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Networking the forest infrastructure towards near real-time monitoring – a white paper

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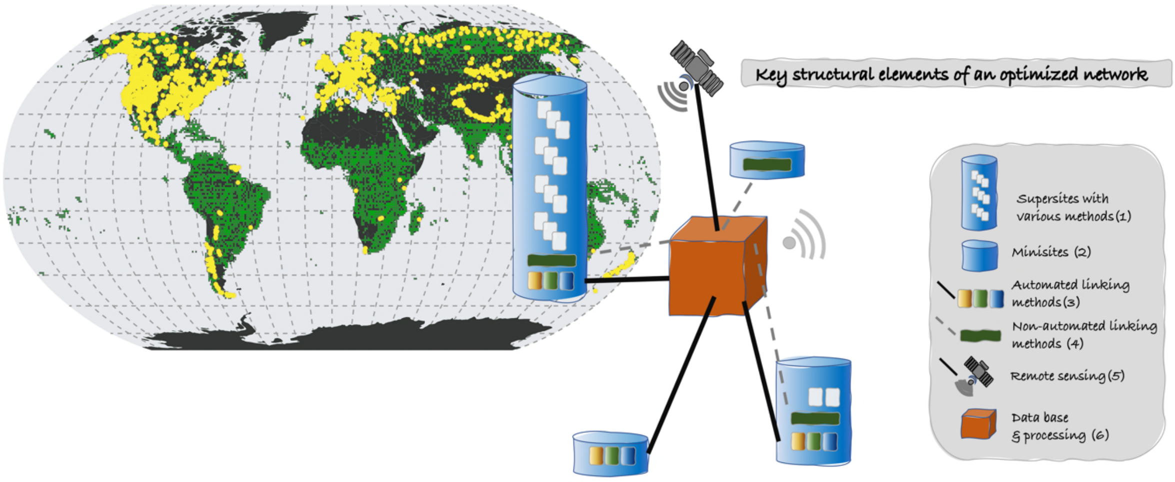
Graphical Abstract

From individual sites to a near real-time forest monitoring network



Highlights

- There is substantial research infrastructure for forest monitoring globally, especially in temperate regions.
- What is missing is their interconnection to enable timely assessments of, e.g., drought impacts.
- We propose to connect existing infrastructures using automated, standardized linking methods.
- Doing so will allow centrally processed data streams to enable near real-time reporting (nowcasting).
- We call for an interdisciplinary and transnational effort towards near real-time forest monitoring.

1. Abstract

Forests account for nearly 90% of the world's terrestrial biomass in the form of carbon and they support 80% of the global biodiversity. To understand the underlying forest dynamics, we need a long-term but also relatively high-frequency, networked monitoring system, as traditionally used in meteorology or hydrology. While there are numerous existing forest monitoring sites, particularly in temperate regions, the resulting data streams are rarely connected and do not provide information promptly, which hampers real-time assessments of forest responses to extreme climate events.

The technology to build a better global forest monitoring network now exists. This white paper addresses the key structural components needed to achieve a novel meta-network.

We propose to complement - rather than replace or unify - the existing heterogeneous infrastructure with standardized, quality-assured linking methods and interacting data processing centers to create an integrated forest monitoring network.
These automated (research topic-dependent) linking methods in atmosphere, biosphere, and pedosphere play a key role in scaling site-specific results and processing them in a timely manner. To ensure broad participation from existing monitoring sites and to establish new sites, these linking methods must be as informative, reliable, affordable, and maintainable as possible, and should be supplemented by near real-time remote sensing data.

The proposed novel meta-network will enable the detection of emergent patterns that would not be visible from isolated analyses of individual sites. In addition, the near real-time availability of data will facilitate predictions of current forest conditions (nowcasts), which are urgently needed for research and decision making in the face of rapid climate change. We call for international and interdisciplinary efforts in this direction.

