |
| Berland and Lange (2017) | Google Street View; Google Earth Pro | Virtual survey; visual assessment | Urban forest inventory; species classification and mapping; DBH measurement | Urban forest (municipality); short term |
| Sun et al. (2017)  | Smartphone | Deep learning model; deep residual networks | Tree and plant species identification | N/A |
| Ramos et al. (2017)  | Mobile devices | Machine Vision System (MVS), including image acquisition system; image processing algorithm; linear estimation models | Fruit harvesting; work planning | Plot; short term |
| Citation            | Data collection tools & technologies | Processing & analysis methods                                                                 | Forestry application(s)                                                                 | Spatial; temporal scale(s)                  |
|---------------------|--------------------------------------|------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------|--------------------------------------------|
| Åkerblom et al. (2017) | TLS                                  | 3D modeling; quantitative structure tree models; k-nearest neighbors, multinominal regression, support vector machine | Forest inventory; tree species identification; automated workflow                        | Forest plot; short term                    |
| Khan et al. (2017)     | Satellite                             | Convolutional neural network (CNN); spatial filling process; classification                       | Land cover mapping; Forest change detection and monitoring                                | Region; long term (29 years)               |
| Ayrey et al. (2017)    | ALS                                  | Segmentation; layer stacking                                                                    | Forest inventory; tree crown delineation                                                | Forest site; short term                    |
| Tomáštík et al. (2017) | Smartphone; mobile device (e.g., tablet); mapping- and a survey-grade receiver               | GNSS positioning                                                                               | Forest mapping and monitoring; under-canopy navigation                                 | Forest site; short term                    |
| Ludovisi et al. (2017) | UAV; thermal infrared camera          | Semi-automated segmentation; image mosaicking                                                  | High-throughput field phenotyping; drought response; tree genetic improvement            | Forest site; short term                    |
| Qu et al. (2017)       | Low earth orbit satellite constellation; Internet of Things (IoT) | Remote sensing (various)                                                                        | Forest monitoring                                                                       | Review/conceptual article                  |
| Hamstead et al. (2018) | Social media (Twitter, Flickr)        | Multiple regression models                                                                      | Park visitation; human behavior and values                                              | City (urban parks); long term (9 years) and short term (3 years) |
| Pierczala et al. (2018) | Unmanned ground vehicle (UGV); laser scanner; wheeled rover | 3D Simultaneous Localisation and Mapping (graph-SLAM); iterative Closest Point (ICP)          | Forest operations                                                                       | Forest site; short term                    |
| Näsi et al. (2018)     | UAV; hyperspectral                    | Feature-based matching                                                                          | Urban forest inventory, monitoring; tree health (disease)                                | Urban forest plots; short term             |
| Donahue et al. (2018)  | Social media (Twitter, Flickr)        | Multiple regression models                                                                      | Park visitation; human behavior and values                                              | City (urban parks); long term (8 years) and short term (3 years) |
| Yu et al. (2018)       | VR                                   | Profile of mood states; Faced Auditory Serial Addition Test (PASAT)                             | Assessing relationships between humans and nature; health response to forests            | N/A (simulated environment)                |
| Calders et al. (2018)  | TLS                                  | 3D modeling; segmentation; Euclidean clustering; Foliage and Needles Naïve Insertion (FaNNI) algorithm | Forest stand reconstruction; species classification and mapping; virtual forests         | Forest site; short term                    |
| Gongal et al. (2018)   | Time of Flight (TOF) 3D camera; CCD camera | Machine vision system; 3D modeling; feature extraction                                          | Robotic harvesting; tree fruit crop estimation                                           | Forest site (orchard); short term          |
| Tabrizian et al. (2018) | Immersive virtual environment (IVE) | Photorealistic 360° panoramas; perceived restorativeness scale                                 | Human behavior and values; health response to forests                                   | N/A (simulated environment)                |
| Citation                         | Data collection tools & technologies                              | Processing & analysis methods                          | Forestry application(s)                                                                 | Spatial; temporal scale(s) |
|---------------------------------|-------------------------------------------------------------------|--------------------------------------------------------|----------------------------------------------------------------------------------------|---------------------------|
| Urbazaev et al. (2018)          | Satellites; ALS; synthetic aperture radar (SAR)                   | Monte Carlo simulation; Cubist machine learning        | Forest monitoring; ecosystem services assessment; aboveground biomass estimation        | Forest region (country); short term |
| Fraser and Congalton (2018)      | UAS; multispectral                                                | SIM                                                    | Data acquisition; forest landscape modeling                                            | Forest sites; short term  |
| Hermosilla et al. (2018)        | Satellites                                                       | Composite-2-Change (C2C); Virtual Land Cover Engine (VLCE); unsupervised hyperclustering approach; random forests; hidden Markov model | Forest landscape modeling; ecosystem monitoring; land cover dynamics; forest disturbance monitoring | Forest region (country); long term (29 years) |
| Koc-San et al. (2018)           | UAV; multispectral                                                | 3D modeling; Canny Edge detection; Hough transform algorithms | Automatic tree detection; tree fruit crop estimation                                   | Forest site (orchard); short term |
| Cabo et al. (2018)              | TLS                                                               | 3D modeling; Root mean square error (RMSE); voxelization | Forest inventory; automatic tree detection; automated workflow                         | Forest plot; short term  |
| Figorilli et al. (2018)         | RFID sensor; smartphone; mobile application                      | Blockchain                                             | Wood products traceability                                                             | N/A                       |
| Fang et al. (2018)              | Smartphone; Autonomous light sensor; mobile application          | Segmentation; greenness index (GI)                     | Automatic LAI estimation; canopy gap fraction estimate                                  | Agriculture plot; short term |
| Bayat et al. (2019)             | N/A                                                               | Artificial neural network (ANN); multi-layer perceptron (MLP) neural network; feed-forward back propagation (FBBP) | Forest parameters and structure; tree survival prediction; tree mortality                   | Forest plot; short term  |
| Navarro et al. (2019)           | Satellites; UAV                                                  | 3D modeling; non-parametric support vector regression (SVR) model; random forest; classification | Aboveground biomass estimation; mangrove monitoring; land cover change                  | Forest site; short term (1 year) |
| Almeida et al. (2019)           | UAV; laser scanner (GatorEye)                                    | 3D modeling; linear regression                         | Forest parameters and structure; forest restoration; forest monitoring                  | Forest plot; long term (2004, 2016, 2018) |
| Safonova et al. (2019)          | UAV                                                               | DNNs; CNNs                                             | Tree damage assessment; forest damage detection; insect outbreak monitoring              | Forest plot; short term (2016, 2018) |
| Vicari et al. (2019)            | TLS                                                              | 3D modeling; unsupervised classification; shortest path analysis; Gaussian model | Leaf and wood separation; aboveground biomass estimation                                | N/A                       |
| Helbich et al. (2019)           | Tencent (Google equivalent Street View (images captured by car-mounted camera available via web platform), satellite | Deep learning; convolutional neural network (FCN-8s)    | Human health and forests; environmental exposure assessment                             | Urban forest (neighborhood); short term |
| Ampatzidis and Partel (2019)    | UAV                                                              | Deep learning; CNNs                                   | Phenotype characterization; tree detection; forest parameters and structure              | Forest plot (orchard); short term |
Table 3
Continued

