REVIEW

A new generation of sensors and monitoring tools to support climate-smart forestry practices[1]

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Abstract: Climate-smart forestry (CSF) is an emerging branch of sustainable adaptive forest management aimed at enhancing the potential of forests to adapt to and mitigate climate change. It relies on much higher data requirements than traditional forestry. These data requirements can be met by new devices that support continuous, in situ monitoring of forest conditions in real time. We propose a comprehensive network of sensors, i.e., a wireless sensor network (WSN), that can be part of a worldwide network of interconnected uniquely addressable objects, an Internet of Things (IoT), which can make data available in near real time to multiple stakeholders, including scientists, foresters, and forest managers, and may partially motivate citizens to participate in big data collection. The use of in situ sources of monitoring data as ground-truthed training data for remotely sensed data can boost forest monitoring by increasing the spatial and temporal scales of the monitoring, leading to a better understanding of forest processes and potential threats. Here, some of the key developments and applications of these sensors are outlined, together with guidelines for data management. Examples are given of their deployment to detect early warning signals (EWS) of ecosystem regime shifts in terms of forest productivity, health, and biodiversity. Analysis of the strategic use of these tools highlights the opportunities for engaging citizens and forest managers in this new generation of forest monitoring.

Key words: climate change, early warning signals, ecosystem regime shifts, wireless sensor network, Internet of Things, citizen science, green technologies.

Résumé : La foresterie intelligente face au climat est une branche émergente de la gestion forestière adaptative et durable dont l'objectif est d'accroître la capacité des forêts de s'adapter au changement climatique et d'en atténuer les effets. Cela comporte beaucoup plus d'exigences en termes de données que la foresterie traditionnelle. Ces exigences en matière de données peuvent être satisfaites grâce à de nouveaux appareils qui permettent de surveiller la forêt in situ en continu et en temps réel. Nous proposons un réseau complet de capteurs, c.-à-d. un réseau de capteurs sans fil, qui peut faire partie d'un réseau mondial d'objets interconnectés individuellement adressables, un Internet des objets (IdO) qui peut rendre les données disponibles presque en temps réel à de nombreux intéressés, incluant des scientifiques, des forestiers et des gestionnaires forestiers, et qui peut en partie motiver les citoyens à participer à une importante collecte de données. L'utilisation de sources in situ de données de suivi comme données d'entraînement validées sur le terrain pour des données de télédétection peut favoriser la surveillance des forêts en augmentant les échelles spatiale et temporelle, permettant ainsi une meilleure compréhension des processus forestiers et des menaces potentielles. Certains des développements et applications clés de ces capteurs sont présentés dans cet article avec des directives pour la gestion des données. Des exemples de leur déploiement pour détecter les signaux d'alerte rapide des changements de régime des écosystèmes en ce qui a trait à la productivité, l'état de

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santé et la biodiversité de la forêt sont présentés. L'analyse de l'utilisation stratégique de ces outils met en évidence les occasions d'intéresser les citoyens et les gestionnaires forestiers à cette nouvelle génération de suivi des forêts. [Traduit par la Rédaction]

Mots-clés : changement climatique, signaux d'alerte rapide, changement de régime des écosystèmes, réseau de capteurs sans fil, Internet des objets, science participative, technologies vertes.

1. Introduction

Forests have traditionally been managed as large blocks with uniform treatments. This approach simplifies management but may miss shifts in forest dynamics over time; however, new technology permits the collection of data at finer spatial and temporal scales than in the past, providing indicators of forest dynamics. For instance, long-term continuous monitoring of physiological processes at the tree level (or smaller) can serve as an early warning system by providing evidence of changes to biological processes that will eventually scale up to losses in productivity or even tree mortality at the stand level. Long-term monitoring can also be used to identify thresholds or tipping points whereby key processes have been perturbed beyond a point from which trees cannot recover. Likewise, large-scale monitoring may provide insights into subtle impacts of chronic events such as drought or increased temperature on spatially diffuse tree mortality and on forest biodiversity.

Forests play a significant and beneficial role in climate change mitigation. Climate-smart forestry (CSF) aims to validate, promote, and deliver the climate-stabilizing benefits of forests on the temperature of the atmosphere consistent with the recommendations set out by the Paris Agreement (UNFCCC 2015). So far, the mitigation benefits of CSF have primarily focused on effective carbon sequestration and energy substitution practices (Nabuurs et al. 2017; Kauppi et al. 2018). Nevertheless, a climate-smart perspective that promotes synergies between climate and other services and removes trade-offs between mitigation and adaptation strategies (Bowditch et al. 2020) is warranted to meet the Paris Agreement's temperature goals. Long-term, large-scale monitoring of anthropogenic disturbances, wood extractions, and other practices are needed to estimate the vulnerability of trees and forests and propose climate-smart management strategies.

Here we review a new generation of tools for forest monitoring across spatial and temporal scales to highlight their potential advantages in forest management and the challenges due to their implementation. Sensors and instruments that operate continuously in situ and mounted on forest harvesting equipment, relaying data to research laboratories and managers' offices in real time, are discussed. We also evaluate the effectiveness of data gathering by citizen scientists and by sensors associated with large-scale remotely sensed data.

2. Monitoring with in situ sensors

2.1. Forest productivity

2.1.1. Tree growth

The impacts of climate change on forest productivity since the middle of the 20th century are documented thoroughly in Boisvenue and Running (2006). While it is difficult to decipher a trend at fine spatial scales, global changes in climate seem to have a net positive impact on forest productivity when water is not limited. To understand the reaction of trees to short-term changes in environmental conditions such as air temperature, soil moisture, and precipitation patterns, continuous monitoring of stem radial variation throughout the year can be helpful (Deslauriers et al. 2007).

Monitoring tree stem circumference using in situ automatic dendrometers allows the effect of climate on tree growth to be distinguished from that of weather over different time scales. These devices measure stem radial variation composed of diurnal rhythms of water storage depletion and replenishment and seasonal tree growth (Deslauriers et al. 2007; Vilas et al. 2019), especially when linked to transpiration. Integrating dendrometer time series and xylogenetic data disentangles swelling caused by stem water replenishment from increases that can be attributed to actual radial growth (Cuny et al. 2015; Cruz-García et al. 2019), leading to a better understanding of wood formation processes and their response to environmental conditions (Cocozza et al. 2016; Steppe et al. 2015). Automatic dendrometers could also be useful tools for monitoring the response of trees to extreme climatic events (Burri et al. 2019), as they can provide high-frequency and long-term information on tree water status across large scales (Vilas et al. 2019), in particular when coupled with sap-flow sensors (Oogathoo et al. 2020, section 2.1.1).

The automatic dendrometers are classified in "point-type" (also known as radial and diametral dendrometers) and "band-type" (also known as circumferential dendrometers). The point dendrometers measure changes in the radius of a branch or main stem with a rod held against the outside surface by a constant force, while the band dendrometers measure changes in circumference with a band wrapped around the branch or main stem and held by a constant force (Fig. 1).

The signal recorded by dendrometers contains three components: long-term seasonal growth patterns, medium-term patterns representing swelling after rainfall and subsequent drying, and daily cycles of water uptake related to tree transpiration (Vospernik et al. 2020). Point dendrometers are particularly useful in studies on wood formation and are more suitable than band dendrometers for large-scale tree growth measurements and water stress monitoring because of their rapid response (hourly or faster) and their ability to record dehydration and rehydration events as well as growth (Wang and Sammis 2008). A summary of dendrometer developments and guidance for dendrometer selection is reported in Clark et al. (2000), while a review of the use of precision dendrometers in research on stem size and wood-property variation can be found in Drew and Downes (2009).

2.1.2. Timber production and transformation

Useful data for monitoring forest functioning and dynamics can also be collected from the sensors installed on machines deployed for timber production. Most modern harvesters and forwarders can already interact with a digital forest inventory management system, both getting information (e.g., for organizing harvest operations of marked trees or forwarding piled logs along predefined paths) and feeding new data to the system such as diameters and lengths of the logs produced. The latter data are generally georeferenced, are communicated between computers in forest machines in the StanForD file structure standard (Arlinger et al. 2010), and are used for invoicing timber produced and delivered; however, the same data can also return a detailed account on the quantity of the round wood yielded in the harvested plot (Rossit et al. 2019) needed for drawing the balance between net annual increment and annual harvesting of a given forested area. In the near future, the contribution of machines to forest monitoring and CSF is expected to grow steadily, as sensors are increasingly deployed in the forest supply chain for early detection of timber quality (along with quantity). Particularly promising for this purpose are optical spectrometers (Sandak et al. 2016, 2020), which can be operated manually or directly by the machines. The latter modality has been successfully tested by Sandak et al. (2019), who installed several sensors for timber quality grading on a

Fig. 1. Examples of an automatic band dendrometer (upper instrument on tree) co-located with an automatic point dendrometer band (middle left on tree) and standard manual band dendrometer (lowest instrument on tree) at the Hubbard Brook Experimental Forest, N.H., USA (photograph by L.E. Rustad).

prototype of processor head. Optical spectrometers have been used to identify resin pockets, resistance, and juvenile wood, while mechanical sensors and sensors able to collect signals generated by stress wave propagation have been employed to measure timber density and provide a branch index value per log.

Data generated during harvesting operations and integrated with information provided by other types of sensors at tree or plot levels could also be valuable in forest management and monitoring. For this purpose, it is essential to automatically relate single logs and quality data to the original standing tree. Among the available options, radio-frequency identification technology (RFID) seems to be the most effective solution for marking trees in the forest (and processed logs) linking their identifier to the entity in the database of a digital forest inventory management system (Pichler et al. 2017). Furthermore, RFID tags have been shown to survive the harsh conditions of timber procurement, effectively transferring the information from the standing tree to the products delivered as logs to the sawmills (Picchi et al. 2015; Picchi 2020).

In the industrial context, for wood quality assessment, more sophisticated and precise sensors than optical spectrometers must be deployed such as three-dimensional (3D) log tomography systems (X-ray) or near-infrared (NIR) hyperspectral imaging. These are used to return a detailed analysis of the logs and optimize the sawing process. Examples of this application are provided by Stängle et al. (2014), who compared terrestrial laser scanning (TLS) with X-ray computed tomography (CT) for analysis of stem and branch scars; Uner et al. (2009), who used X-ray CT to highlight the effects of thinning on timber density; and Ma et al. (2018), who applied NIR spectroscopy to assess wood stiffness and fibre coarseness of boards. X-ray CT is also a powerful imaging procedure for measuring density distributions and water content in the xylem with high spatial resolution, representing a link with xylem physiology and wood anatomy (Tognetti et al. 1996; Fromm et al. 2001).

The integration of such sensors and tools, i.e., sensors installed on timber harvesting machines with RFID tags on logs with tools in the industries, provides infrastructure for the sensing, wireless transfer, and cloud-elaboration of the data produced within the timber supply chain (Fig. 2) and represents a clear opportunity for forest monitoring and inventory purposes.

In a long-term application, sawmill and machine-installed sensors could be used to adjust and enhance the models for interpretation of the raw data provided by the in situ sensors installed to monitor tree health and physiological parameters thanks to the capacity to relate the data collected along the supply chain with that recorded on the original tree in the field. We suggest that the analysis could be akin to retrospective epidemiological cohort studies in human health, where the consequences of the exposure to a given factor (e.g., historical data on drought stress) are identified through the analysis of industrial data, e.g., timber properties or branch and tree-ring development.

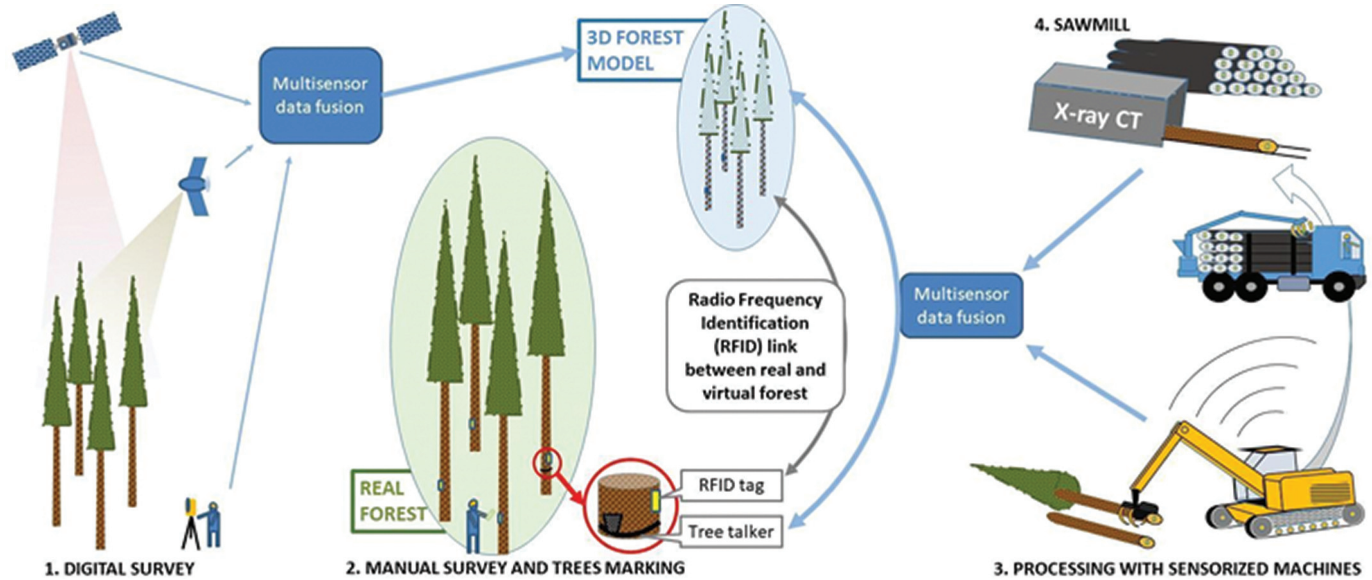
2.2. Forest health

2.2.1. Evapotranspiration

The energy associated with the latent heat flux, i.e., evapotranspiration, is a fundamental component of the Earth's surface energy balance. Evapotranspiration, which links soil, vegetation, and the atmosphere, is controlled by many environmental variables such as solar radiation, vapour pressure deficit (VPD), air temperature, and soil water content (SWC). Atmosphere–vegetation–soil feedback occurs as trees may lower surface temperature by evaporative cooling, which depends on the latent heat of evaporation (evapotranspiration rate), the incoming radiation, and the convection of heat away from the leaves. Plant water stress and eventual tree mortality occur when the transpiration demand of leaves exceeds available water. In most temperate climates, evapotranspiration is expected to decrease with decreasing soil moisture and increasing VPD (Tognetti et al. 2009; Juice et al. 2016). While this expectation is also met in dry boreal forests such as in Western Canada (Pappas et al. 2018), it is not met in moist humid boreal forests, as demonstrated by Oogathoo et al. 2020, who harnessed a network of forest plots equipped with Granier-type sap-flow probes (Granier et al. 1996), which measure transpiration flow as the ascent of sap within xylem tissue, coupled with point dendrometers. Indeed, in the moist boreal forests of Eastern Canada, soil moisture was found to exert little influence on sap-flow rates, which continued to be driven by VPD and radiation even during a drought (Oogathoo et al. 2020). There is thus likely a threshold of absolute rather than relative soil moisture beyond which the drivers of transpiration change. Researchers should consider absolute versus relative drought conditions when comparing ecosystems. These contrasting results highlight the importance of a network of sensors deployed across local, regional, and continental scales to accurately assess differences in tree evapotranspiration to climate stress such as drought (e.g., Poyatos et al. 2016, 2020).