2. Introduction

2.1. Globally relevant needs for forest research

Forests play an important role in regulating water, carbon, energy, and nutrient cycles, but this role is being challenged by global change such as warming, increasing frequency of severe droughts and other weather extremes, nitrogen deposition, and changing societal demands (Bar-On et al., 2018; Bonan, 2016; Braun et al., 2017; Keenan and Williams, 2018). Forests host 80% of the Earth's biodiversity (Cazzolla Gatti et al., 2022) and are therefore the focus of many conservation efforts (UNEP, 2020). They provide important resources to society (timber, energy), ecosystem services (e.g., water and air purification) and recreational activities. Understanding the processes that drive and regulate forest ecosystems is also fundamental to global efforts that aim at mitigating anthropogenic CO_2 emissions through carbon storage, but also to sustainably replace fossil fuel products (Cabon et al., 2022; Cook-Patton et al., 2020; Green and Keenan, 2022). To gain such understanding, carbon fluxes, storage, and residence times must be quantified with precision, which in turn depends on high quality data on forest demography, biotic and abiotic conditions in air and soil, water, and nutrient cycling, and much more (Fatichi et al., 2019; Friend et al., 2014; Korner, 2015).

In short, a variety of measurements and analyses are needed to assess and understand, for example, the potential of forests to act as nature-based climate solutions (Baldocchi and Penuelas, 2019; Seddon, 2022), how forests respond to climate change (Anderegg et al., 2022; Fei et al., 2017; Kröel-Dulay et al., 2022; Ruiz-Benito et al., 2020), and how forest management can be promoted to build climate-smart forests (Verkerk et al., 2020). In addition, forest organisms, especially long-lived trees, require long-term observations over decades (Korner, 2015; Meir et al., 2018), but also assessments that allow us to detect and understand short-term impacts of environmental drivers (Etzold et al., 2022). Bridging these temporal scales places special demands on measurement technology, including data management, quality control, observation infrastructure, and its long-term maintenance under field conditions (Hartmann et al., 2018).

Understanding fundamental ecosystem processes is crucial. Therefore, there is increasing need for the timely monitoring of forest conditions to enable researchers, decision makers, and forest users to adapt their activities and decisions to current and predicted conditions, e.g., from the effects of global warming. This can range from (re)positioning sensors for research purposes (e.g., AmeriFlux, link) to guiding administrative decisions such as determining wildfire risk (currently based solely on meteorological data) or warning from falling branches due to drought or insect infestation. In addition, information on forest vitality provided in near real-time on attractively designed websites has tremendous potential to raise public awareness of the global importance of forest conservation and solutions at local to global scales (BayTreeNet link, EFI-NEON link) and related ecosystem services. Overall, a monitoring system like those traditionally used for weather, snow, and river runoff should also be established to track forest conditions.

But does this mean that we need a novel, globally unified network of forest research infrastructures? No. Rather, this white paper calls for a meta-network that integrates existing forest monitoring infrastructures through standardized linking methods. Such an optimized network would allow data from different infrastructures to be processed and homogenized to provide the best up-to-date information on forests across scales. A key strength of this approach is that it utilizes existing infrastructure and offers the potential to scale observations from individual sites to entire regions by linking local ground-based information with remote global information (Mahecha et al., 2017). In addition, such a meta-network will provide new opportunities for cross-disciplinary research and the inclusion of sites from underrepresented areas such as the boreal or tropical regions.