| Citation                  | Data collection tools & technologies | Processing & analysis methods                                                                 | Forestry application(s)                                  | Spatial; temporal scale(s) |
|---------------------------|--------------------------------------|------------------------------------------------------------------------------------------------|---------------------------------------------------------|---------------------------|
| Abdulridha et al. (2019)  | Multispectral camera                 | Segmentation, feature extraction, classification, neural network multilayer perceptron (MLP); k-nearest neighbors | Disease detection                                        | Forest plot (orchard); short term |
| Saah et al. (2019)        | Satellites; open-sourced software tool | Various (user defined)                                                                           | Various (user defined)                                   | Global; long term          |
| Piermattei et al. (2019)  | TLS                                  | 3D modeling; mean-shift algorithm; SfM                                                           | Forest parameters and structure; automatic tree detection | Forest plot; short term    |
| Müller et al. (2019)      | Laser scanners; UAV, satellites, machine sensors, RFID | Predictive analytics, artificial intelligence; big data and cloud computing; human-machine; machine-machine (various methods) | Industry 4.0; forest operations; wood supply chain       | Review article            |
| Krause et al. (2019)      | UAV                                  | Nearest neighbor interpolation, local maximum algorithm; SfM                                     | Forest inventory; forest structure and parameters; economic and ecological stand valuation, tree growth models | Forest plot; short term |
| Marques et al. (2019)     | UAV                                  | Segmentation, clustering, parameter extraction                                                   | Tree crop monitoring and management; automatic tree detection | Forest (orchard) site; longitudinal (2014, 2015, 2017) |
| Aubry-Kientz et al. (2019)| ALS                                  | ITC delineation algorithms: AMS3D, Graph-Cut, itcSegment, Profiler, SEGMA                         | Forest inventory; automatic tree detection; forest canopy mapping | Forest plot; short term (snapshot) |
| Burt et al. (2019)        | TLS imagery; open-source software    | Segmentation; Euclidean clustering, principal component analysis, region-based segmentation, shape fitting; connectivity testing | Forest inventory; automatic tree detection and stem, crown segmentation; forest canopy mapping | Forest site, stand, and/or plot; short term (snapshot) |
| Sudhakar et al. (2020)    | UAV                                  | Computer vision; Maximally Stable Extremal Regions; color-based FFD; motion-based FFD            | Forest fire monitoring; forest fire detection            | Forest region; short term (snapshot) |
| Chen et al. (2020)        | UAV; laser scanner; hand-held sensor | 3D modeling; semantic segmentation; LiDAR; simultaneous localization and mapping (SLAM) problem; Semantic LOAM (SLOAM) algorithm; convolutional neural network; virtual reality | Forest inventory; forest parameters and structure; forest operations | Forest site; short term (snapshot) |
| Wang et al. (2020)        | TLS                                  | 3D modeling; point cloud segmentation and regularization procedures binary classification; recursive segmentation | Leaf and wood separation; forest structure and parameters; automated processing chain | Tree; short term (snapshot) |
| Citation               | Data collection tools & technologies | Processing & analysis methods | Forestry application(s)                                                                 | Spatial; temporal scale(s)                        |
|-----------------------|--------------------------------------|-----------------------------|----------------------------------------------------------------------------------------|--------------------------------------------------|
| Pulvirenti et al. (2020) | Satellite; multispectral             | Classification; fuzzy logic  | Forest fire monitoring; mapping of burned forest areas; near real-time mapping; automated processing chain | Region (country); short term (snapshot, near real time) |
| Novo et al. (2020)    | MLS                                  | M-estimator Sample Consensus; near neighbor algorithms; segmentation; classification | Forest fire management; evacuation planning; canopy mapping; crown projection          | Forest site (road); short term (snapshot)         |