Drought is triggered by weather patterns, which determine the amount of moisture and heat in the atmosphere. A lack of precipitation for a protracted period of time results in a reduction in soil moisture, in turn decreasing the amount of water available for plants. To be considered a drought, the reduction in available moisture will be below the climate normal and the drought timing

Fig. 2. Example of interaction among sensors installed or deployed for forest monitoring, forest inventory, and timber supply chain: (1) forest survey with digital sensors enables the creation of a three-dimensional (3D) forest model; (2) on-the-ground and highly detailed data are collected manually and with stationary sensors; the link with the 3D forest model is provided by traceability systems such as RFID tags; (3) forest machines used for timber production deploy timber quality sensors, providing tree-specific ground-truthing data; and (4) the traceability system allows linking the highly detailed data generated in the sawmill for log analysis with the single trees and related data stored in the 3D forest model.



should be clearly stated using a specific metric, because severity and length will influence effects (Slette et al. 2019). Drought-induced imbalance in water supply and demand can be exacerbated by global warming (Jung et al. 2010; Van Loon et al. 2016). Although the documented increases in forest dieback across biomes are correlated with regional warming, causation has not been established, which would require long-term and high-frequency records of tree functions in prolonged drought conditions.

Data from trees monitored with coupled sap-flow sensors, which at the tree level estimate transpiration (Cermák et al. 2015), and automatic dendrometer bands can be used to relate tree rehydration, dehydration, and sap flow to the commencement of growth in ring-porous and diffuse-porous trees, as well as in conifers (Oogathoo et al. 2020). These real-time measurements can be linked to other physiological (e.g., water potential, stomatal conductance, photosynthetic efficiency, and hydraulic architecture) and biometric (e.g., basal area, crow projection, tree height, and root volume) measurements to evaluate tree function and forest health. Thus, real-time sap-flow monitoring can be used to provide a mechanistic understanding of how key climate parameters influence water transport in trees and thus how different species in different regions respond to climatic stress.

A combination of sap flow measurements (i.e., mensuration of stomatal conductance as regulator of transpiration over a short time period) and stable isotope data (i.e., carbon isotope ratio, $\delta^{13}C$, to derive water use efficiency) may also provide an individual tree based estimate of gross primary productivity (GPP) (Klein et al. 2016; Vernay et al. 2020). Transpiration could also be further scaled up, e.g., from stand to watershed, using remote-sensing images (Cermák et al. 2015).

2.2.2. Leaf temperature

Differences in temperature between leaves of neighbouring trees can be used to detect drought stress because drought reduces transpiration and transpiration reduces leaf temperature (Leuzinger and Körner 2007; Lapidot et al. 2019). At dry sites, further increases in summer temperatures and drought due to climate change might change the competitive abilities of tree species in favour of those that are able to maintain transpiration and growth. Temperatures of multiple trees and large canopy areas can be compared, thereby quantifying differences in leaf temperature due to direct versus indirect solar radiation and identifying microclimatic environments within forest stands (Bowling et al. 2018). Large differences in leaf temperature (>1 °C) can help explain partial or complete mortality of leaves in the crown due to either biotic or abiotic factors. Moderate differences in leaf temperature (~1 °C) can be an indication of decreased stomatal conductance due to drought stress or can serve as an early warning of pest or pathogen infection.

Common tools for leaf temperature measurements include thermal resistance sensors, thermocouples, infrared (IR) thermometers, and IR thermographic cameras. Thermal resistance sensors and thermocouple and IR thermometers provide simple and accurate single-point temperature measurement of the temperature of individual leaves when correctly installed in contact with the underside of the leaf, whereas IR thermographic cameras allow a broader area to be considered. Leaf temperature measured using IR thermographic cameras can be used to derive leaf transpiration and stomatal conductance through leaf energy balance equations (Vialet-Chabrand and Lawson 2019) due to the inverse proportional relationship between transpiration and leaf-to-air temperature differences. Variation in leaf temperature distribution can be an indicator of soil moisture stress, and its measurement by means of IR thermographic cameras, though challenging, can be applied to stress detection. Canopy temperature measured by IR thermographic cameras is affected by canopy architecture and leaf traits (Bridge et al. 2013), which, in turn, influence the degree of coupling between the canopy and the atmosphere. A drawback of the IR thermographic cameras is that measurements may be affected by the emissivity of individual leaves; for this reason, calibration against "black" and "white" standards is therefore required to obtain accurate temperature values This is necessary for absolute rather than relative temperature comparisons and to make broader assessments of stand-level water use among sites. In addition, the major impediment to the use of IR thermographic cameras, beyond its high price, is that temperature differences between leaves are relatively small compared with those of other objects in the environment, so obtaining the appropriate resolution of false-colour images to compare between trees or leaves can be difficult against a background of large environmental temperature gradients (Yu et al. 2016). IR imaging technologies, in conjunction with remotely sensed data from satellites or unmanned aerial vehicles (UAVs), may enable detailed surveys of canopy temperature, water status, and pathogen attack in forest stands over large areas (Scherrer et al. 2011; Lapidot et al. 2019).

2.2.3. Defoliation and crown dieback

Crown defoliation and dieback can be a key metric for inference of forest canopy health, particularly if crown transparency can be explicitly connected to tree physiology (Dobbertin et al. 2010). Changes in canopy density occur with seasonal leaf phenology and through insect defoliation. These two processes are often correlated as climate stress related phenological changes in the timing of tree bud and leaf development may increase a tree's susceptibility to pests and pathogens, as found in Norway spruce (*Picea abies* L. Karst.) (Schlyter et al. 2006), balsam fir (*Abies balsamea* (L.) P. Mill.), and black spruce (*Picea mariana* (Mill.) Britton, E.E. Sterns & Poggenb) (Pureswaran et al. 2019) subject to insect defoliation. Early detection of pathogen outbreaks in forests is crucial in mitigating their damage (MacLean 2019). Long-term monitoring of canopy openness, through leaf area index (LAI) or plant area index (PAI), can be performed through a network of ground- or tower-based sensors or by using ground-based cameras. Detailed measurements of LAI can be obtained with repeated measurements over time from a fixed upward-pointing camera position (Chianucci 2020) allowing for the monitoring of seasonal changes in vegetation canopies (Wingate et al. 2015; Hufkens et al. 2018; Brown et al. 2020). For simplicity, two methods have been tested for repeated photographic estimates of canopy openness: a restricted-view approach, which is based on upward images acquired with a camera mounted with a normal lens, and a wide-view approach, which is based on collecting upward images with the camera mounted with a fisheye lens. The first approach allows for maximizing the full frame due to the narrow field of view, but it requires independent measurements of leaf inclination angle to estimate LAI from gap fraction (Chianucci 2020). The second approach enables a larger footprint and increased angular sampling, which can be used to estimate canopy leaf angle distribution, removing the requirement for ancillary information in the retrieval of LAI. When used with photon sensors, fish-eye photography can provide accurate estimates of changes in canopy light interception (Brown et al. 2020), foliage area, and potentially long-term forest canopy health. Furthermore, by combining LAI with sap-flow measurements (see section 2.2.1), a link can be created that allows assessment of the physiological effects of drought stress on water loss (Wang et al. 2012). To interpret possible drought effects, LAI measurements allow for the assessment of potential transpirational cooling of the stand (Bréda 2003). Increasingly, these approaches allow ecological and physiological phenotypic data to be linked to genetic and molecular data (Kim et al. 2014), adding value to both perspectives and providing guidance for climate-smart forest management using a combination of these two viewpoints.

2.2.4. Phenology

The monitoring of forest phenology enables us to collect data on the status and development stages of forest trees over the course of the year, determine their dependence on local (e.g., meteorological and site) conditions including extreme events, and document and explain possible changes in the timing of these stages (Vilhar et al. 2013).

Changes in leaf emergence and tree growth can be used to determine how trees are responding to climate change (Rossi et al. 2011). In turn, phenological shifts can affect climate (Richardson et al. 2013). Indeed, the earlier presence of green land cover and the delay in autumnal senescence and leaf fall of deciduous canopies may alter seasonal climate through the effects of biogeochemical processes (especially photosynthesis and carbon sequestration) and physical properties (mainly surface energy and water balance) of vegetated land surfaces (Peñuelas et al. 2009). Changes in budburst, flowering, and fruiting phenology can result in asynchronies between these food resources and a diverse range of microbes, insects, birds, and mammals in forests, as well as the emergence of defoliators that can have negative effects on canopy structure and health (Pureswaran et al. 2015; Pureswaran et al. 2019).

Digital repeat photography for phenological monitoring such as those deployed in phenocam networks across Europe, North America, and Asia (Nagai et al. 2018) offers an automated and cost-effective way to characterize temporal changes in vegetation. In short, digital cameras, installed overlooking the vegetation of interest, record images throughout the day, from sunrise to sunset, in time-lapse mode. Information about vegetation colour such as "canopy greenness" is extracted from the imagery and used to quantify phenological changes. Specific phenophase transition dates, e.g., corresponding to the onset of spring green-up, can be identified from the seasonal trajectory of canopy greenness. Image analysis can be conducted for individual organisms or at the canopy scale (Seyednasrollah et al. 2019). A major limitation in using these cameras is that large differences can occur in phenology estimates (Liu et al. 2019). In particular, the cardinal direction and inclination angle of the camera have a large effect on the estimate of spring budburst. To address the first issues, the sensor direction must be standardized. The effect due to the inclination angle is harder to adjust as it differs according to the species composition of the canopy (Liu et al. 2019). Camera exposure settings are also a concern when estimating changes in phenology, particularly in autumn when leaf colour change affects the results (Mizunuma et al. 2013). The error associated with the use of inconsistent exposure settings over leaf flush, for example, can exceed the total difference in PAI over that period. To deal with these aspects and effectively track the phenological progression of canopy development in forest stands, a proposed solution is to combine digital cameras with photosynthetically active radiation (PAR) sensors for canopy-cover assessments of LAI and PAI (Toda and Richardson 2018).

2.2.5. Soil conditions

Low soil moisture is one of the dominant drivers of forest dieback (Adams et al. 2017; Choat et al. 2018) and, together with air temperature, forest productivity, and silvicultural practices, also influences decomposition of soil organic matter (SOM), rates of soil carbon dioxide (CO_2) emissions, and soil rhizosphere communities with consequences for the carbon balance of forest ecosystems (Valentini et al. 2000; Janssens et al. 2001; Reichstein et al. 2003). Soil moisture measurements can be confounded by inherent heterogeneity of forest soils and can be influenced by sensor placement and density (Rundel et al. 2009). A variety of sensors for indirect estimation of SWC are available on the market, differing in technology, frequency of measurement, energy requirement, and price (Susha Lekshmi et al. 2014). The most reliable and commonly used sensors for continuous SWC measurements at the point scale are those based on electromagnetic methods such as time domain reflectometry (TDR), which are precise but relatively expensive, and frequency domain reflectometry (FDR) and capacitance sensors, which are less expensive and relatively accurate but more susceptible to soil environmental effects (Matula et al. 2016; Bogena et al. 2017) such as soil texture, electrical conductivity, and temperature (Kizito et al. 2008); however, to create high-density wireless sensor networks in remote areas requires that single sensor costs are minimized while sensor lifetimes are maximized (Matula et al. 2016). Consequently, FDR-based and capacitance sensors are the most widely used in SWC sensor networks both at the plot (Pascual et al. 2019) and catchment scales (Bogena et al. 2010). Recently, an increase in the deployment of inexpensive and stand-alone sensors in ecological research studies is already contributing to databases linked to biogeography and plant traits that can be used to develop valuable neural network models to predict soil conditions (Hashimoto et al. 2015).

Microbial activity and SOM decomposition, as well as root respiration, are affected by soil moisture availability. Soil gas emissions can be measured in the field with IR and laser-based gas analyzers connected to multiple automated dynamic chambers (Wingate et al. 2010; Courtois et al. 2019). These gas analyzers are able to record simultaneous and continuous measurement of up to five greenhouse gases (N_2O, CH_4, CO_2, NH_3, and H_2O) as well as their isotopic compositions (Midwood and Millard 2011). Major drawbacks of such installations are the costs and energy requirements of the analyzers and pumps, which limit their deployment in remote areas without a stable power supply.