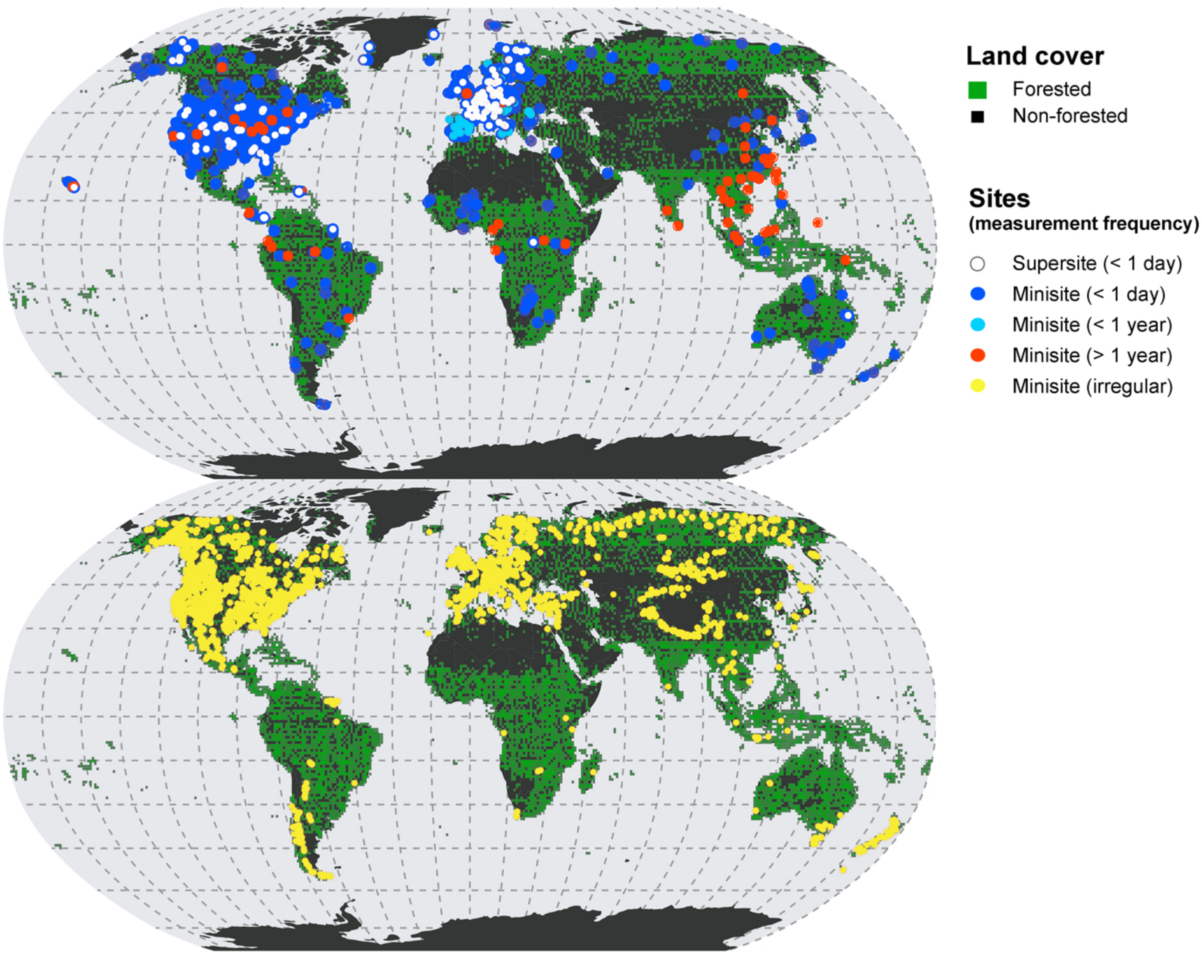


Fig. 1. Forest research infrastructure. Green and black squares indicate forested and non-forested land covers (Zanaga et al., 2021). Circles indicate the location of existing forest observation infrastructure. White circles indicate forest research supersites with a high density of measurement devices and a high measurement frequency. Other-colored circles refer to smaller infrastructures with a lower density of devices (minisites) and various database update frequencies of <1 day (automatic measurements and data transmission), <1 and >1 year (manual measurements and non-automatic data transmission). The lower map includes locations where records were found in databases that were not regularly updated, e.g., wood samples, sap flow and dendrometer data sets etc.. Note that only infrastructures with easily accessible site-level coordinates are included in this figure. More infrastructure is listed in Table S1.

2.2. Existing forest research infrastructure

A variety of forest research infrastructures exists worldwide for monitoring forest functioning and dynamics (Fig. 1). Some of these sites are considered ‘supersites’, i.e., research sites with a high density of instruments, whereas other ‘minisites’ are equipped with only a limited number of instruments but conduct basic long-term observations that are highly replicated in space (Salomon et al., 2022). Together, they cover a wide range of methods (observations, measurements, analytical approaches, statistical models) in the pedosphere, biosphere, and atmosphere, in different biomes and environmental conditions, and are sometimes complemented by remote sensing data from in situ instrumentation, drones, aircrafts, and satellites. In addition, there are thousands of grid points used for National Forest Inventories. Manually conducted inventories, which typically focus on quantifying forest structure and composition, generally provide information at lower temporal resolution than is provided by automated infrastructure. But due to their systematic sampling design, such inventories (e.g., National Forest Inventories) measure forest tree communities in a spatially representative manner (Fischer and Traub, 2019). A non-exhaustive list of measurement infrastructures in forests can be found in Table S1. Undoubtedly, there are many more. Nevertheless, the density of observations in forests, especially in the temperate zone, is impressive. This coverage is much sparser across forests in the boreal, tropical, or subtropical regions (Fig. 1).