| Proto et al. (2020)   | N/A                                  | Multiple linear regression; ANN; Multi- Layer Feed Forward Networks (MLFN) structure; general regression neural network | Forest operations; cost estimation; productivity                                       | Forest site; short term (2016)                     |
| Heikinheimo et al. (2020) | Social media (Flickr, Twitter, Instagram); sports tracking (Strava); mobile phone data | Content classification; spatio-temporal analyses | Green space management; use and valuation of green space; human behavior and values | Urban forest (city); short term (1–2 years)        |
| Shao et al. (2020)    | TLS; MLS                             | 3D modeling; odometry; global optimization; feature extraction; feature correspondence; motion estimation | Forest inventory; forest structure and parameters; non-destructive estimation; forest plot mapping | Forest plot; short term (snapshot)                |
| Kislov and Korznikov (2020) | Satellites (very high resolution)    | CNNs; deep learning; naive Bayes classifier; logistic regression with L2 regularization; support vector machine; adaptive boosting | Recognition and mapping of windthrow areas; forest management; forest disturbance | Forest region; short term (snapshot)              |
| Apostol et al. (2020) | ALS; UAV                             | 3D modeling; object-based image analysis; classification; Nearest Neighbor algorithm; Monte Carlo simulations; linear regression; digital aerial photogrammetry; Canopy Maxima algorithm | Forest inventory; forest structure and parameters; tree-species identification; individual tree detection | Forest plot; short term (snapshot)                |
| Pourghasemi et al. (2020) | Satellites                         | Boosted regression tree (BRT); general linear model (GLM); mixture discriminant analysis (MDA); learning-vector quantization (LVQ) | Forest fire management; risk assessment; forest fire prediction | Forest region; short term (snapshot)              |
| Nezami et al. (2020)  | UAV; hyperspectral                   | DNNs; 3D convolutional neural networks (3D-CNN); feature extraction; classification; multi-layered perceptron; confusion matrix | Forest inventory; tree species classification                                           | Forest plot; short term (snapshot)                |
| Dalla Corte et al. (2020) | UAV; laser scanner; hyperspectral (GatorEye) | 3D modeling; classification; voxelization | Forest inventory; forest structure and parameters; automatic tree detection             | Forest site; short term (snapshot)                |
We found that machine learning techniques were widely used for data collection, processing, and analysis of remote sensing imagery, and are increasing in popularity in forest ecosystem research. More sophisticated statistical methods, coupled with advancements and innovations in computational capacity, provide the opportunity to work with big data and, in some cases, enhance modeling and predictive capabilities at higher levels of spatial and temporal resolution (Almeida et al., 2020; Li et al., 2019). In a similar vein, open-source code and data-sharing practices are also gaining considerable interest in ecological and forestry research (Liang & Gamarra, 2020; Reichman et al., 2011), which could allow for greater access to advanced techniques for non-specialists. Scripts and packages made publicly available on open-source platforms allow for modifications to fit specific requirements, which could relate to the unit of analysis itself (such as type of tree, forest, ecosystem) and analytical needs (e.g., computational requirements or limitations) (Vicari et al., 2019). Cloud-based computing will also support computationally heavy analytical procedures (Almeida et al., 2020). For example, Google Earth Engine, a cloud-based geospatial platform, provides ready access to remote sensing imagery from a user-friendly dashboard, and supports multiple Application Programming Interfaces and programming languages (Tamiminia et al., 2020). Global Forest Watch (https://www.globalforestwatch.org) began as a network of non-governmental organizations whose mandate was to monitor the state of forests in various countries and is now an interactive web dashboard with an accompanied mobile application. This digital interface is designed to provide near real time information on forest change and ecosystem management activities with direct, regular input from satellite imagery (Crowley & Cardille, 2020).