Temperature strongly influences the biophysical and biochemical processes in soils, and estimating soil temperature provides useful information for understanding the energy exchange between atmosphere and land (Hillel 1998). In general, soil temperature is measured in situ in correspondence with meteorological stations (Holmes et al. 2012). At these sites, accurate long-time continuous series of soil temperature measurements can be gathered at multiple depths through the soil profile (Hamilton et al. 2007). Permanent nodes and mobile devices may inform models to provide temporal patterns of soil surface energy balance in specific forest patches; however, these measurements are necessarily sparse across forest landscapes, limiting their ability to truly represent the spatial dynamics of soil temperature. To address this issue, statistical models and interpolation techniques can be used, though heterogeneous terrain, complex topography, and land cover add uncertainty to the estimates of soil temperatures (Wu et al. 2016). Land surface temperature retrieved from satellite images (i.e., multispectral imagery in visible NIR) may provide an alternative to soil temperature estimation in bare soil (Hassan-Esfahani et al. 2015); however, the use of remotely sensed data is still challenging under the forest canopy (Shati et al. 2018), as well as the relationship between soil temperature and vegetation indices.

2.3. Biodiversity

Biodiverse ecosystems can be more stable and adaptable against climate-induced stressors and disturbances (Pires et al. 2018). Real-time biodiversity monitoring will rely on techniques that can help assess changes in forest composition, including plant and animal species distributions and abundance (Steenweg et al. 2017). Many case studies have already demonstrated the feasibility of using strategically placed digital wildlife cameras that are triggered by the movement of animals, from insects to reptiles to mammals to birds. Data from multiple fixed cameras that cover an extensive area can be used to quantify relationships between animal distribution range changes that can be correlated to ecosystem disturbances caused by change in either climate or silvicultural management practices or anthropic activities such as tourism (Astaras et al. 2017), hunting (Bater et al. 2011), or illegal forestry activities, which generate their own signature acoustic spectra (Burivalova et al. 2019).

The combination of data from phenology cameras, as described in section 2.2.4, and wildlife cameras can provide empirical evidence for relationships between the behaviour of animal and insect species and plant phenology and highlight climate change induced synchronous or asynchronous relationships. High biodiversity may buffer the negative effects of species-specific phenological shifts and should thus be monitored. Researchers currently recommend that future efforts should not focus solely on phenological synchrony but also monitor the time elapsed between the abundance peaks of interacting species, as well as the strength of their interaction, by integrating information throughout the season, simultaneously accounting for the full pattern of phenology and abundance (Cohen et al. 2018). In addition, testing for shifts in peaks and interactions requires data covering a diversity of species from diverse climates (Wolkovich et al. 2013). Indeed, there is a strong need for observational field data outside the temperate midlatitudes and a need for the measurement of climatic drivers beyond temperature (Wolkovich et al. 2013). In the past, this has been hampered by the need for time-consuming ground-level studies, but advances in remote photo and video technologies can help increase worldwide coverage of observational data.

The lack of standardized metadata, field protocols, databases, and baselines currently limits the extensive use of cameras to provide effective measurements of global biodiversity change through a global camera network. Modest investments and collaborative efforts carried out to overcome these limitations could harness the power of remote-camera technology and expand current local-camera and crowdsourcing projects (see section 3) into nationally or internationally coordinated efforts (Steenweg et al. 2017). Forests support a diverse array of sounds produced by mammals, birds, amphibians, and insects that can be studied within the soundscape ecology. Microphone networks can provide an additional layer of data, complementing that obtained with wildlife camera networks. Acoustical data may help to enable the understanding of coupled nature–human dynamics across different spatial and temporal scales (Pijanowski et al. 2011) by describing how the sounds of a forest change over the season or over the long term in response to forest management and changes in climate. For example, relatively inexpensive, open-source field-deployable microphone recording systems, e.g., the acoustic detector AudioMoth (Hill et al. 2018) based on artificial intelligence algorithms, can be deployed in the environment, and recorded data can be analyzed with a range of open-source software. A very recent pilot study demonstrated the potential of AudioMoth to detect bat echolocation by analyzing very large data sets generated from continuous forest monitoring by low-cost acoustic sensors (Prince et al. 2019). Machine-learning techniques have been applied to bird acoustic recordings for automated recognition of bird song units, identification of the daily activity of individual bird species in different areas, and assessment of variations in bird songs over the season and in different forest tree mixtures (Ross et al. 2018).

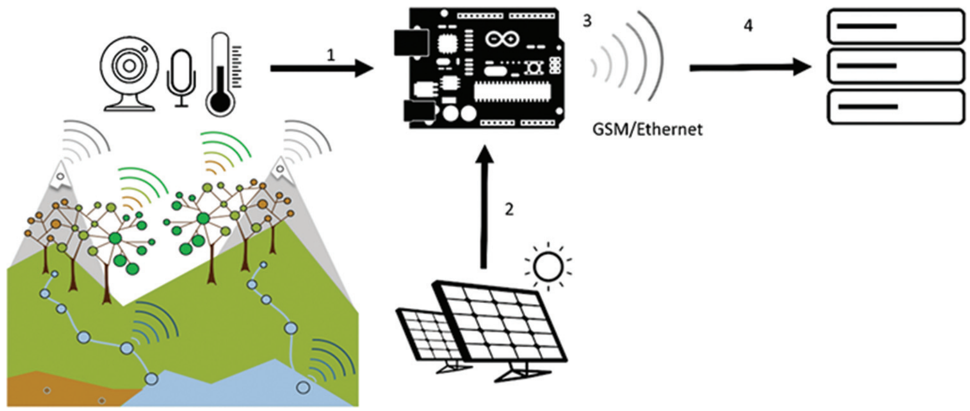
The integration of landscape imaging and soundscapes with other in situ data streams from climate sensors will enable scientists and stakeholders to better connect patterns in biodiversity change with local causes of biodiversity declines and (or) changes in forest function that inadvertently affect climate or carbon sequestration potential.

2.4. Data collection and wireless data transmission

Data collected in the forest from different untethered computing devices equipped with embedded sensors and actuators can potentially be transferred to remote central servers via a wireless communications technology for real-time displaying, storing, processing, and analyzing (Ali et al. 2017). Such an organized group of sensors is called a wireless sensor network (WSN). Every sensor considered in the above sections reacts as a sensor node because it detects and responds to a specific input and generates an output, i.e., an electrical signal, which is transmitted to a microcontroller for further processing. By using wireless communications technology, e.g., the Global System for Mobile Communications (GSM), the microcontroller transfers the data to the Internet so that the end users can access the data via a server from their office (Fig. 3).

A WSN can use generalist or specialist sensors. The sensors that we described in the above sections are specialist sensors as they belong to a new generation of sensors developed with a particular goal, e.g., measuring tree diameter increment growth (i.e., dendrometers) and transpiration (i.e., sap-flow probes). On the contrary, generalist sensors are commercial off-the-shelf sensors

Fig. 3. Field data collection from sensors that acquire data in microcontrollers (1) connected to, e.g., autonomous supply of energy (2) and send the data through GSM/Ethernet technologies (3) to a local server (4).



that have been used for decades to monitor environmental cues (e.g., thermistors, rain gauges, pressure transducers, etc.). The development of specialist sensors has been increasing in recent years due to new microcontrollers with high programming versatility (electronics programming in integrated development environments, IDE), standard compliance, and GSM technologies used by mobile devices. Despite this, technological challenges remain that slow the deployment of automated sensors, as illustrated in Table 1.

Dead zones and areas with sparse or no reception, e.g., in large areas of Russia and Canada where communication towers may be 100s or 1000s of kilometres from a monitoring site, are problematic and pose particular challenges for WSN implementation. Although such problems may seem intuitive in northern treed peatlands of Canada, they are significant limitations in much of Canada's commercial forests as well (for a map of Canadian cellular towers, see, for example, https://www.ertyu.org/steven_nikkel/cancellsites.html). Distance sites may therefore require relay nodes, but in practice, their physical placement is constrained; relay nodes forward transmission back to the base station and the cloud. This problem of node deployment is NP-hard (Yang et al. 2012), consequently demanding the exploration of other solutions. Here, the possibilities of harnessing satellite communications may need exploration.

The supply of energy to the instruments deployed in the field is another issue that has historically hindered WSN development and deployment. Lithium batteries, which can power individual sensors for up to 10 years, are a recent improvement, but concerns exist about the sustainability of lithium production and recharging constraints. These concerns may be solved by green technologies, designed to be more efficient in energy consumption and conservation and (or) to utilize greener energy sources than used previously (Deshpande et al. 2014). Solar and nascent developments in nighttime photovoltaic cells (Deppe and Munday 2020) offer potential options but require a clear view of the sky for optimum performance. Thermoelectric power generation utilizing the temperature difference between the soil and the air can power wireless sensors (Huang et al. 2019). Research in biophotovoltaics (Tschörtner et al. 2019) is still at an early stage, as is that of harvesting cosmic rays (Vanamala and Nidamarty 2020). Forests, by their very nature, offer intriguing possibilities for energy harvesting: experiments aimed at harvesting energy from tree movement have been conducted in the past, allowing the development and successful application of devices to power a wireless sensor node (McGarry and Knight 2012). The possibilities of harvesting energy from tree trunks, particularly in natural forests, has also been demonstrated, and an energy harvesting based sensor node has been prototyped (Souza et al. 2016).

Although powering the sensing component is feasible with current and evolving technologies, data transmission is more problematic as it is a power-intensive process. Thus, the degree to which low-power, long-range protocols, e.g., LoRaWAN, may be available over extended periods is problematic. At the same time, the amount of data transmittable through such technologies is limited. Additionally, conditions typical of many forests are challenging for data transmission due to their remoteness, rough terrain, and the presence of obstacles. Nevertheless, it worth noting that recent advances in network technologies are towards faster speeds, with an undesirable side effect of reducing the distance of transmission.

Sensors identified by a unique address can dynamically join the worldwide network and collaborate and cooperate efficiently to achieve different tasks (Christin et al. 2009). In this way, a WSN can be part of the Internet of Things (IoT), a worldwide network of interconnected uniquely addressable objects, based on standard communication protocols (Khan and Abbasi 2016). The rapid emergence of IoT-based devices and communication techniques associated with wireless sensors open new opportunities for collecting massive data and unravelling functional processes. Wireless sensors connected to the Internet can contribute to creating smart-forest early warning systems and detect ecological thresholds beyond which forests will be at risk. Indeed, real-time data from IoT may be used to detect early EWSs of hazardous and extreme climatic events, disease outbreak, forest mortality, etc., allowing managers and scientists to react rapidly. In all cases, difficulties in deploying sensor installations should not be underestimated; planning, designing, and deploying WSNs in forest environments are challenging and time-consuming.

3. Monitoring with remote sensing

3.1. Overview of remote-sensing platforms

Techniques and instruments to remotely sense ecosystem properties and function have advanced considerably in the last decade (Pettorelli et al. 2018). Data from remote-sensing platforms, including satellites, airborne sensors, and UAVs, can be integrated with data from tree- and stand-level sensors to scale up in situ information across large regions to better understand forest processes and threats, as well as to make possible studies in remote locations with difficult access (Marvin et al. 2016).

Satellite imagery represents an essential tool for detecting potential EWSs before sudden regime shifts in forest ecosystems. Satellites are typically multisensor platforms. The speed of data acquisition and its subsequent availability to users are currently increasing due to a conflation of automated processing chains, big data technologies, and cloud computing. A continued increase in

Table 1. Advantages and challenges of the new generation of specialist sensors used for forest monitoring over time.

Step (see Fig. 1)	Advantages	Challenges
1	Can cover large areas Many measurements: radiation, cloudiness, sounds	The distance among sensor nodes in large ecosystems (radio systems)
2	Autonomous monitoring with solar panels or lithium batteries	Efficient use of energy Supply of energy over long period Lithium-ion batteries and solar panels (for these, large openings are required which in closed-canopy forests is a problem)
3	Good GSM/Ethernet coverage Easy implementation	Distance to communication towers
4	HTML–PHP–MySQL free software	Data storage

Note: HTML, HyperText Markup Language; PHP, Hypertext Preprocessor; MySQL, Open Source Structured Query Language.

temporal, spatial, and spectral resolution is expected, depending on the size of the satellite constellation, i.e., the set of similar types of satellites with an identical function designed to operate in similar, complementary orbits for a shared purpose under shared control (Wood 2003). Commercial operators claim that hourly revisit times are possible, with submetric spatial resolution. The constellation's observation capabilities, combined with the short revisiting intervals, will be a formidable asset for early detection of forest disturbances. The limited swath, i.e., the area imaged on the Earth's surface as the satellite revolves around the Earth, of remote-sensing programs such as AVHRR, LANDSAT, and SPOT has been overcome by the features of the Sentinel-2 constellation, which has a swath of 290 km, in comparison with the swath width of LANDSAT 5 TM, LANDSAT 7, and ETM+, which is 185 km, and that of SPOT-5, which is 120 km (Li and Roy 2017).

UAVs may be regarded as lightweight, agile, remote-sensing platforms capturing high-resolution data that complement the wide-area sensing capabilities of satellites and the point-based sensing provided by in situ networks. Indeed, the exceptionally high resolution of UAV-borne observations is comparable with those collected by single-point sensors (Liang et al. 2019). The applicability of UAV-borne sensing in forestry is extensive (Torresan et al. 2017), but several issues affect the performance of UAVs, including power consumption and regulation (Coops et al. 2019). Nevertheless, many efforts are put in the fundamental future research agenda necessary for the deployment of fleets (also called swarms) of UAVs, i.e., a set of drones. Fleets equipped with identical sensors may collaborate for acquiring ecological data over large areas. Alternatively, fleets may be equipped with different sensors when acquiring synchronously ecological information (Tahir et al. 2019).

3.2. Forest productivity

In past decades, changing climate has been identified as a major driver of shifts in forest productivity (Beer et al. 2010). Such observations have been made throughout the world by combining dendrochronological, observational, flux, and satellite data (Babst et al. 2019). Forest growth and productivity can also be characterized using remotely sensed data via physiological measurements, dimension analysis, and relationships of growth to foliage, concentrations, and light (Coops 2015).