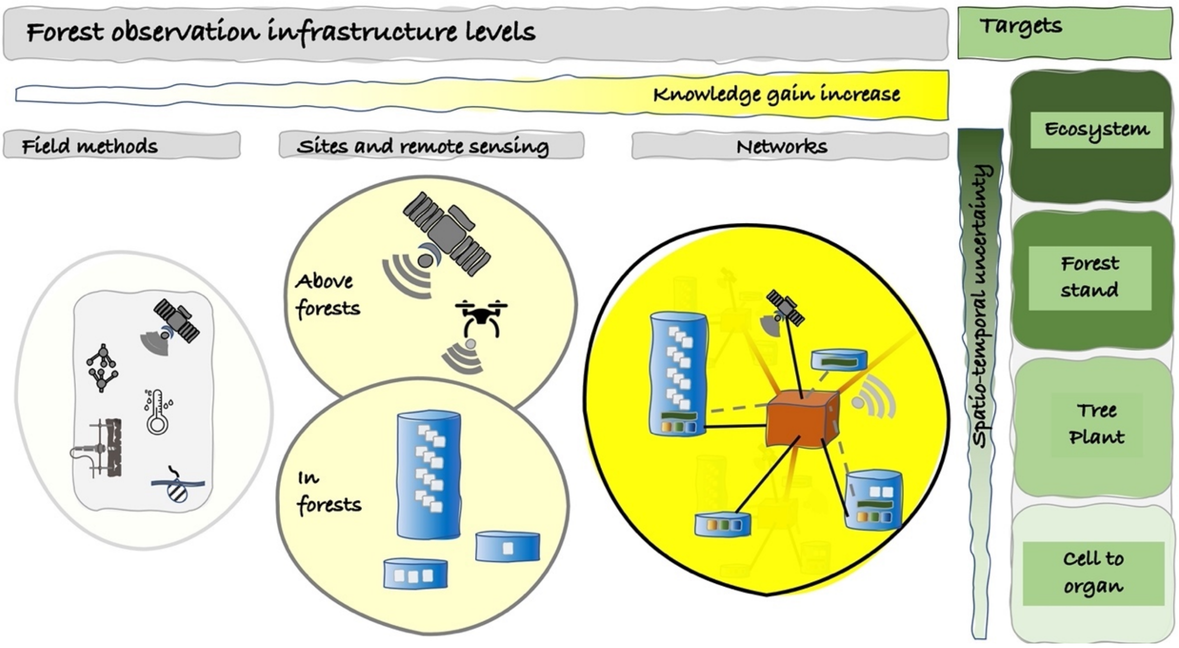


Fig. 2. Forest observation infrastructure levels. The target of each infrastructure is to gain knowledge and reduce spatiotemporal uncertainty of structures and processes in forests, from the cellular to the ecosystem level. Knowledge gain increases and spatiotemporal uncertainty decreases with the number of methods combined (as indicated with symbols for, e.g., remote sensing, eddy covariance, temperature sensors, dendrometer, soil water potential sensor, or generally with grey boxes), the number of sites included (blue stacks of different sizes and with different methods), and the way data from the different sources are linked through a database (brown cube) to form a network. Many methods that are suitable for one specific site may be incompatible with those of other

sites, while the linking methods (colored method boxes) are standardized for all sites. Large networks can consist of substructures with several interlinked databases and processing units as indicated by the faded symbols.

Each existing network has its strengths and weaknesses, depending on the infrastructure developed to address specific research or application questions. Consequently, the characteristics and specificities of existing forest research and monitoring networks are diverse, spanning across a wide range of temporal and spatial scales (Musche et al., 2019). The range of variables monitored is much more diverse than in meteorology, for example, because methods in the biosphere and pedosphere are included in addition to those in the atmosphere (Besson et al., 2022). The diversity of measurements and networks makes it difficult to link them together, and, in general, the overlap of standardized methods is not satisfactory. Thus, so far, we can obtain only fragmentary information on forest functioning and dynamics without exploring the full potential of linked forest monitoring efforts. The proposed meta-network in this white paper is an attempt to provide a concept towards a solution to this challenge.