### 4.1.2. Recent Phenomena and Emerging Applications

Arguably, the area of greatest advancement in the commercial forest sector’s intersection with emerging technology and data is in forest inventory and monitoring, which represent large areas of investment. Given the extensive spatial and temporal scales that must be accommodated in forest resource planning compared to other sectors and disciplines, and the cost and time constraints of doing so, the need for robust, affordable, and manageable technology and data for forest inventories and monitoring is critical (Ke & Quackenbush, 2011; Santoro et al., 2011). At the core of this trend is LiDAR, coupled with the growing sophistication and accessibility of machine learning algorithms for developing enhanced forest inventories (EFI) (Heinzel & Koch, 2011; Mohan et al., 2017). EFI data provide high-resolution inventories of key forest attributes (e.g., height, volume) that inform high-investment data and information flows, such as wood supply (Müller et al., 2019; White et al., 2016). The use of LiDAR in urban forest research and management is certainly also increasing (Alonzo et al., 2016). However, the integration of these technologies and data are less established in urban forestry, given the cost of data acquisition compared to less traditionally valued economic returns (e.g., human health and wellbeing benefits in urban forests compared to fiber production in commercial forests). Moreover, in cities there is often demand/pressure to acquire LiDAR data during leaf-off periods outside of the growing season in order to have better coverage of built/gray infrastructure (Klingberg et al., 2017).

Within the literature base, although the number of keywords associated with LiDAR does not appear to be rising as dramatically over time compared to other thematic groupings, it remains one of the most popular