Top-of-atmosphere measurements of solar radiance from satellite observations are used to estimate the photosynthetically active radiation (PAR), which, successively, following light use efficiency modelling approaches, is used to estimate gross primary production (GPP) and net primary productivity (NPP) as indicators of forest productivity. The characterization of forest growth and productivity via physiological measurements allows researchers to obtain near real-time data products available for the final users in fewer than 3 h from data acquisition from a number of online instruments, e.g., through NASA's LANCE (Land, Atmosphere Near real-time Capability for Earth Observations) system. Nevertheless, the sensitivity of near real-time satellite GPP products, here also included MODIS products, is directly constrained by uncertainties in the modelling process, especially in complex forest ecosystems (Tang et al. 2015; Xie et al. 2019).

In assessing forest productivity by dimension analysis, Light Detection and Ranging (LiDAR) and Radio Detection and Ranging (RADAR) permit the direct detection of the 3D distribution of vegetation canopy components as well as subcanopy topography, providing highly accurate estimates of vegetation height (Fig. 4).

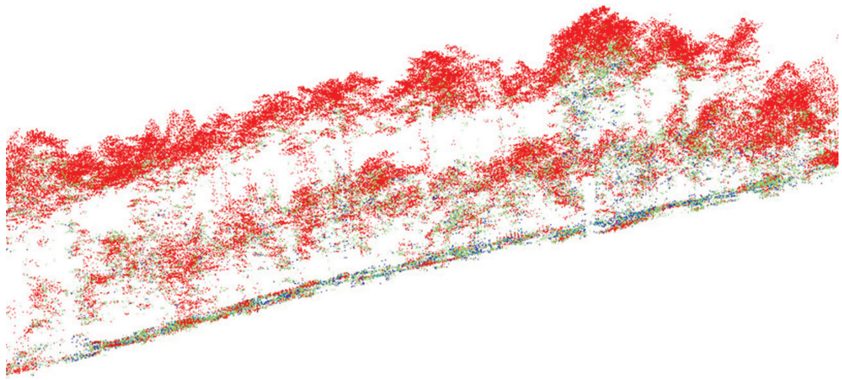
The added value of LiDAR over satellite images derives from its ability to map a vertical structure of ecosystems that is used to develop relationships between direct field measurements of tree sizes (i.e., biomass and volume) and the metrics extracted from LiDAR data. Airborne laser scanning (ALS) is the consolidated technique to retrieve tree or stand parameters and to detect forest changes using multitemporal laser surveys, whether single- or multi-spectral single-photon LiDAR (White et al. 2016; Yu et al. 2017; Wästlund et al. 2018). In general, ALS in forestry is only convenient for large-scale continuous forest cover (e.g., Canada, USA, and Scandinavian countries) and is less affordable where the forest cover is fragmented, as in most European countries. Such fragmentation means that the vector will be much of the time over a land cover different from forested areas and consequently the cost per surface unit of forest is not advantageous. In addition, the agreement between customer and vendor, the planification of the flight campaign, and the acquisition and rendering of the data are operations within a chain that often takes considerable time (Gatziolis and Andersen 2008). Spaceborne LiDAR has already provided important results in retrieving forest biometric parameters, contributing to the long-term vegetation monitoring over large spatial contexts (Chen et al. 2019). The footprint size (e.g., 25 m in Global Ecosystem Dynamics Investigation, GEDI, mission) and the space that separates the footprints in the long-track direction (e.g., 60 m in GEDI mission) make the spaceborne LiDAR appropriate for applications in forest management.

Productivity via light and foliar concentration, i.e., the third approach, uses the amount of foliage in stands, measured by LAI, as a key indicator of forest growth principally due to its importance for photosynthesis, transpiration, evapotranspiration, and, in turn, GPP. It is worth mentioning that a proper determination of the bidirectional reflectance distribution function (BRDF) is of relevance when retrieving vegetation parameters by defining optimal geometries (Verger et al. 2004). Efforts, e.g., the Compact High Resolution Imaging Spectrometer (CHRIS) PRoject for On Board Autonomy (PROBA), go in the direction of improving the current understanding of directional properties of reflection from natural surfaces such as forests (Barducci et al. 2004).

3.3. Forest health

Remote sensing is a key resource for up scaling in situ forest measurements related to forest health (Masek et al. 2015). Besides,

Fig. 4. Slice of a point cloud acquired by a LiDAR system, with points coloured by return number (red, first return; green, second return; blue, third return), evidencing the two-layered structure of a forest.



in situ sampled data are required to add value to physical imaging remote-sensing observations and to interlink the forest health assessment with biotic and abiotic factors (Pause et al. 2016).

Early warning metrics for drought-induced tree physiological stress and mortality from LANDSAT multispectral imageries can provide a critical foundation for elucidating the physiological mechanisms underpinning tree mortality in mature forests and guiding management responses to these climate-induced disturbances (Anderegg et al. 2019). Later stages of drought stress are detectable with more common red and IR bands of multispectral sensors (e.g., normalized difference vegetation index, NDVI; Lewińska et al. 2016). Shortwave IR combined with NIR imaging can also be used to capture a fast reduction of tree foliage and the consequent reductions in tree carbon capture and evapotranspiration (Otsu et al. 2018).

Hyperspectral sensors have demonstrated their potential in the detection of early stages of forest stress with repeated measures (Tian et al. 2020). Hyperspectral imagery is promising and is expected to improve on vegetation indices such as photochemical reflectance index (PRI), which is currently broadly used to detect changes in leaf and thus tree health (Norman et al. 2016). Radiative transfer models of the leaf, tree, and canopy stand reflectance are also being utilized to better leverage the reflectance as measured by multispectral and hyperspectral satellite sensors. This approach also shows promise in understanding how the remotely acquired observation relates to forest architecture and biophysical characteristics related to stress. The potential of simulating broadleaf forest canopy spectral reflectance of models such as ProSAIL (Jacquemoud et al. 2009), KUUSK (Kuusk 1995), and ProFLAIR (Omari et al. 2013) has been proved.

The remote sensing of solar-induced fluorescence (SIF) is another approach to assess photosynthetic capacity at the canopy level (Frankenberg and Berry 2018). The increased interest in this approach is motivated by the link of fluorescence to photosynthetic efficiency, which could be exploited for large-scale monitoring of trees status and functioning (Meroni et al. 2009). Potential exists to combine SIF, reflectance, and chlorophyll content (or canopy chlorophyll content indices, CCCIs) to extract more information from these data, which provide diagnostic information about biotic and abiotic stressors affecting canopy photosynthesis (Peteinatos et al. 2016). New hybrid indices that combine remotely sensed data with climatic data and forest characteristics are also being developed (Tadesse et al. 2020) and show promise to providing reliable, large-scale indicators of forest drought stress.

Multiple concurrent disturbances often affect the same forest area and simultaneously impact forest health, i.e., insect and disease, wildfire and wind, and anthropogenic activities (e.g., logging). In addition, one disturbance regime (e.g., wildfire) may influence forest responses to other disturbances (e.g., disease) or vice versa, causing interactions between disturbances. Differentiating between insect- or disease-caused damage and other types of damage is not possible using single sensors. For this, the development of a multisensory and multiplatform approach of analysis and data processing, taking advantage of the strengths of individual sensors, is desirable (Chen et al. 2017). For example, LANDSAT time series can be chosen for temporal analysis of diseases and insect progression, while hyperspectral imaging could be used for tracking the early signs of forest damage. The integration of multiple platforms and multiple sensors shapes and adapts the user's abilities to estimate changes in biophysical and biochemical parameters in forests (Chen et al. 2017), increasing accurate assessments of forest damage offering forest managers an opportunity to perform efficient disease and insect control for a CSF.

3.4. Biodiversity

Remote sensing can provide information on species and structural diversity parameters and their changes over time (Innes and Koch 1998). Automated forest interpretation at the tree level using different sources of remotely sensed data allows the assessment of tree species composition. ALS data alone represent an effective source of data for detecting and delineating tree crowns in conifer-dominated forests (Hastings et al. 2020) by processing the raw point cloud to compute a wide range of vegetation metrics from the height probability distributions and from the relative frequency distributions of vegetation heights. In mixed temperate forests, successful crown delineation using ALS data are lower than in coniferous forests due to the physical canopy traits that in turn influence tree height, crown architecture (crown spreading and leaf display), and how crowns interact with neighbouring crowns (Hastings et al. 2020; Torresan et al. 2020); however, the integration of ALS data with aerial high-resolution multispectral or hyperspectral images (e.g., Dalponte et al. 2019), as well as with high resolution aerial NIR images (Persson et al. 2004), allow for tree species classification. Also, satellite imagery, e.g., high spatial resolution 8-band WorldView-2 and 5-band RapidEye (Immitzer et al. 2012) and WorldView-3 (Fang et al. 2020), has proven to be valid in species classification. Dense high spatial resolution multispectral satellite image time series (SITS) have been used to discriminate tree species in temperate forests based on phenological differences (Sheeren et al. 2016). In addition, multitemporal synthetic aperture radar (SAR) has the potential for monitoring phenology and classifying forests (Rüetschi et al. 2018; Proietti et al. 2020). An exciting recent advance in remote sensing is the increasing ability to monitor the amount and variability of deadwood in forest stands. The presence of deadwood in forest ecosystems provides critical habitat for thousands of species in forests (Parisi et al. 2018; Sandström et al. 2019), thereby serving as an indicator of biodiversity (Oettel et al. 2020). Standing dead trees can be identified and characterized within managed stands using high-density ALS data (Marchi et al. 2018), which can also be used to estimate the number of standing dead trees within diameter classes (Bater et al. 2009). High spatial resolution aerial photographs taken from UAV with different angles is a tested solution to increase the detection rate of fallen trees in deciduous broadleaved forests (Inoue et al. 2014).

4. Monitoring with citizen science

Participatory sensing, crowdsourcing, and volunteered geographic information (VGI), which refer to the general public's involvement in scientific activities, are novel approaches that have yet to be fully exploited in research (Fritz et al. 2017). Citizen scientists may be involved in all stages of scientific research, including hypothesis generation, data collection and analyses (Bonney et al. 2009), and active participation in or co-creation of the scientific data product such as in the case of Earth observation imagery (Grainger 2017). In particular, engaged citizens without professional status can provide valuable data on forest monitoring, supporting and complementing data collected from sensors deployed in the field and remotely sensed data, i.e., citizen science (Heigl et al. 2019). Research in this area has increased rapidly in the last two decades, and there are now many examples of citizen science projects covering a diverse set of fields such as forest biodiversity, phenology, tree and forest cover, deforestation, biomass (Molinier et al. 2016), soil moisture (Fritz et al. 2017), and land cover and land-use classification (Laso Bayas et al. 2016; Salk et al. 2016). Initial case studies involving the use of sensors and UAVs in citizen science are documented (Kim et al. 2016; O'Grady et al. 2016; Paul et al. 2018). Synergistic use of data from different platforms such as satellites and UAVs will drive future collaborations with citizen scientists.

The added value of citizen observations includes cost savings, making data available at a higher frequency than achieved with researchers and technician field surveys (Fritz et al. 2017). Besides, citizen science benefits research by making science open and transparent. Instead of hiding behind academic walls and difficult-to-access scientific journals than can perpetuate distrust of science (Cooper 2016), it creates stronger public engagement and greater interest and knowledge transfer (Carleton et al. 2020). Challenges regarding citizen science include quality, equity, inclusion, and governance (Brovelli et al. 2020) and, increasingly, legal issues relating to privacy, ethics, and licensing (Mooney et al. 2019); however, how professional scientists perceive the value of participatory science represents a reliable indicator of their likelihood to engage and collaborate. Working with indigenous communities and traditional knowledge gathering has revealed that professional scientists also benefit when trained in the citizen science perspective. Integrating traditional and scientific knowledge can be successful and give good results; however, careful planning and preparation, supported by strong personal relationships, are prerequisites (Huntington et al. 2011).

Crucial elements in successful citizen science programs include sufficient training and the type, scale, and location of the study area under investigation. For the first aspect, studies suggest that with adequate training and supervision, volunteers can undertake tasks such as the monitoring of pheromone traps and mail samples (Carleton et al. 2020) or collecting and recording tree measurement data for carbon stock estimation (Harrison et al. 2020) to ensure reliable results. As well as training, needs for calibration and instrumentation must also be considered. Some scientific objectives can be met with relatively little additional training or instrumentation; however, others will require substantial capacity building. For the moment, it may be sufficient to accept that some objectives are beyond the current reach of citizen science, while recognizing that in the future, it may be possible to facilitate training and enhance instrument availability. For the second aspect, i.e., the scale of the planned project, unevenness of coverage in participatory projects is an acknowledged problem: the number of volunteers is invariably higher in urban areas than in remote areas (Carleton et al. 2020). For this reason, for mountain or boreal forests, the availability of a local citizen science community may prove problematic and demand creative solutions.

Technology has transformed citizen science in the last decade from an approach that was paper-based to one in which mobile apps and web-based platforms are central (Sturm et al. 2017). Technology also offers the opportunity for communities to develop and possess their own apps and tools. In addition, open-source software exists but often comes with many caveats: such software is rarely up to date, and it is difficult to tailor to the needs of individual projects. Initiating independent projects provides many challenges, some of which are insurmountable at present. Citizen scientists who wish to design and launch their initiatives usually lack the tools to do so, and on the other hand, professional scientists who wish to engage with citizen scientists are limited by suitable toolkits and infrastructure. The lack of best-practice principles for mobile app and platform development in citizen science is being filled by some initiatives that collect recommendations that provide support and advice for planning, design, and data management of mobile apps and platforms (Sturm et al. 2017; Luna et al. 2018).