2.3. Near real-time information

A critical issue for obtaining concurrent information on forest conditions is the turnover time needed to collect data, clean and process it, and make it available to the public, stake holders and scientists. The time to update most data points in a network database ranges from hours to a decade, and in some cases there is no regular updating interval of the collected data at all (Fig.1, Table S1). Moreover, even in cases where data are regularly updated at high temporal resolution, additional challenges emerge for further data processing and homogenization. This includes, for example, the selection of standardized protocols for data pre- and post-processing, data scalability, automated and standardized data processing (Heiskanen et al., 2022; Hurley et al., 2022; Knüsel et al., 2021; Peters et al., 2021; Poyatos et al., 2021), timely data sharing with third parties, as has recently been discussed for biodiversity databases (Feng et al., 2022).

The conversion of current raw data into near real-time state reports, e.g., in meteorology, is referred to as nowcasting (Wapler et al., 2019). Nowcasts use models that combine information from historical data, current raw measurements (now), and real-time modeling to predict and display the current conditions (cast). We adopt this term also for a comparable use with forest observations. So far, there are only a few networks capable of producing nowcasts based on vegetation surveys (e.g., Phaenonet at a seasonal resolution, link).

TreeNet (link nowcasts) may be the only network so far that calculates daily indicators of tree growth and tree water status from tree measurements and integrates them across sites, species and regions (Zweifel et al., 2021a) or combines them with e.g. hydrological data (link NCCS). Somewhat more common is the online visualization of vegetation measurement data, e.g., of trees (link TreeWatch (Steppe et al., 2016)) or forest stand fluxes (link ICOS (Heiskanen et al., 2022)), but these data are not processed into easily understandable indicators and thus require expert knowledge to access and to interpret the measurements. Other attempts have been made to model drought stress on forests from daily meteorological data, but do not include near real-time vegetation response measurements (e.g., CatDrought). Products of satellite data are also highly promising (e.g. link Global Forest Watch, link VegScape, (Zhang et al., 2022)), but they do not include near real-time measurements of the vegetation and typically operate at a coarser temporal resolution (link EFCM, (Buras et al., 2021); link Biomass Carbon Monitor, (Wigneron et al., 2021)). However, the ability to nowcast based on diverse measurements should be one of the key features of an optimized monitoring network for the future (Besson et al., 2022; Dietze et al., 2018). The success of such a network depends primarily on the availability of automated data collection, transmission, and data storage to continuously feed the underlying models (Reichstein et al., 2019).

2.4. Priority for data integration and timeliness

For improving forest observations, great potential lies in the availability of data, their access time (including quality control during ongoing measurements), and generally in the networking of the different infrastructures. Even if there are knowledge gaps to close and methodical improvements to make (Babst et al., 2021; Novick et al., 2022), it is most important to improve the timely integration of the existing data (Besson et al., 2022; Dietze et al., 2018). The difficulties to better integrating data are manifold, ranging from incompatible measurement and processing methods, to a lack of approaches for data homogenization, missing devices for timely data transfer, or poor data accessibility. As a result, there have been recent calls for more open-access forest data. These data should be "findable, accessible, interoperable, and reusable" (FAIR) (de Lima et al., 2022; Wilkinson et al., 2016). Overall, this lack of integration and interoperability limits the potential to scale individual site results spatially and temporally.

3. Proposed network design

3.1. Framework

To establish a framework to overcome the current limits of data integration, we used a systems analysis approach that examines natural or artificial systems for their functionality as a result of the components and their respective interactions (e.g., (Barrier, 2003)). We thus ask, what kind of structural changes would be necessary to create an optimized (meta-) forest observation network that combines existing infrastructures, integrates new sites (preferably also in previously poorly surveyed forests, e.g., in the tropics), can provide forest nowcasts, and thus serves both the scientific community and a growing number of stakeholders.

This white paper aims to provide a general impetus for a discussion of research and observation networks to improve their efficiency, find allies, and build structures that will serve a broader goal in the future than "just" the retrospective pursuit of a handful of (site-) specific research questions. The ideas emerged in the run-up to and during the 10th anniversary conference of the TreeNet network in Bad Bubendorf, Switzerland, 2022.

3.2. What is our optimized network supposed to provide data for?

Just as there are virtually infinite questions about forests and how they function, there are arguably infinite requirements for an adequate forest observation infrastructure. Therefore, we first identified the general stakeholders of forest information and their data needs.