| Citation            | Data collection tools & technologies | Processing & analysis methods                                      | Forestry application(s)                                                                 | Spatial; temporal scale(s)          |
|---------------------|--------------------------------------|-------------------------------------------------------------------|----------------------------------------------------------------------------------------|-------------------------------------|
| Yan et al. (2020)   | UAV; laser scanner                   | 3D modeling; self-adaptive bandwidth estimation; segmentation; mean-shift algorithm | Forest inventory; forest structure and parameters; automatic tree detection             | Forest plot; short term (snapshot)   |
| Pitkänen et al. (2020) | Satellite                         | Automatic change detection modeling chain; AutoChange (AC) method; hierarchical unsupervised spectral clustering | Forest change detection; sustainable forest management; automated modeling chain        | Forest site; short term (2015–2017) |
tools for forest research and management (Dassot et al., 2011; Mohan et al., 2017). LiDAR is often used in conjunction with other remote sensing technologies such as UAVs and satellite imagery (Ke et al., 2010; Tigges et al., 2013), particularly to assess tree parameters and forest structure. Although LiDAR is not a particularly novel technology, as initial applications go back to the 1960–70s, the business case may be changing to suit more needs. There is considerable private sector research and investment in autonomous vehicles, spurring demand for sophisticated advanced driver-assistance systems, which often incorporate LiDAR and/or Time-of-Flight technologies (Heineke et al., 2017). These developments could further the uptake of autonomous forestry vehicles in both rural and urban contexts.

Few examples of mobile applications were found in identified high-impact papers, which given the timeline, is to be expected. The first smartphones with connective capabilities similar to what we see today only emerged in the mid- to late-2000’s, becoming more mainstream a few years later alongside improvements in hardware and wireless communication (Islam & Want, 2014). Very recently, technology companies producing smartphones and tablets have started integrating sensor systems relevant to forest management; for example, Samsung and Apple have introduced 3D Time-of-Flight and laser scanning (respectively) in some mobile devices to enhance augmented reality capabilities (Apple Inc., 2020; Samsung Group, 2020), which have the potential to further support terrestrial/mobile LiDAR-based forest characterization and modeling, depending on mobile application development. As highlighted in some of the reviewed papers (Pulvirenti et al., 2020), researchers seem interested in providing more access to data and relevant analysis capabilities, particularly in user-friendly formats. As smartphone usage expands globally (Silver, 2019), along with better broadband connectivity and data storage capabilities, crowdsourced and citizen science-based forest ecological research may also become more feasible and reliable. Smartphones have been used in urban tree mapping and monitoring campaigns in urban areas, as part of the broader Public Participation GIS (PPGIS) movement (Hawthorne et al., 2015). Nevertheless, there is still some uncertainty about the use of smartphones as an effective tool for citizen-based environmental monitoring and research, as concrete benefits highlighted by researchers in this space tend to be speculative with limited evidence of “real world” uptake (Andrchuk et al., 2019).

Virtual environments, although not found to be common in this review, seem to be generating some interest in recent years. Our findings suggest that these tools are primarily used to understand human-nature relationships and perceptions about green space design, as well as psychological and physiological response to nature exposure (Annerstedt et al., 2013; Tabrizian et al., 2018). Virtual environments can also prove useful for forest inventory and canopy mapping applications. Recreating forests in three-dimensional models, modeled with data gathered from sensors in the field, can enable data collection, analysis, and forest stand assessments while reducing field-based resources (Chen et al., 2020). Beyond this study, some research has speculated how augmented reality-based smartphone applications (e.g., Pokémon Go) could influence conservation behaviors and enhance relationships between users and nature (Dorward et al., 2017). The intersections with virtual environments, citizen science, and mobile technology hold particular promise for both forest ecosystem stewardship and civic engagement (Foster et al., 2017; Sieber et al., 2016).

Lastly, there is a tendency in the literature to focus on only research or broad-scale analytical tasks (e.g., inventory and monitoring) in this area of study. However, there have been advancements in smart technology and data flows in forest operations and industry supply chains as well. This emerging trend is commonly termed Forestry 4.0 (or “internet of the forest”) in industry circles (FPInnovations, 2021). For example, internet-enabled “smart” harvesters enable forest product optimization and communications with supply chain needs in real time during operations, or machinery optimization to reduce greenhouse gas emissions (Müller et al., 2019).

4.2. Forest Ecosystem Management

4.2.1. Challenges for Forest Ecosystem Researchers and Managers

Key challenges identified by researchers in relation to applying various digital technologies to forest ecosystem management primarily relate to data quality and accuracy, data modeling and assumptions/bias, and capacity, expertise, and regulations. Many publications highlighted difficulties associated with working in more complex forest environments, which can result in occluded objects (Trochta et al., 2017; Wang
et al., 2020) and noise in data sets (Chen et al., 2020), particularly when differentiating spectral signatures from satellite, multi-, and hyper-spectral data. Seasonality and data quality/availability were also identified as limitations when using remote sensing imagery (Fang et al., 2018; Yao et al., 2012).