5. Data management

All preceding sections present a new generation of sensors and monitoring tools that will generate massive amounts of data. Big data analytics offer intriguing possibilities for the radical transformation of how forests are managed (Liu et al. 2018, 2020). Such analytics seek to deliver information from which all actors in the forestry chain can derive actionable insights. Data sources are diverse, including in situ sensors, forest machinery sensors, satellites, citizen scientists, legacy information systems, and even social media. Such diversity represents the complexity of forests in three dimensions — ecological, economic, and social. When considered in its totality, such data will likely continue to grow exponentially over time. What constitutes big data is not its size per se; instead, the construct relates to the degree to which the data can be processed to meet business requirements on time. Thus, attributes such as volume, variety, velocity, and veracity are core to big data. No specific big data toolkit is necessary for forestry. Instead, the immediate data management problems are quite mundane and archetypical of heterogeneous data sources such as from intensive tree-level monitoring to citizen science to remotely sensed data. These include diverse data structures, from different collecting organizations in forests around a nation or around the world, and complex data organization (Zou et al. 2019). Additional problems follow from these, including a chronic lack of metadata, use of proprietary formats, and lack of support for new standards or refining and improving existing standards.

As awareness of the value of data increases, the ownership of data becomes a pertinent question. Consider, for example, when hiring a contractor to undertake a thinning operation: who owns the data collected by the contractor's machinery, the contractor or the plantation owner? Ownership rules will influence both returns and the development of technologies (Coble et al. 2018). Big data necessary for forest management is characterized by its heterogeneity, as it must be obtained from a variety of public and private sources, each with its own licensing conditions. Thus, it is vital that the Findable, Accessible, Interoperable, and Reusable (FAIR) data principles (Wilkinson et al. 2016) be applied where possible. Where data are being made open, the correct licensing scheme must be specified; otherwise, such data cannot be used.

6. Conclusions

Effective CSF consists of balancing short- and long-term goals of adaptation to and mitigation of climate-induced changes, together with the need for wood production, the protection of forest health and biodiversity, and the provision of important ecosystem services (Bowditch et al. 2020) such as reliable flows of clean water and reducing soil erosion (Verkerk et al. 2020). Analysis of these criteria, i.e., adaptation and mitigation, requires more data than has previously been possible to collate, but a new generation of increasingly reliable sensors and data transmission and processing tools makes these analyses steadily more feasible. In addition, the mounting of sensors on forest machinery and the recruitment of citizen scientists provide new avenues for collecting monitoring data. These ground-based measurements provide mutual support for remote sensing by satellite, airborne, and UAV sensors, which have until now been limited by groundtruthing, while simultaneously providing elaborate and powerful measures of forest condition. In principle, technology is sufficiently mature to monitor a forest in real time and across large temporal and spatial scales; in practice, the costs are still prohibitive. The solution to meeting real-time monitoring requirements, however, may not necessarily demand the development of radical new technologies. Instead, a complementary approach may suffice that includes repurposing of existing technologies for operation in harsh forest environments, innovative combinations of existing technology suites, identification of alternative data sources, and the novel conflation of existing data. Although we have focused primarily on commercial forest zones, the practices that we describe could also be applied to other forested regions such as the vast treed peatland areas in northern Canada, United States, Fennoscandia, and Russia. Combining all sources of data here considered with their potentialities will permit different actors to develop integrated platforms to monitor and respond to climate change at local to continental scales. The moment is ripe for the convergence of new ideas about what should be measured and how. The possibility of data-rich climate-smart forestry appears to be on the verge of realization — and just in time. The responsibility of forest management to implement climate-change adaptation and mitigation practices requires the synthesis of knowledge that cannot be achieved in a data vacuum. This review synthesizes examples of how this vacuum can be filled.

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References

Adams, H.D., Zeppel, M.J.B., Anderegg, W.R.L., Hartmann, H., Landhäusser, S.M., Tissue, D.T., et al. 2017. A multi-species synthesis of physiological mechanisms in drought-induced tree mortality. Nat. Ecol. Evol. **1**(9): 1285–1291. doi:10.1038/s41559-017-0248-x. PMID:29046541.

Ali, A., Ming, Y., Chakraborty, S., and Iram, S. 2017. A comprehensive survey on real-time applications of WSN. Future Internet, **9**(4): 77. doi:10.3390/fi9040077.

Anderegg, W.R.L., Anderegg, L.D.L., and Huang, C-y. 2019. Testing early warning metrics for drought-induced tree physiological stress and mortality. Global Change Biol. **25**(7): 2459–2469. doi:10.1111/gcb.14655. PMID:30983066.

Arlinger, J., Möller, J.J., and Sorsa, J. 2010. StanForD 2010. Skogforsk, Uppsala, Sweden. pp. 1–16.

Astaras, C., Linder, J.M., Wrege, P., Orume, R.D., and Macdonald, D.W. 2017. Passive acoustic monitoring as a law enforcement tool for Afrotropical rainforests. Front. Ecol. Environ. **15**(5): 233–234. doi:10.1002/fee.1495.

Babst, F., Bouriaud, O., Poulter, B., Trouet, V., Girardin, M.P., and Frank, D.C. 2019. Twentieth century redistribution in climatic drivers of global tree growth. Sci. Adv. **5**(1): eaat4313. doi:10.1126/sciadv.aat4313. PMID:30746436.

Barducci, A., Guzzi, D., Marcoionni, P., and Pippi, I. 2004. Methodology for at-surface BRDF retrieval from CHRIS-PROBA observations of the San Rossore (Italy) forestry. *In* Imaging Spectrometry X. Vol. 5546. p. 213. doi:10.1117/12.561594.

Bater, C.W., Coops, N.C., Gergel, S.E., LeMay, V., and Collins, D. 2009. Estimation of standing dead tree class distributions in northwest coastal forests using lidar remote sensing. Can. J. For. Res. **39**(6): 1080–1091. doi:10.1139/X09-030.

Bater, C.W., Coops, N.C., Wulder, M.A., Nielsen, S.E., McDermid, G., and Stenhouse, G.B. 2011. Design and installation of a camera network across an elevation gradient for habitat assessment. Instrum. Sci. Technol. **39**(3): 231–247. doi:10.1080/10739149.2011.564700.

Beer, C., Reichstein, M., Tomelleri, E., Ciais, P., Jung, M., Carvalhais, N., et al. 2010. Terrestrial gross carbon dioxide uptake: global distribution and covariation with climate. Science, **329**: 834–838. doi:10.1126/science.1184984. PMID:20603496.

Bogena, H.R., Herbst, M., Huisman, J.A., Rosenbaum, U., Weuthen, A., and Vereecken, H. 2010. Potential of wireless sensor networks for measuring soil water content variability. Vadose Zone J. **9**(4): 1002–1013. doi:10.2136/vzj2009.0173.

Bogena, H.R., Huisman, J.A., Schilling, B., Weuthen, A., and Vereecken, H. 2017. Effective calibration of low-cost soil water content sensors. Sensors, **17**(1): 208. doi:10.3390/s17010208.

Boisvenue, C., and Running, S.W. 2006. Impacts of climate change on natural forest productivity — Evidence since the middle of the 20th century. Global Change Biol. **12**(5): 862–882. doi:10.1111/j.1365-2486.2006.01134.x.

Bonney, R., Cooper, C.B., Dickinson, J., Kelling, S., Phillips, T., Rosenberg, K.V., and Shirk, J. 2009. Citizen science: A developing tool for expanding science knowledge and scientific literacy. Bioscience, **59**(11): 977–984. doi:10.1525/bio.2009.59.11.9.

Bowditch, E., Santopuoli, G., Binder, F., del Río, M., La Porta, N., Kluvankova, T., Lesinski, J., Motta, R., Maciej, P., Panzacchi, P., Pretzsch, H., Temperli, C., Tonon, G., Smith, M., Velikova, V., Weatherall, A., and Tognetti, R. 2020. What is Climate-Smart Forestry? A definition from a multinational collaborative process focused on mountain regions of Europe. Ecosyst. Serv. **43**: 101113. doi:10.1016/j.ecoser.2020.101113.

Bowling, D.R., Logan, B.A., Hufkens, K., Aubrecht, D.M., Richardson, A.D., Burns, S.P., et al. 2018. Limitations to winter and spring photosynthesis of a Rocky Mountain subalpine forest. Agric. For. Meteorol. **252**: 241–255. doi:10.1016/j.agrformet.2018.01.025.

Bréda, N.J.J. 2003. Ground-based measurements of leaf area index: A review of methods, instruments and current controversies. J. Exp. Bot. **54**(392): 2403–2417. doi:10.1093/jxb/erg263. PMID:14565947.

Bridge, L.J., Franklin, K.A., and Homer, M.E. 2013. Impact of plant shoot architecture on leaf cooling: A coupled heat and mass transfer model. J. R Soc. Interface, **10**(85): 20130326. doi:10.1098/rsif.2013.0326.

Brovelli, M.A., Ponti, M., Schade, S., and Solís, P. 2020. Manual of Digital Earth. Springer, Singapore. doi:10.1007/978-981-32-9915-3.

Brown, L.A., Ogutu, B.O., and Dash, J. 2020. Tracking forest biophysical properties with automated digital repeat photography: A fisheye perspective using digital hemispherical photography from below the canopy. Agric. For. Meteorol. **287**: 107944. doi:10.1016/j.agrformet.2020.107944.

Burivalova, Z., Allnutt, T.F., Rademacher, D., Schlemm, A., Wilcove, D.S., and Butler, R.A. 2019. What works in tropical forest conservation, and what does not: Effectiveness of four strategies in terms of environmental, social, and economic outcomes. Conserv. Sci. Pract. **1**(6): e28. doi:10.1111/csp2.28.

Burri, S., Haeler, E., Eugster, W., Haeni, M., Etzold, S., Walthert, L., et al. 2019. How did Swiss forest trees respond to the hot summer 2015? Die Erde, **150**(4): 214–229. doi:10.12854/erde-2019-420.

Carleton, R.D., Owens, E., Blaquière, H., Bourassa, S., Bowden, J.J., Candau, J.-N., et al. 2020. Tracking insect outbreaks: a case study of community-assisted moth monitoring using sex pheromone traps. Facets, **5**(1): 91–104. doi:10.1139/facets-2019-0029.

Cermák, J., Nadezhdina, N., Trcala, M., and Simon, J. 2015. Open field-applicable instrumental methods for structural and functional assessment of whole trees and stands. iFor. Biogeosci. For. **8**: 226–278. doi:10.3832/ifor1116-008.

Chen, B., Pang, Y., Li, Z., North, P., Rosette, J., Sun, G., et al. 2019. Potential of forest parameter estimation using metrics from photon counting LiDAR data in Howland Research Forest. Remote Sens. **11**(7): 856. doi:10.3390/rs11070856.

Chen, G., He, Y., De Santis, A., Li, G., Cobb, R., and Meentemeyer, R.K. 2017. Assessing the impact of emerging forest disease on wildfire using Landsat and KOMPSAT-2 data. Remote Sens. Environ. **195**: 218–229. doi:10.1016/j.rse.2017.04.005.

Chianucci, F. 2020. An overview of in situ digital canopy photography in forestry. Can. J. For. Res. **50**(3): 227–242. doi:10.1139/cjfr-2019-0055.

Choat, B., Brodribb, T.J., Brodersen, C.R., Duursma, R.A., López, R., and Medlyn, B.E. 2018. Triggers of tree mortality under drought. Nature, **558**(7711): 531–539. doi:10.1038/s41586-018-0240-x. PMID:29950621.

Christin, D., Reinhardt, A., Mogre, P.S., and Steinmetz, R. 2009. Wireless sensor networks and Internet of Things: selected challenges. *In* Proceedings of the 8th GI/ITG KuVS Fachgespräch "Drahtlose sensornetze", August 2009. Available from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.330.8624.

Clark, N.A., Wynne, R.H., and Schmoldt, D.L. 2000. A review of past research on dendrometers. For. Sci. **46**(4): 570–576. doi:10.1093/forestscience/46.4.570.

Coble, K.H., Mishra, A.K., Ferrell, S., and Griffin, T. 2018. Big data in agriculture: A challenge for the future. Appl. Econ. Perspect. Pol. **40**(1): 79–96. doi:10.1093/aepp/ppx056.

Cocozza, C., Palombo, C., Tognetti, R., La Porta, N., Anichini, M., Giovannelli, A., and Emiliani, G. 2016. Monitoring intra-annual dynamics of wood formation with microcores and dendrometers in *Picea abies* at two different altitudes. Tree Physiol. **36**(7): 832–846. doi:10.1093/treephys/tpw009. PMID:26941291.

Cohen, J.M., Lajeunesse, M.J., and Rohr, J.R. 2018. A global synthesis of animal phenological responses to climate change. Nat. Clim. Change, **8**(3): 224–228. doi:10.1038/s41558-018-0067-3.

Cooper, C. 2016. Citizen science: how ordinary people are changing the face of discovery. The Overlook Press, Wooster, New York. [ISBN: 978-1-4683-0867-9; ASIN: B01F0DFLZU.]

Coops, N.C. 2015. Characterizing forest growth and productivity using remotely sensed data. Curr. For. Rep. **1**(3): 195–205. doi:10.1007/s40725-015-0020-x.

Coops, N.C., Goodbody, T.R.H., and Cao, L. 2019. Four steps to extend drone use in research. Nature, **572**: 433–435. doi:10.1038/d41586-019-02474-y. PMID:31431743.

Courtois, E.A., Stahl, C., Burban, B., Van den Berge, J., Berveiller, D., Bréchet, L., et al. 2019. Automatic high-frequency measurements of full soil greenhouse gas fluxes in a tropical forest. Biogeosciences, **16**: 785–796. doi:10.5194/bg-16-785-2019.

Cruz-García, R., Balzano, A., Čufar, K., Scharnweber, T., Smiljanić, M., and Wilmking, M. 2019. Combining dendrometer series and xylogenesis imagery — DevX, a simple visualization tool to explore plant secondary growth phenology. Front. For. Global Change, **2**: 60. doi:10.3389/ffgc.2019.00060.

Cuny, H.E., Rathgeber, C.B.K., Frank, D., Fonti, P., Makinen, H., Prislan, P., et al. 2015. Woody biomass production lags stem-girth increase by over one month in coniferous forests. Nat. Plants, **1**: 15160. doi:10.1038/nplants.2015.160.

Dalponte, M., Frizzera, L., and Gianelle, D. 2019. Individual tree crown delineation and tree species classification with hyperspectral and LiDAR data. PeerJ. **6**(1): e6227. doi:10.7717/peerj.6227. PMID:30648002.