The main stakeholders are: (i) scientists who need high-quality data from various measurement facilities to identify relevant mechanisms from the organ to ecosystem level that define forest condition and performance, but also to quantify large-scale dynamics; (ii) forest managers and government administrators who need clear thresholds and signals to answer applied questions and to guide decision-making; and (iii) various stakeholders, from politicians to the public, who need near real-time information on forest status to respond adequately to current conditions and threats. The latter is particularly relevant as extreme events like the summer drought and heatwave experienced in 2022 in Europe receive increasing societal attention (e.g. link BBC news).

Based on the above range of stakeholders, the following requirements are defined for the novel network. It needs to:

- Deepen mechanistic understanding of forest ecosystem processes through high quality, multi-layered data.
- Provide spatially and temporally scalable data to obtain larger-scale patterns and longer-term temporal dynamics for development and implementation of models and remote sensing products to answer applied questions.
- Deliver near real-time data for nowcasting and projections to support decision makers and the public with timely information on forest condition.

3.3. Key structural elements of a new meta-network

The requirements defined above, and the current forest science infrastructure landscape have led us to propose the following key structural elements of a network that will better link a variety of observations, methods, and sites, promising greater knowledge gains due to integrated data processing from many sources (Fig. 2). It contains different types of research sites that are mainly differentiated by their ground-based instrumentation, complemented by remote sensing methods (e.g., drone or satellite based), the interconnection of these data sources via linking methods, high-frequency data transfer, and interacting data processing units. Figure 3 illustrates this overall structure.

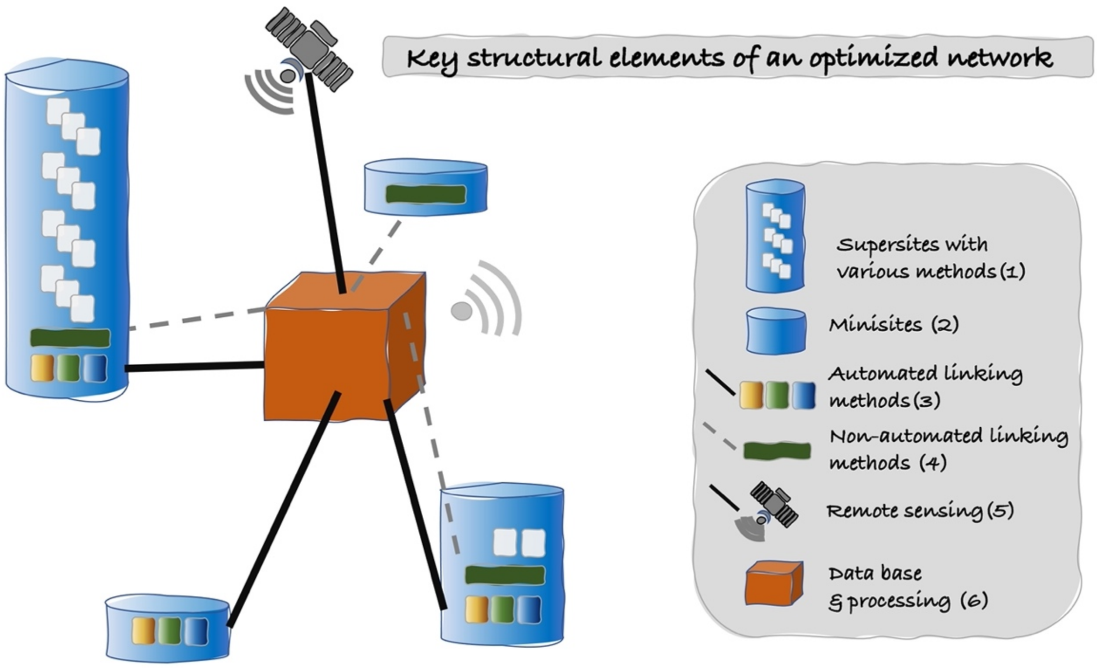


Fig. 3. Key structural elements of a meta-network with supersites, minisites, remote sensing, and a central data processing unit. Automated linking methods are interfaced with the database in

near real-time (bold lines), while non-automated linking methods (e.g., manually surveyed forest features) are updated less frequently (dashed lines). All intermediate forms of sites are conceivable between minisites and supersites.