Concerns about data modeling were also mentioned in relation to model overfitting (Bayat et al., 2019; Nezami et al., 2020), scalability (Merino et al., 2011) and transferability (e.g., applying models to different ecosystems and contexts), and the creation of models based on assumptions that do not accurately reflect complex forest environments. In situations with human data, researcher bias was a concern, particularly when using and developing machine learning algorithms relying on researcher-defined inputs (Heikinheimo et al., 2020). In some cases, machine learning algorithms rely on large training data sets, often collected using field-based methods, which may not be available for particular physical environments (such as mixed forests) and subsequently may impact the robustness of modeling processes and outputs (Åkerblom et al., 2017; Helbich et al., 2019; Townshend et al., 2012). Related, data standards and standardization are likely to feature as key technical challenges into the future, particularly with the use of open data and data sharing systems. The adoption of existing data and data management standards (e.g., GML and ForestGML) have been suggested as “starting point[s] towards compatibility and data exchange in the virtual forest” (Müller et al., 2019, p. 214; Rossman et al., 2014).

Moreover, from the data governance perspective there is concern that the rate of adoption will lead to the replacement of established resource management methods (Hetemäki et al., 2010). For example, traditional aerial photo interpretation for forest inventories or networks of field-based permanent sample plots often inform LiDAR-derived EFIs in commercial forestry; in the case of the latter, they are even used to train the machine learning algorithms used to develop EFIs. Furthermore, identifying trees at the species level with high accuracy using machine learning algorithms, particularly in more diverse and complex forest environments, is still a key challenge for automating or semi-automating forest inventories (Almeida et al., 2020; Apostol et al., 2020). Where vast amounts of data are being collected and processed, adequate resources and expertise were identified as challenges; for example, payload carrying capacity is a limitation for UAV usage (Pádua et al., 2017), while equipment cost and availability dictates data management, processing, and computational capabilities (Calders et al., 2018; Fraser & Congalton, 2018; Krause et al., 2019; Piermattei et al., 2019). Furthermore, regulatory concerns (e.g., line-of-sight rules) were also identified as a hurdle to more widespread adoption and utilization of UAVs (Pádua et al., 2017; Zarco-Tejada et al., 2014). Vulnerabilities around the pace of technological adoption over traditional methods (and relative affordability of doing so in the short term) are discussed among practitioners but do not seem as widely established in the literature.

Interestingly, few papers explicitly discussed technological applications and methods that apply in both rural and urban areas. This is potentially a missed opportunity, as forest ecosystem management in both of these contexts could inform the other. For example, forest-fire monitoring and management in more rural and remote locations could impact the wildland-urban interface, depending on spread and scale of the fire as well as emergency response and longer-term management strategies (Stewart et al., 2007). In some areas of the world, particularly where urban sprawl is occurring, the wildland-urban interface is growing and raising wildfire risk (Radeloff et al., 2018). The comparatively longer establishment and development of certain disciplines within commercial forestry compared to urban forestry (e.g., inventory, wildfire detection and suppression) are of course key examples of synergies here. However, there are also examples from urban forestry that can inform commercial forestry, such as leveraging mobile technology for both civic engagement and ecosystem monitoring (Foster et al., 2017). Although the distinction between rural and urban contexts is often necessary, reflecting differences in ecology, jurisdiction, and management goals, caution should be exercised when defining what might be considered a more “real” or “natural” forest without considering possible alignment and synergies for managing these systems in practice (Chiarucci & Piovesan, 2020).

4.2.2. Opportunities for Research and Practice

Many of the opportunities identified by forestry researchers working with digital technologies relate to automating resource-intensive data collection, management, and analysis practices. Traditionally, forest inventories have relied on laborious field-based work, and many researchers emphasized the potential for remote sensing techniques to replace more intensive ground-based methods (Berland & Lange, 2017; Liang
et al., 2014; Tigges et al., 2013; Wu et al., 2013). Some technologies, such as UAVs, were also identified as lower-cost and more accessible alternatives for certain use cases, such as forest fire detection and monitoring (Yuan et al., 2017), compared to costlier systems (Koh & Wich, 2012; Zarco-Tejada et al., 2014). Where higher computational capacity is available, remote sensing imagery and machine learning techniques were cited to perform better at finer spatial and temporal resolutions (Khan et al., 2017) and handle larger data sets (Tigges et al., 2013).