Deppe, T., and Munday, J.N. 2020. Nighttime photovoltaic cells: electrical power generation by optically coupling with deep space. ACS Photonics, **7**(1): 1–9. doi:10.1021/acsphotonics.9b00679.

Deshpande, A., Montiel, C., and McLauchlan, L. 2014. Wireless sensor networks — a comparative study for energy minimization using topology control. *In* IEEE Green Technologies Conference, IEEE, 3–4 April 2014. pp. 44–48. doi:10.1109/GREENTECH.2014.30.

Deslauriers, A., Rossi, S., and Anfodillo, T. 2007. Dendrometer and intra-annual tree growth: What kind of information can be inferred? Dendrochronologia, **25**(2): 113–124. doi:10.1016/j.dendro.2007.05.003.

Dobbertin, M., Eilmann, B., Bleuler, P., Giuggiola, A., Graf Pannatier, E., Landolt, W., et al. 2010. Effect of irrigation on needle morphology, shoot and stem growth in a drought-exposed *Pinus sylvestris* forest. Tree Physiol. **30**(3): 346–360. doi:10.1093/treephys/tpp123. PMID:20067912.

Drew, D.M., and Downes, G.M. 2009. The use of precision dendrometers in research on daily stem size and wood property variation: a review. Dendrochronologia, **27**(2): 159–172. doi:10.1016/j.dendro.2009.06.008.

Fang, F., McNeil, B.E., Warner, T.A., Maxwell, A.E., Dahle, G.A., Eutsler, E., and Li, J. 2020. Discriminating tree species at different taxonomic levels using multi-temporal WorldView-3 imagery in Washington, D.C., USA. Remote Sens. Environ. **246**: 111811. doi:10.1016/j.rse.2020.111811.

Frankenberg, C., and Berry, J. 2018. Solar induced chlorophyll fluorescence: origins, relation to photosynthesis and retrieval. Compr. Remote Sens. **3**: 143–162. doi:10.1016/B978-0-12-409548-9.10632-3.

Fritz, S., Fonte, C.C., and See, L. 2017. The role of Citizen Science in Earth Observation. Remote Sens. **9**(4): 357. doi:10.3390/rs9040357.

Fromm, J.H., Sautter, I., Matthies, D., Kremer, J., Schumacher, P., and Ganter, C. 2001. Xylem water content and wood density in spruce and oak trees detected by high-resolution computed tomography. Plant Physiol. **127**(2): 416–425. doi:10.1104/pp.010194. PMID:11598217.

Gatziolis, D., and Andersen, H.E. 2008. A guide to LIDAR data acquisition and processing for the forests of the Pacific Northwest. USDA Forest Service, Gen. Tech. Rep. PNW-GTR 768. pp. 1–32. doi:10.2737/PNW-GTR-768.

Grainger, A. 2017. Citizen observatories and the new Earth observation science. Remote Sens. **9**(2): 153. doi:10.3390/rs9020153.

Granier, A., Biron, P., Bréda, N., Pontailler, J.Y., and Saugier, B. 1996. Transpiration of trees and forest stands: Short and long-term monitoring using sapflow methods. Global Change Biol. **2**(3): 265–274. doi:10.1111/j.1365-2486.1996.tb00078.x.

Hamilton, M., Graham, E.A., Rundel, P.W., Allen, M.F., Kaiser, W., Hansen, M.H., and Estrin, D.L. 2007. New approaches in embedded network sensing for terrestrial ecological observatories. Environ. Eng. Sci. **24**: 192–204. doi:10.1089/ees.2006.0045.

Harrison, B., Martin, T.E., and Mustari, A.H. 2020. The accuracy of volunteer surveyors for obtaining tree measurements in tropical forests. Ambio, **49**(1): 98–106. doi:10.1007/s13280-019-01147-4. PMID:30771204.

Hashimoto, S., Carvalhais, N., Ito, A., Migliavacca, M., Nishina, K., and Reichstein, M. 2015. Global spatiotemporal distribution of soil respiration modeled using a global database. Biogeosciences, **12**(13): 4121–4132. doi:10.5194/bg-12-4121-2015.

Hassan-Esfahani, L., Torres-Rua, A., Jensen, A., and McKee, M. 2015. Assessment of surface soil moisture using high-resolution multi-spectral imagery and artificial neural networks. Remote Sens. **7**: 2627–2646. doi:10.3390/rs70302627.

Hastings, J.H., Ollinger, S.V., Ouimette, A.P., Sanders-DeMott, R., Palace, M.W., Ducey, M.J., et al. 2020. Tree species traits determine the success of LiDAR-based crown mapping in a mixed temperate forest. Remote Sens. **12**(2): 309. doi:10.3390/rs12020309.

Heigl, F., Kieslinger, B., Paul, K.T., Uhlik, J., and Dörler, D. 2019. Toward an international definition of citizen science. Proc. Natl. Acad. Sci. U.S.A. **116**(17): 8089–8092. doi:10.1073/pnas.1903393116. PMID:31015357.

Hill, A.P., Prince, P., Piña Covarrubias, E., Doncaster, C.P., Snaddon, J.L., and Rogers, A. 2018. AudioMoth: evaluation of a smart open acoustic device for monitoring biodiversity and the environment. Methods Ecol. Evol. **9**(5): 1199–1211. doi:10.1111/2041-210X.12955.

Hillel, D. 1998. Environmental soil physics. Academic Press, USA. pp. 309–334.

Holmes, T.R.H., Jackson, T.J., Reichle, R.H., and Basara, J.B. 2012. An assessment of surface soil temperature products from numerical weather prediction models using ground-based measurements. Water Resour. Res. **48**(2): W02531. doi:10.1029/2011WR010538.

Huang, Y., Xu, D., Kan, J., and Li, W. 2019. Study on field experiments of forest soil thermoelectric power generation devices. PLoS ONE, **14**(8): e0221019. doi:10.1371/journal.pone.0221019. PMID:31398217.

Hufkens, K., Filippa, G., Cremonese, E., Migliavacca, M., D'Odorico, P., Peichl, M., et al. 2018. Assimilating phenology datasets automatically across ICOS ecosystem stations. Int. Agrophysics, **32**(4): 677–687. doi:10.1515/intag-2017-0050.

Huntington, H.P., Gearheard, S., Mahoney, A.R., Salomon, A.K., Huntington, H.P., Gearheard, S., et al. 2011. Integrating traditional and scientific knowledge through collaborative natural science field research: identifying elements for success. Arctic, **64**(4): 437–445.

Immitzer, M., Atzberger, C., and Koukal, T. 2012. Tree species classification with Random Forest using very high spatial resolution 8-band WorldView-2 satellite data. Remote Sens. **4**(9): 2661–2693. doi:10.3390/rs4092661.

Innes, J.L., and Koch, B. 1998. Forest biodiversity and its assessment by remote sensing. Global Ecol. Biogeogr. Lett. **7**(6): 397–419. doi:10.2307/2997712.

Inoue, T., Nagai, S., Yamashita, S., Fadaei, H., Ishii, R., Okabe, K., et al. 2014. Unmanned aerial survey of fallen trees in a deciduous broadleaved forest in eastern Japan. PLoS ONE, **9**(10): e109881. doi:10.1371/journal.pone.0109881. PMID:25279817.

Jacquemoud, S., Verhoef, W., Baret, F., Bacour, C., Zarco-Tejada, P.J., Asner, G.P., et al. 2009. PROSPECT + SAIL models: A review of use for vegetation characterization. Remote Sens. Environ. **113**(Suppl. 1): S56–S66. doi:10.1016/j.rse.2008.01.026.

Janssens, I.A., Lankreijer, H., Matteucci, G., Kowalski, A.S., Buchmann, N., Epron, D., et al. 2001. Productivity overshadows temperature in determining soil and ecosystem respiration across European forests. Global Change Biol. **7**(3): 269–278. doi:10.1046/j.1365-2486.2001.00412.x.

Juice, S.M., Templer, P.H., Phillips, N.G., Ellison, A.M., and Pelini, S.L. 2016. Ecosystem warming increases sap flow rates of northern red oak trees. Ecosphere, **7**(3): e01221. doi:10.1002/ecs2.1221.

Jung, M., Reichstein, M., Ciais, P., Seneviratne, S.I., Sheffield, J., Goulden, M.L., et al. 2010. Recent decline in the global land evapotranspiration trend due to limited moisture supply. Nature, **467**(7318): 951–954. doi:10.1038/nature09396. PMID:20935626.

Kauppi, P., Hanewinkel, M., Lundmark, T., Nabuurs, G.J., Peltola, H., Trasobares, A., and Hetemäki, L. 2018. Climate Smart Forestry in Europe. European Forest Institute. [ISBN 978-952-5980-68-4 (print); ISBN 978-952-5980-67-7 (pdf).]

Khan, Z.A., and Abbasi, U. 2016. Evolution of wireless sensor networks toward Internet of Things. *In* Emerging communication technologies based on wireless sensor networks: current research and future applications. CRC Press. pp. 179–199.

Kim, H.K., Park, J., and Hwang, I. 2014. Investigating water transport through the xylem network in vascular plants. J. Exp. Bot. **65**(7): 1895–1904. doi:10.1093/jxb/eru075. PMID:24609652.

Kim, J., Choi, S.C., Ahn, I.Y., Sung, N.M., and Yun, J. 2016. From WSN towards WoT: open API scheme based on oneM2M platforms. Sensors, **16**(10): 1645. doi:10.3390/s16101645.

Kizito, F., Campbell, C.S., Campbell, G.S., Cobos, D.R., Teare, B.L., Carter, B., and Hopmans, J.W. 2008. Frequency, electrical conductivity and temperature analysis of a low-cost capacitance soil moisture sensor. J. Hydrol. **352**(3–4): 367–378. doi:10.1016/j.jhydrol.2008.01.021.

Klein, T., Rotenberg, E., Tatarinov, F., and Yakir, D. 2016. Association between sap flow-derived and eddy covariance-derived measurements of forest canopy CO_2 uptake. New Phytol. **209**: 436–446. doi:10.1111/1365-2745.12621.

Kuusk, A. 1995. A fast, invertible canopy reflectance model. Remote Sens. Environ. **51**(3): 342–350. doi:10.1111/nph.13597.

Lapidot, O., Ignat, T., Rud, R., Rog, I., Alchanatis, V., and Klein, T. 2019. Use of thermal imaging to detect evaporative cooling in coniferous and broadleaved tree species of the Mediterranean maquis. Agric. For. Meteorol. **271**: 285–294. doi:10.1016/j.agrformet.2019.02.014.

Laso Bayas, J.C., See, L., Fritz, S., Sturn, T., Perger, C., Dürauer, M., et al. 2016. Crowdsourcing in-situ data on land cover and land use using gamification and mobile technology. Remote Sens. **8**(11): 905. doi:10.3390/rs8110905.

Leuzinger, S., and Körner, C. 2007. Tree species diversity affects canopy leaf temperatures in a mature temperate forest. Agric. For. Meteorol. **146**(1–2): 29–37. doi:10.1016/j.agrformet.2007.05.007.

Lewińska, K.E., Ivits, E., Schardt, M., and Zebisch, M. 2016. Alpine forest drought monitoring in South Tyrol: PCA based synergy between scPDSI data and MODIS derived NDVI and NDII7 time series. Remote Sens. **8**(8): 639. doi:10.3390/rs8080639.

Li, J., and Roy, D.P. 2017. A global analysis of Sentinel-2A, Sentinel-2B and Landsat-8 data revisit intervals and implications for terrestrial monitoring. Remote Sens. **9**(9): 902. doi:10.3390/rs9090902.

Liang, X., Wang, Y., Pyörälä, J., Lehtomäki, M., Yu, X., Kaartinen, H., et al. 2019. Forest in situ observations using unmanned aerial vehicle as an alternative of terrestrial measurements. For. Ecosyst. **6**(1): 20. doi:10.1186/s40663-019-0173-3.

Liu, F., Wang, X., and Wang, C. 2019. Measuring vegetation phenology with near-surface remote sensing in a temperate deciduous forest: effects of sensor type and deployment. Remote Sens. **11**(9): 1063. doi:10.3390/rs11091063.

Liu, J., Feng, Y., Zhu, Q., and Sarkis, J. 2018. Green supply chain management and the circular economy: Reviewing theory for advancement of both fields. Int. J. Phys. Distrib. Logist. Manage. **48**(8): 794–817. doi:10.1108/IJPDLM-01-2017-0049.

Liu, J., Chen, M., and Liu, H. 2020. The role of big data analytics in enabling green supply chain management: a literature review. J. Data Inf. Manage. **2**(2): 75–83. doi:10.1007/s42488-019-00020-z.

Luna, S., Gold, M., Albert, A., Ceccaroni, L., Claramunt, B., Danylo, O., et al. 2018. Developing mobile applications for environmental and biodiversity citizen science: considerations and recommendations. *In* Multimedia tools and applications for environmental & biodiversity informatics. *Edited by* A. Joly, S. Vrochidis, K. Karatzas, A. Karppinen, and P. Bonnet. Springer, Cham. pp. 9–30. doi:10.1007/978-3-319-76445-0_2.

Ma, T., Inagaki, T., and Tsuchikawa, S. 2018. Non-destructive evaluation of wood stiffness and fiber coarseness, derived from SilviScan data, via near infrared hyperspectral imaging. J. Near Infrared Spectrosc. **26**(6): 398–405. doi:10.1177/0967033518808053.

MacLean, D.A. 2019. Protection strategy against spruce budworm. Forests, **10**(12): 1137. doi:10.3390/f10121137.

Marchi, N., Pirotti, F., and Lingua, E. 2018. Airborne and terrestrial laser scanning data for the assessment of standing and lying deadwood: current situation and new perspectives. Remote Sens. **10**(9): 1356. doi:10.3390/rs10091356.

Marvin, D.C., Koh, L.P., Lynam, A.J., Wich, S., Davies, A.B., Krishnamurthy, R., et al. 2016. Integrating technologies for scalable ecology and conservation. Global Ecol. Conserv. **7**: 262–275. doi:10.1016/j.gecco.2016.07.002.