1. Supersites

Forest ecosystem researchers that focus on understanding processes rely heavily on in-depth observations and experiments with a high density of measurements and methods at supersites (Fischer et al., 2011; Mikkelsen et al., 2013), preferentially at high temporal resolution over long time periods. To meet the needs of dynamically evolving research, sites require a high degree of freedom to evolve and be structured. This may involve continuous measurements (Etzold et al., 2011; Steppe et al., 2015), novel technologies and analytical methods (Hurley et al., 2022), highly labor-intensive approaches that can only be achieved manually (Arend et al., 2021) and may involve destructive sampling (Rademacher et al., 2021), or manipulation of environmental conditions through, for example, rain shelter (Grams et al., 2021), irrigation (Bose et al., 2022), forest management treatments (Sterck et al., 2021), or long-term free-air carbon enrichment systems (Jiang et al., 2020). In most cases, this type of infrastructure requires additional investment for canopy access (e.g., crane, mobile elevator, scaffolding), main power supply, monitoring of gas fluxes (eddy-covariance) and soil conditions (soil profiling), or protection of central gauges and infrastructure from the weather by buildings.

The high density and multi-layered measurement methods spanning from the organ to the stand level, as well as the high temporal resolution of the measurements (sub-hourly resolution), create unique infrastructures and provide the opportunity to conduct in-depth research to study forest ecosystem mechanisms. Some supersite networks have established well-defined method standardizations and quality control for all parts of the data stream to optimize the data transfer (e.g. ICOS link (Gielen et al., 2018), ICP Forests link). Supersites are essential for a fundamental mechanistic understanding of ecosystem processes but cannot be replicated sufficiently in space as often as desired due to high infrastructure costs. Such supersite infrastructure is often also very conspicuous and its strong influence on the visual appearance of a forest is likely to receive varying degrees of acceptance by the public. In a meta-network, they must therefore be integrated into a larger network with less densely equipped but more abundant minisites through standardized linking methods (Fig. 3, see points 3 and 4) to allow for the scaling of site-specific results across space and through time.

2. Minisites

The second important structural element of our network are minisites with continuous (i.e., automated instruments) and episodic (i.e., field surveys/inventories) long-term measurements that provide broad spatial coverage of environmental conditions and forest ecosystem types. There are different types of minisites: those that more closely resemble traditional inventory sites (manual sample collection, no technical infrastructure) and those that have automated, permanently installed sensors. However, all levels in between and towards supersites are conceivable (Fig. 3). The more spatial variation and environmental gradients are covered, the more these minisites can help scale findings, relate them to remote sensing data, and use them for modeling.

Such an optimized network should be open to new partners and grow and evolve organically with them. New partners may already have their own sites or networks and need a practical way to be included and connected while still maintaining their autonomy. Thus, an optimized network must not only cover the forest ecosystems of interest across its gradients, but also include new partners with a local focus to take advantage of synergies when, for example, supersites are combined with minisites. This leads directly to our next two key structural elements, which focus on methods for linking independent sites.

3. Automated linking methods

The third key structural element of our network is standardized, quality-assured, automated measurement methods (e.g., water potential measurements in air, plants, and soil, (Novick et al., 2022)) installed across as many sites as possible and thus linking the heterogeneous individual infrastructures into an optimized network (Fig. 3)(Heiskanen et al., 2022). They also allow for a better interpretation and integration of observations not made at all sites, e.g., by supersites. Not only must the measurements be recorded automatically, but the data must also be transferred independently and promptly to a central database, where it is checked for measurement quality and plausibility. This is an essential prerequisite for the application of both, near real-time models and nowcasting.

We propose that these automated linking methods include data obtained in the pedosphere (e.g., soil water potential), the biosphere (e.g., point dendrometer), and the atmosphere (e.g., temperature) to capture both the abiotic conditions in the air and soil, as well as the biotic responses of the forest to these conditions. The data from these three domains will form a framework in which location-specific measurements can be scaled across space and through time. The selection of appropriate automatic linking methods depends on the research topic. A biodiversity network may require different linking methods than an ecophysiological network (Besson et al., 2022).