Data fusion approaches, referring to combining multiple technologies and data inputs in tandem to produce more accurate and/or precise information, also appear to present new opportunities for both research and practice. For example, forestry research could broadly benefit from crowdsourced and open-source data sharing and management systems, which include smartphone applications (Sun et al., 2017) and web-based platforms (Lopez-Gonzalez et al., 2011; Saah et al., 2019), with data collected using varied methods in different contexts. Cooperative surveillance, or multiple UAVs used in conjunction, was also suggested as a way to use multiple sources of information and data inputs to monitor more complex forest environments (Yuan et al., 2015). Other, similar data fusion opportunities proposed for future research included combining LiDAR-equipped UAVs with self-driving cars to carry out completely autonomous forest inventories (Jaakkola et al., 2017). Multi-sensor tools were also used to assess forest structure and function; for example, integrated hardware and software such as GatorEye, combining LiDAR, hyperspectral, and thermal sensors on a UAV, featured in studies that emphasized the advantages of more cost-effective, agile, and autonomous approaches to forest inventorying and monitoring (Almeida et al., 2019; Dalla Corte et al., 2020).

Research on technological applications for urban forest ecosystem management was not prominent in this study, although our trend analysis did show more uptake starting in 2018. This trend is corroborated by other bibliometric reviews (Larouche et al., 2019; Polinko & Coupland, 2021), highlighting an increase in research output on urban ecosystems attributed to urbanization processes and urban population growth, spurring interest in urban sustainable development. With the recognition that cities are playing increasingly important roles in climate change adaptation and mitigation, as well as sustainable development more broadly, urban forest and other urban green infrastructure practitioners will be called upon to more efficiently and effectively plan and manage these resources to support broader sustainability and resiliency objectives (Elmqvist et al., 2015; Endreny, 2018). As more ubiquitous computing and integration of digital infrastructure into the urban fabric continues (Kitchin, 2014), vast amounts of data are being created—and the question remains how these might inform urban forest and urban natural asset management. The growing smart cities discourse, referring to the use of data and connected technologies to support urban planning and municipal service delivery (Impact Canada Initiative, 2021), will likely play a role in driving future technological applications in urban forestry and urban green space management (Nitoslawski et al., 2019).

4.3. Limitations and Future Research

In order to determine which screened abstract/title publications would be included in the full-text review, we decided on using a measure of impact, namely, number of citations. We recognize that this is a fraught metric, particularly given known biases in science publishing, not to mention that the number of citations a research output receives does not necessarily guarantee a similar level of impact in practice. Furthermore, literature can lag behind the state of practice given publishing times and, in this context, potentially rapid technological advancement that is, not reflected in scholarly literature. Nevertheless, in the case of a broad review with a large number of database search results, the number of citations does provide a concrete metric around which to scope a review. The choice to rank articles published in every year from 2017 to 2020, in addition to those published between 2010 and 2020, was intended to account for findings being potentially skewed towards earlier years.

The dominance in research output from Annex I countries (with the exception of China) could be due, in part, to potential gaps in the database search. For example, the omission of gray literature and the fact that the search was limited to studies published in English or French may have biased the results towards research produced by Western countries. We also expect that our findings reflect what some researchers understand to be a digital divide (Silver, 2019; Viard & Economides, 2014). The global digital divide describes the phenomena of unequal development of the Internet throughout the world, and has been attributed to the evolution of and differences in economic, regulatory, cultural, and political characteristics between
nations (Guillén & Suárez, 2005). In the context of this review, the distribution of research output suggests that, at the global scale, some countries have greater access to computing and information resources in the context of forestry research and forest ecosystem management—these are also the countries that, for the most part, have higher relative proportions of the population considered to be internet users (Roser et al., 2015).