Masek, J.G., Hayes, D.J., Hughes, M.J., Healey, S.P., and Turner, D.P. 2015. The role of remote sensing in process-scaling studies of managed forest ecosystems. For. Ecol. Manage. **355**: 109–123. doi:10.1016/j.foreco.2015.05.032.

Matula, S., Bátõková, K., and Legese, W. 2016. Laboratory performance of five selected soil moisture sensors applying factory and own calibration equations for two soil media of different bulk density and salinity levels. Sensors, **16**(11): 1912. doi:10.3390/s16111912.

McGarry, S., and Knight, C. 2012. Development and successful application of a tree movement energy harvesting device, to power a wireless sensor node. Sensors, **12**(9): 12110–12125. doi:10.3390/s120912110.

Meroni, M., Rossini, M., Guanter, L., Alonso, L., Rascher, U., Colombo, R., and Moreno, J. 2009. Remote sensing of solar-induced chlorophyll fluorescence: review of methods and applications. Remote Sens. Environ. **113**(10): 2037–2051. doi:10.1016/j.rse.2009.05.003.

Midwood, A.J., and Millard, P. 2011. Challenges in measuring the $\delta^{13}C$ of the soil surface CO_2 efflux. Rapid Commun. Mass Spectrom. **25**(1): 232–242. doi:10.1002/rcm.4857. PMID:21181784.

Mizunuma, T., Wilkinson, M., L. Eaton, E., Mencuccini, M., I. L. Morison, J., and Grace, J. 2013. The relationship between carbon dioxide uptake and canopy colour from two camera systems in a deciduous forest in southern England. Funct. Ecol. **27**(1): 196–207. doi:10.1111/1365-2435.12026.

Molinier, M., López-Sánchez, C.A., Toivanen, T., Korpela, I., Corral-Rivas, J.J., Tergujeff, R., and Häme, T. 2016. Relasphone — mobile and participative in situ forest biomass measurements supporting satellite image mapping. Remote Sens. **8**(10): 869. doi:10.3390/rs8100869.

Mooney, P., Touya, G., Juul, N., Mooney, P., Touya, G., Juul, N., et al. 2019. Considerations of privacy, ethics and legal issues in volunteered geographic information. *In* Mapping and the citizen sensor. *Edited by* G. Foody, L. See, S. Fritz, P. Mooney, A.-M. Olteanu-Raimond, C.C. Fonte, and V. Antoniou. Ubiquity Press, London. pp. 119–135.

Nabuurs, G.J., Delacote, P., Ellison, D., Hanewinkel, M., Hetemäki, L., Lindner, M., and Ollikainen, M. 2017. By 2050 the mitigation effects of EU forests could nearly double through climate smart forestry. Forests, **8**(12): 484. doi:10.3390/f8120484.

Nagai, S., Akitsu, T., Saitoh, T.M., Busey, R.C., Fukuzawa, K., Honda, Y., et al. 2018. 8 million phenological and sky images from 29 ecosystems from the Arctic to the tropics: the Phenological Eyes Network. Ecol. Res. **33**(6): 1091–1092. doi:10.1007/s11284-018-1633-x.

Norman, S.P., Koch, F.H., and Hargrove, W.W. 2016. Review of broad-scale drought monitoring of forests: Toward an integrated data mining approach. For. Ecol. Manage. **380**: 346–358. doi:10.1016/j.foreco.2016.06.027.

Oettel, J., Lapin, K., Kindermann, G., Steiner, H., Schweinzer, K.M., Frank, G., and Essl, F. 2020. Patterns and drivers of deadwood volume and composition in different forest types of the Austrian natural forest reserves. For. Ecol. Manage. **463**: 118016. doi:10.1016/j.foreco.2020.118016.

O'Grady, M.J., Muldoon, C., Carr, D., Wan, J., Kroon, B., and O'Hare, G.M.P. 2016. Intelligent sensing for citizen science: challenges and future directions. Mobile Netw. Appl. **21**(2): 375–385. doi:10.1007/s11036-016-0682-z.

Omari, K., White, H.P., Staenz, K., and King, D.J. 2013. Retrieval of forest canopy parameters by inversion of the proflair leaf-canopy reflectance model using the LUT approach. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. **6**(2): 715–723. doi:10.1109/JSTARS.2013.2240264.

Oogathoo, S., Houle, D., Duchesne, L., and Kneeshaw, D. 2020. Vapour pressure deficit and solar radiation are the major drivers of transpiration of balsam fir and black spruce tree species in humid boreal regions, even during a short-term drought. Agric. For. Meteorol. **291**: 108063. doi:10.1016/j.agrformet.2020.108063.

Otsu, K., Pla, M., Vayreda, J., and Brotons, L. 2018. Calibrating the severity of forest defoliation by pine processionary moth with Landsat and UAV imagery. Sensors, **18**(10): 3278. doi:10.3390/s18103278.

Pappas, C., Matheny, A.M., Baltzer, J.L., Barr, A.G., Black, T.A., Bohrer, G., et al. 2018. Boreal tree hydrodynamics: asynchronous, diverging, yet complementary. Tree Physiol. **38**(7): 953–964. doi:10.1093/treephys/tpy043. PMID:29741658.

Parisi, F., Pioli, S., Lombardi, F., Fravolini, G., Marchetti, M., and Tognetti, R. 2018. Linking deadwood traits with saproxylic invertebrates and fungi in European forests — a review. iFor. Biogeosci. For. **11**(3): 423–436. doi:10.3832/ifor2670-011.

Pascual, A., Rivera, R., Gómez, R., and Domínguez-Lerena, S. 2019. Monitoring water-soil dynamics and tree survival using soil sensors under a big data approach. Sensors, **19**(21): 4634. doi:10.3390/s19214634.

Paul, J.D., Buytaert, W., Allen, S., Ballesteros-Cánovas, J.A., Bhusal, J., Cieslik, K., et al. 2018. Citizen science for hydrological risk reduction and resilience building. WIREs Water, **5**(1): e1262. doi:10.1002/wat2.1262.

Pause, M., Schweitzer, C., Rosenthal, M., Keuck, V., Bumberger, J., Dietrich, P., et al. 2016. In situ/remote sensing integration to assess forest health — a review. Remote Sens. **8**: 471. doi:10.3390/rs8060471.

Peñuelas, J., Rutishauser, T., and Filella, I. 2009. Phenology feedbacks on climate change. Science, **324**: 887–888. doi:10.1126/science.1173004. PMID:19443770.

Persson, Å., Holmgren, J., Söderman, U., and Olsson, H. 2004. Tree species classification of individual trees in Sweden by combining high resolution laser data with high resolution near-infrared digital images. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. **36**(8): 204–207. Available from http://www.isprs.org/proceedings/XXXVI/8-W2/PERSSON.pdf.

Peteinatos, G.G., Korsaeth, A., Berge, T.W., and Gerhards, R. 2016. Using optical sensors to identify water deprivation, nitrogen shortage, weed presence and fungal infection in wheat. Agriculture, **6**(2): 24. doi:10.3390/agriculture6020024.

Pettorelli, N., Schulte to Bühne, H., Tulloch, A., Dubois, G., Macinnis-Ng, C., Queirós, A.M., et al. 2018. Satellite remote sensing of ecosystem functions: opportunities, challenges and way forward. Remote Sens. Ecol. Conserv. **4**(2): 71–93. doi:10.1002/rse2.59.

Picchi, G. 2020. Marking standing trees with RFID tags. Forests, **11**(2): 150. doi:10.3390/f11020150.

Picchi, G., Kühmaier, M., and Marques, J.deD.D. 2015. Survival test of RFID UHF tags in timber harvesting operations. Croat. J. For. Eng. **36**(2): 165–174.

Pichler, G., Poveda Lopez, J.A., Picchi, G., Nolan, E., Kastner, M., Stampfer, K., and Kühmaier, M. 2017. Comparison of remote sensing based RFID and standard tree marking for timber harvesting. Comput. Electron. Agric. **140**: 214–226. doi:10.1016/j.compag.2017.05.030.

Pijanowski, B.C., Villanueva-Rivera, L.J., Dumyahn, S.L., Farina, A., Krause, B.L., Napoletano, B.M., et al. 2011. Soundscape ecology: The science of sound in the landscape. Bioscience, **61**(3): 203–216. doi:10.1525/bio.2011.61.3.6.

Pires, A.P.F., Srivastava, D.S., and Farjalla, V.F. 2018. Is biodiversity able to buffer ecosystems from climate change? What we know and what we don't. Bioscience, **68**(4): 273–280. doi:10.1093/biosci/biy013.

Poyatos, R., Martínez-Vilalta, J., Molowny-Horas, R., Steppe, K., Oren, R., Katul, G., and Mahecha, M. 2016. SAPFLUXNET: a global database of sap flow measurements to unravel the ecological factors of transpiration regulation in woody plants. Tree Physiol. **36**(12): 1449–1455. doi:10.1093/treephys/tpw110.

Poyatos, R., Granda, V., Flo, V., Adams, M.A., Adorján, B., Aguadé, D., et al. 2020. Global transpiration data from sap flow measurements: the SAPFLUXNET database. Earth Syst. Sci. Data Discuss. **2020**: 1–57. doi:10.5194/essd-2020-227.

Prince, P., Hill, A., Piña Covarrubias, E., Doncaster, P., Snaddon, J.L., and Rogers, A. 2019. Deploying acoustic detection algorithms on low-cost, open-source acoustic sensors for environmental monitoring. Sensors, **19**: 553. doi:10.3390/s19030553.

Proietti, R., Antonucci, S., Monteverdi, M.C., Garfì, V., Marchetti, M., Plutino, M., et al. 2020. Monitoring spring phenology in Mediterranean beech populations through in situ observation and Synthetic Aperture Radar methods. Remote Sens. Environ. **248**: 111978. doi:10.1016/j.rse.2020.111978.

Pureswaran, D.S., De Grandpré, L., Paré, D., Taylor, A., Barrette, M., Morin, H., et al. 2015. Climate-induced changes in host tree–insect phenology may drive ecological state-shift in boreal forests. Ecology, **96**(6): 1480–1491. doi:10.1890/13-2366.1.

Pureswaran, D.S., Neau, M., Marchand, M., De Grandpré, L., and Kneeshaw, D. 2019. Phenological synchrony between eastern spruce budworm and its host trees increases with warmer temperatures in the boreal forest. Ecol. Evol. **9**(1): 576–586. doi:10.1002/ece3.4779. PMID:30680138.

Reichstein, M., Rey, A., Freibauer, A., Tenhunen, J., Valentini, R., Banza, J., et al. 2003. Modeling temporal and large-scale spatial variability of soil respiration from soil water availability, temperature and vegetation productivity indices. Global Biogeochem. Cycles, **17**(4): 1104. doi:10.1029/2003GB002035.

Richardson, A.D., Keenan, T.F., Migliavacca, M., Ryu, Y., Sonnentag, O., and Toomey, M. 2013. Climate change, phenology, and phenological control of vegetation feedbacks to the climate system. Agric. For. Meteorol. **169**: 156–173. doi:10.1016/j.agrformet.2012.09.012.

Ross, S.R.P.J., Friedman, N.R., Dudley, K.L., Yoshimura, M., Yoshida, T., and Economo, E.P. 2018. Listening to ecosystems: data-rich acoustic monitoring through landscape-scale sensor networks. Ecol. Res. **33**(1): 135–147. doi:10.1007/s11284-017-1509-5.

Rossi, S., Morin, H., Deslauriers, A., and Plourde, P.Y. 2011. Predicting xylem phenology in black spruce under climate warming. Global Change Biol. **17**(1): 614–625. doi:10.1111/j.1365-2486.2010.02191.x.

Rossit, D.A., Olivera, A., Viana Céspedes, V., and Broz, D. 2019. A Big Data approach to forestry harvesting productivity. Comput. Electron. Agric. **161**: 29–52. doi:10.1016/j.compag.2019.02.029.

Rüetschi, M., Schaepman, M.E., and Small, D. 2018. Using multitemporal sentinel-1 C-band backscatter to monitor phenology and classify deciduous and coniferous forests in northern Switzerland. Remote Sens. **10**(1): 55. doi:10.3390/rs10010055.

Rundel, P.W., Rundel, P.W., Graham, E.A., Allen, M.F., Fisher, J.C., and Harmon, T.C. 2009. Environmental sensor networks in ecological research. New Phytol. **182**: 589–607. doi:10.1111/j.1469-8137.2009.02811.x. PMID:19422546.

Salk, C., Sturn, T., See, L., and Fritz, S. 2016. Local knowledge and professional background have a minimal impact on volunteer citizen science performance in a land-cover classification task. Remote Sens. **8**(9): 774. doi:10.3390/rs8090774.

Sandak, A., Sandak, J., Böhm, K., Zitek, A., and Hinterstoisser, B. 2016. Near infrared spectroscopy as a tool for in-field determination of log/biomass quality index in mountain forests. J. Near Infrared Spectrosc. **24**(6): 587–594. doi:10.1255/jnirs.1231.

Sandak, J., Sandak, A., Marrazza, S., and Picchi, G. 2019. Development of a sensorized timber processor head prototype — part 1: Sensors description and hardware integration. Croat. J. For. Eng. **40**(1): 25–37. doi:10.5281/zenodo.2585761.

Sandak, J., Sandak, A., Zitek, A., Hintestoisser, B., and Picchi, G. 2020. Development of low-cost portable spectrometers for detection of wood defects. Sensors, **20**(2): 545. doi:10.3390/s20020545.

Sandström, J., Bernes, C., Junninen, K., Lõhmus, A., Macdonald, E., Müller, J., and Jonsson, B.G. 2019. Impacts of dead wood manipulation on the biodiversity of temperate and boreal forests. A systematic review. J. Appl. Ecol. **56**(7): 1770–1781. doi:10.1111/1365-2664.13395.

Scherrer, D., Bader, M.K.F., and Körner, C. 2011. Drought-sensitivity ranking of deciduous tree species based on thermal imaging of forest canopies. Agric. For. Meteorol. **151**(12): 1632–1640. doi:10.1016/j.agrformet.2011.06.019.

Schlyter, P., Stjernquist, I., Bärring, L., Jönsson, A.M., and Nilsson, C. 2006. Assessment of the impacts of climate change and weather extremes on boreal forests in northern Europe, focusing on Norway spruce. Clim. Res. **31**(1): 75–84. doi:10.3354/cr031075.

Seyednasrollah, B., Young, A.M., Hufkens, K., Milliman, T., Friedl, M.A., Frolking, S., and Richardson, A.D. 2019. Tracking vegetation phenology across diverse biomes using version 2.0 of the PhenoCam Dataset. Sci. Data, **6**(1): 222. doi:10.1038/s41597-019-0229-9.

Shati, F., Prakash, S., Norouzi, H., and Blake, R. 2018. Assessment of differences between near-surface air and soil temperatures for reliable detection of high-latitude freeze and thaw states. Cold Reg. Sci. Technol. **145**: 86–92. doi:10.1016/j.coldregions.2017.10.007.

Sheeren, D., Fauvel, M., Josipovíc, V., Lopes, M., Planque, C., Willm, J., and Dejoux, J.F. 2016. Tree species classification in temperate forests using Formosat-2 satellite image time series. Remote Sens. **8**(9): 734. doi:10.3390/rs8090734.

Slette, I.J., Post, A.K., Awad, M., Even, T., Punzalan, A., Williams, S., et al. 2019. How ecologists define drought, and why we should do better. Global Change Biol. **25**(10): 3193–3200. doi:10.1111/gcb.14747.

Souza, C.P., Carvalho, F.B.S., Silva, F.A.N., Andrade, H.A., Silva, N.D.V., Baiocchi, O., and Müller, I. 2016. On harvesting energy from tree trunks for environmental monitoring. Int. J. Distrib. Sens. Networks, **12**: 9383765. doi:10.1155/2016/9383765.

Stängle, S.M., Brüchert, F., Kretschmer, U., Spiecker, H., and Sauter, U.H. 2014. Clear wood content in standing trees predicted from branch scar measurements with terrestrial LiDAR and verified with X-ray computed tomography. Can. J. For. Res. **44**(2): 145–153. doi:10.1139/cjfr-2013-0170.

Steenweg, R., Hebblewhite, M., Kays, R., Ahumada, J., Fisher, J.T., Burton, C., et al. 2017. Scaling-up camera traps: monitoring the planet's biodiversity with networks of remote sensors. Front. Ecol. Environ. **15**(1): 26–34. doi:10.1002/fee.1448.

Steppe, K., Sterck, F., and Deslauriers, A. 2015. Diel growth dynamics in tree stems: linking anatomy and ecophysiology. Trends Plant Sci. **20**(6): 335–343. doi:10.1016/j.tplants.2015.03.015. PMID:25911419.

Sturm, U., Schade, S., Ceccaroni, L., Gold, M., Kyba, C., Claramunt, B., et al. 2017. Defining principles for mobile apps and platforms development in citizen science. Res. Ideas Outcomes, **3**: e21283. doi:10.3897/rio.3.e21283.

Susha Lekshmi, S.L., Singh, D.N., and Shojaei Baghini, M. 2014. A critical review of soil moisture measurement. Measurement, **54**: 92–105. doi:10.1016/j.measurement.2014.04.007.

Tadesse, T., Hollinger, D.Y., Bayissa, Y.A., Svoboda, M., Fuchs, B., Zhang, B., et al. 2020. Forest Drought Response Index (ForDRI): a new combined model to monitor forest drought in the eastern United States. Remote Sens. **12**: 3605. doi:10.20944/preprints202009.0673.v1.

Tahir, A., Böling, J., Haghbayan, M.H., Toivonen, H.T., and Plosila, J. 2019. Swarms of unmanned aerial vehicles — a survey. J. Ind. Inf. Integr. **16**: 100106. doi:10.1016/j.jii.2019.100106.

Tang, X., Li, H., Liu, G., Li, X., Yao, L., Xie, J., and Chang, S. 2015. Sensitivity of near real-time MODIS gross primary productivity in terrestrial forest based on eddy covariance measurements. Chin. Geogr. Sci. **25**(5): 537–548. doi:10.1007/s11769-015-0777-7.

Tian, J., Schneider, T., Kempf, C., Xia, Y., Lusseau, M., Hill, J., et al. 2020. Early detection of forest drought stress with very high resolution stereo and hyperspectral imagery. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. **V-2-2020**: 781–787. doi:10.5194/isprs-annals-V-2-2020-781-2020.

Toda, M., and Richardson, A.D. 2018. Estimation of plant area index and phenological transition dates from digital repeat photography and radiometric approaches in a hardwood forest in the northeastern United States. Agric. For. Meteorol. **249**: 457–466. doi:10.1016/j.agrformet.2017.09.004.

Tognetti, R., Giovannelli, A., Lavini, A., Morelli, G., Fragnito, F., and d'Andria, R. 2009. Assessing environmental controls over conductances through the soil–plant–atmosphere continuum in an experimental olive tree plantation of southern Italy. Agric. For. Meteorol. **149**(8): 1229–1243. doi:10.1016/j.agrformet.2009.02.008.

Tognetti, R., Raschi, A., Béres, C., Fenyvesi, A., and Ridder, H.W. 1996. Comparison of sap flow, cavitation and water status of *Quercus petraea* and *Quercus cerris* trees with special reference to computer tomography. Plant. Cell Environ. **19**(8): 928–938. doi:10.1111/j.1365-3040.1996.tb00457.x.

Torresan, C., Berton, A., Carotenuto, F., Di Gennaro, S.F., Gioli, B., Matese, A., et al. 2017. Forestry applications of UAVs in Europe: a review. Int. J. Remote Sens. **38**(8–10): 2427–2447. doi:10.1080/01431161.2016.1252477.

Torresan, C., Carotenuto, F., Chiavetta, U., Miglietta, F., Zaldei, A., and Gioli, B. 2020. Individual tree crown segmentation in two-layered dense mixed forests from UAV LiDAR data. Drones, **4**(2): 10. doi:10.3390/drones4020010.

Tschörtner, J., Lai, B., and Krömer, J.O. 2019. Biophotovoltaics: green power generation from sunlight and water. Front. Microbiol. **10**: 866. doi:10.3389/fmicb.2019.00866.

Uner, B., Oyar, O., Var, A.A., and Altnta, O.L. 2009. Effect of thinning on density of *Pinus nigra* tree using X-ray computed tomography. J. Environ. Biol. **30**(3): 359–362. PMID:20120459.

United Nations Framework Convention on Climate Change (UNFCCC). 2015. Adoption of the Paris Agreement. Proposal by the President, Draft decision –/CP.21. Conference of the Parties, Twenty-first Session, Paris, 30 November to 11 December. Available from http://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf.

Valentini, R., Matteucci, G., Dolman, A.J., Schulze, E.D., Rebmann, C., Moors, E.J., et al. 2000. Respiration as the main determinant of carbon balance in European forests. Nature, **404**(6780): 861–865. doi:10.1038/35009084. PMID:10786790.

Vanamala, U.M., and Nidamarty, L.P. 2020. Galactic cosmic energy - a novel mode of energy harvesting. *In* International Conference on Emerging Trends in Engineering (ICETE). Springer International Publishing. pp. 458–465.

Van Loon, A.F., Gleeson, T., Clark, J., Van Dijk, A.I.J.M., Stahl, K., Hannaford, J., et al. 2016. Drought in the Anthropocene. Nat. Geosci. **9**(2): 89–91. doi:10.1038/ngeo2646.

Verger, A., Camacho-de Coca, F., and Meli, J. 2004. Testing parametric BRDF models with CHRIS/PROBA acquisitions over agricultural crops. *In* Remote Sensing for Agriculture, Ecosystems, and Hydrology VI. Vol. 5568. doi:10.1117/12.565551.

Verkerk, P.J., Costanza, R., Hetemäki, L., Kubiszewski, I., Leskinen, P., Nabuurs, G.J., et al. 2020. Climate-smart forestry: the missing link. For. Policy Econ. **115**: 102164. doi:10.1016/j.forpol.2020.102164.

Vernay, A., Tian, X., Chi, J., Linder, S., Mäkelä, A., Oren, R., et al. 2020. Estimating canopy gross primary production by combining phloem stable isotopes with canopy and mesophyll conductances. Plant. Cell Environ. **43**(9): 2124–2142. doi:10.1111/pce.13835. PMID:32596814.

Vialet-Chabrand, S., and Lawson, T. 2019. Dynamic leaf energy balance: Deriving stomatal conductance from thermal imaging in a dynamic environment. J. Exp. Bot. **70**(10): 2839–2855. doi:10.1093/jxb/erz068. PMID:30793211.
Vilas, M.P., Adams, M.P., Ball, M.C., Meynecke, J.O., Santini, N.S., Swales, A., and Lovelock, C.E. 2019. Night and day: Shrinking and swelling of stems of diverse mangrove species growing along environmental gradients. PLoS ONE, **14**(9): e0221950. doi:10.1371/journal.pone.0221950. PMID:31479477.
Vilhar, U.Š., Beuker, E., Mizunuma, T., Skudnik, M., Lebourgeois, F., Soudani, K., and Wilkinson, M. 2013. Tree phenology. Dev. Environ. Sci. **12**: 169–182. doi:10.1016/B978-0-08-098222-9.00009-1.
Vospernik, S., Nothdurft, A., and Mehtätalo, L. 2020. Seasonal, medium-term and daily patterns of tree diameter growth in response to climate. Forestry, **93**(1): 133–149. doi:10.1093/foresj/cpz059.
Wang, J., and Sammis, T.W. 2008. New automatic band and point dendrometers for measuring stem diameter growth. Appl. Eng. Agric. **24**(6): 731–742. doi:10.13031/2013.25361.
Wang, W., Peng, C., Kneeshaw, D.D., Larocque, G.R., and Luo, Z. 2012. Drought-induced tree mortality: ecological consequences, causes, and modeling. Environ. Rev. **20**(2): 109–121. doi:10.1139/a2012-004.
Wästlund, A., Holmgren, J., Lindberg, E., and Olsson, H. 2018. Forest variable estimation using a high altitude single photon lidar system. Remote Sens. **10**(9): 1422. doi:10.3390/rs10091422.
White, J.C., Coops, N.C., Wulder, M.A., Vastaranta, M., Hilker, T., and Tompalski, P. 2016. Remote sensing technologies for enhancing forest inventories: a review. Can. J. Remote Sens. **42**(5): 619–641. doi:10.1080/07038992.2016.1207484.
Wilkinson, M.D., Dumontier, M., Aalbersberg, I.J., Appleton, G., Axton, M., Baak, A., et al. 2016. Comment: The FAIR Guiding Principles for scientific data management and stewardship. Sci. Data, **3**(1): 160018. doi:10.1038/sdata.2016.18.
Wingate, L., Ogée, J., Burlett, R., Bosc, A., Devaux, M., Grace, J., et al. 2010. Photosynthetic carbon isotope discrimination and its relationship to the carbon isotope signals of stem, soil and ecosystem respiration. New Phytol. **188**(2): 576–589. doi:10.1111/j.1469-8137.2010.03384.x. PMID:20663061.
Wingate, L., Ogeé, J., Cremonese, E., Filippa, G., Mizunuma, T., Migliavacca, M., et al. 2015. Interpreting canopy development and physiology using a European phenology camera network at flux sites. Biogeosciences, **12**(20): 5995–6015. doi:10.5194/bg-12-5995-2015.
Wolkovich, E.M., Jonathan Davies, T., Schaefer, H., Cleland, E.E., Cook, B.I., Travers, S.E., et al. 2013. Temperature-dependent shifts in phenology contribute to the success of exotic species with climate change. Am. J. Bot. **100**(7): 1407–1421. doi:10.3732/ajb.1200478. PMID:23797366.
Wood, L. 2003. Satellite Constellation Networks. *In* Internetworking and computing over satellite networks. *Edited by* Y. Zhang. Springer, Boston, Mass. Available from http://doi-org-443.webvpn.fjmu.edu.cn/10.1007/978-1-4615-0431-3_2.
Wu, W., Tang, X.P., Ma, X.Q., and Liu, H.B. 2016. A comparison of spatial interpolation methods for soil temperature over a complex topographical region. Theor. Appl. Climatol. **125**: 657–667. doi:10.1007/s00704-015-1531-x.
Xie, X., Li, A., Jin, H., Tan, J., Wang, C., Lei, G., et al. 2019. Assessment of five satellite-derived LAI datasets for GPP estimations through ecosystem models. Sci. Total Environ. **690**: 1120–1130. doi:10.1016/j.scitotenv.2019.06.516. PMID:31470475.
Yang, D., Misra, S., Fang, X., Xue, G., and Zhang, J. 2012. Two-tiered constrained relay node placement in wireless sensor networks: computational complexity and efficient approximations. IEEE Trans. Mobile Comput. **11**(8): 1399–1411. doi:10.1109/TMC.2011.126.
Yu, L., Wang, W., Zhang, X., and Zheng, W. 2016. A review on leaf temperature sensor: measurement methods and application. *In* Computer and Computing Technologies in Agriculture IX. CCTA 2015. IFIP Advances in Information and Communication Technology, Vol. 478. *Edited by* D. Li and Z. Li. Springer International Publishing. pp. 216–230. doi:10.1007/978-3-319-48357-3_21.
Yu, X., Hyyppä, J., Litkey, P., Kaartinen, H., Vastaranta, M., and Holopainen, M. 2017. Single-sensor solution to tree species classification using multispectral airborne laser scanning. Remote Sens. **9**(2): 108. doi:10.3390/rs9020108.
Zou, W., Jing, W., Chen, G., Lu, Y., and Song, H. 2019. A survey of big data analytics for smart forestry. IEEE Access, **7**: 46621–46636. doi:10.1109/ACCESS.2019.2907999.