This review shed light on some obvious gaps in digital forestry research. Indigenous forest management did not emerge in the full-text synthesis of highest impact papers, and only one screened article (out of 1,169 records) focused on Indigenous knowledge in the context of technology adoption for monitoring and managing forests (Bellfield et al., 2015). Bellfield et al. (2015) explored the use of smartphones for community-based forest data collection, monitoring, and sharing—within the broader goal of integrating local and Indigenous knowledge in REDD+ programs. Community forestry, more generally referring to the governance of forests by local communities across a broad spectrum of land ownership models (Charnley & Poe, 2007), also seems underrepresented in our findings. Only a handful of studies on community-based forest monitoring and management were identified during the screening process, the majority of which made use of smartphones and other mobile devices: Wang et al. (2016) explored the potential for community monitoring of forest pests using mobile phones; Rana and Miller (2019) used machine learning techniques to assess the impacts of different community forest management policies; Pratihast et al. (2016) combined community data acquired through mobile devices with satellite imagery to develop a near-real-time forest monitoring system; and Ferster et al. (2013) adopted a public participation approach to wildfire management in the wildland-urban interface using a smartphone application. Given the importance of traditional knowledge and the contributions of local and Indigenous communities to sustainable forest management around the world (FAO & FILAC, 2021; Lawler & Bullock, 2017), along with historical precedents for community displacement and resettlement due to technological change (United Nations Department of Economic and Social Affairs, n.d.), it would be worthwhile for research programs to study the range of potential impacts of new technologies on traditional knowledge systems and management practices.

In addition to addressing these gaps, future research should focus on practitioner and policymaker knowledge and perspectives, and explore how diverse governance systems will shape the collection and use of forest data and information (Rantala et al., 2020). As discussed, some of the technologies, methods, and uses discussed in this paper still hold a degree of uncertainty, whether related to technology uptake and implementation among forest managers, ability, and capacity to innovate, and/or resource availability (e.g., time, cost). Eliciting perspectives from experts could provide more information on forest management practices and specific technological applications beyond research, and shed light on the ability (and willingness) of government, industry, and other managing bodies to incorporate new data-driven techniques in existing workflows. Assessing perceived risks associated with more automated workflows, as well as potential impacts on forestry-related work, will likely be warranted as diverse remote sensing techniques become increasingly common. Employing horizon scanning and forecasting techniques with both technology and forestry experts and stakeholders may also shed light on disciplinary and science-policy gaps, along with priority areas for both forestry- and technology-focused research and innovation (Holopainen et al., 2020; Sutherland et al., 2011). It is clear that a social science research agenda around uptake, use, implications, and limitations of new data and technology in forestry and urban forestry is needed.

5. Conclusions

A range of digital software and hardware applications are currently being used in forest ecosystem management. We found that forest inventorying and monitoring, particularly to assess landscape change, biotic and abiotic disturbances, and support sustainable forest management, constituted the majority of use cases for technology applications. More emerging contexts and tools include urban forest and green infrastructure management, data fusion approaches for remote sensing (including more automated data workflows), and smart devices, along with mobile applications, for data collection and analysis.

The trends highlighted in this study suggest that digital-based technologies will likely play increasingly prominent roles in forest monitoring, planning, and management. The continued adoption of digital-based tools will also likely engender new research questions about forest ecosystems as dynamic social, ecological,
and technological landscapes, and future research should more closely examine how we can anticipate and adapt to technological uncertainty and change. In other words, it may be worth thinking about how diverse technological trends can be harnessed to support forest ecosystem resilience around the world, in varying contexts and at multiple scales. Nevertheless, digital technologies are not a panacea for our most pressing forest-related issues. Current and emerging technologies addressed in this paper are just part of the forest ecosystem management toolbox, and it will be critical to consider local and context-specific needs, historical and land-use legacies, as well as capacity, expertise, and access to data and computing resources, when integrating new tools and technologies into forest management practices.

**Conflict of Interest**

The authors declare no conflicts of interest relevant to this study.

**Data Availability Statement**

The raw data (and metadata) that informed the analyses for this study is available via the University of British Columbia Dataverse portal, an interdisciplinary and open-access repository powered by the Dataverse Project: “Digital Forests Literature Scoping Review”, https://doi.org/10.5683/SP2/NFEFZ4, Scholars Portal Dataverse, DRAFT VERSION.

**Acknowledgments**

This work was funded by the Social Sciences and Humanities Research Council of Canada (SSHRC), as part of the Knowledge Synthesis Grant program Living Within the Earth’s Carrying Capacity (grant #872-2019-1012) titled “Will smarter forests take us farther? Fostering resilient forest ecosystems in the digital era.”

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