In any case, the automated linking methods must be robust, so that they can function reliably for years, and be designed so that power consumption and maintenance are low. The credo for selecting these methods must be, on the one hand, to have methods that are as meaningful as possible and have the potential to link many sites, and on the other hand, to minimize the investment (labor and money) and the impact on the forest ecosystem. The fewer of these standardized methods are needed and the easier they are to use, the less financial and human effort is required and the easier it is to integrate new sites, as well as existing infrastructure or new partners with limited budgets. Choosing robust, automated linking methods will determine whether networking remains a visionary idea or is actually implemented in existing infrastructure and underrepresented areas such as tropical or boreal forests. In other words, a balance must be struck between introducing numerous relevant but impractical (technically demanding, expensive, error-prone) linking methods and reducing this collection of methods to the most important and efficient ones.

Table S2 lists potential automated linking methods for an ecophysiological forest network and qualifies them in terms of technical feasibility (easy to install, run, and being quality-controlled), reliability (long service life in the field and high robustness), energy consumption (low energy consumption, no need for main power), data transfer (low data density), data processing (existing tools to process the raw data in an automated way), invasiveness (little harm to plants and environment), public acceptance (low visibility), and cost (low investment and maintenance costs). While there are many good options for the atmosphere and soil, the options for automated vegetation measurements that are suitable as linking methods are more limited. This is due to the general difficulty of reliably and automatically measuring biosphere responses, such as those of trees, over a period of years. Low ratings were given to methods that require AC power or depend on structures such as towers, etc. to operate, which is not compatible with the idea of an easy-to-use, automated linking method that is applicable to remote, structurally weak locations.

4. Non-automated linking methods

The fourth important structural element relates to the need to know the environment in which scientific investigations of any kind are conducted to interpret the data across sites. Many of the basic methods of traditional site and forest inventories that quantify a slowly changing environment and vegetation characteristics over the long-term, such as plant composition, soil texture, etc. are manually measured and cannot be automated in any case even when using high-tech methods, for example, terrestrial lidar scanning of canopy structure (Calders et al., 2015; Eitel et al., 2013). Therefore, they are not directly applicable to the needs for nowcasting. However, some of these methods have the potential to serve as linking methods if standardized. Non-automated linking methods should ideally include atmosphere (e.g., climatic site characteristics), biosphere (e.g., tree dimension traits), and pedosphere (e.g., soil texture), as indicated for the automated ones. Table S3 lists potential non-automated linking methods and qualifies them in a similar manner to the automated ones.

The frequency with which such (manual) measurements need to be repeated depends on the processes observed. While changes in soil chemistry are generally slow and only become apparent over periods of several years or decades, seasonal processes such as leaf phenology require more frequent measurements (which, in the case of leaf phenology, are also often automated by phenocams). Systematic, regular sampling and archiving of plant and soil material can also provide a database for retrospective analyses of forest functioning and dynamics. The spatial resolution of biosphere data should be mapped at the individual tree level to allow for species-specific resolution of the data. Tree-level results can then be extrapolated to larger spatial scales using, for example, remote sensing products (Kwok, 2018), process-based modeling (Mahnken et al., 2022), machine learning methods (Besson et al., 2022), or a combination thereof (Koppa et al., 2022).

5. Remote sensing

The fifth key element of our meta-network is remote sensing data from in situ instrumentation, drones, aircrafts, and satellites (Figs. 2 and 3). Remote sensing provides a unique birds-eye perspective and enables the measurement of spatially explicit and globally consistent indicators of forest state (e.g., forest cover and change (Hansen et al., 2013)), and processes (e.g., gross primary productivity, evapotranspiration (Mu et al., 2007; Running et al., 2004)). It thus has the potential to outperform all other ground-based linking methods mentioned above. In situ instrumentation offering high temporal resolution allows linking remote sensing (Buman et al., 2022) to detailed classical site assessments (e.g., meteorology, eddy-covariance, sap-flow). Measurement campaigns using drones and aircrafts are flexible and provide, at least for core areas around test sites, data with high spatial resolution but infrequent temporal resolution. Satellite systems offer a complementary global coverage with limited (but ever increasing) spatial resolution and with up to several decades of spectral information (Seddon et al., 2016).

Integrating remote sensing in a meta-network is mutually beneficial to link monitoring sites and scale local measurements across space, but also to advance remote sensing approaches. Satellite remote sensing can be particularly conducive as an automated linking method in an optimized network, as the information can be continuously transmitted to a data processing infrastructure and cover all ground monitoring sites with a standardized approach. Further, the combined use of satellite data and ground-based observations allows interpreting and scaling point measurements via spatial context information, can inform about observational gaps in the network, and enables up-to-date mapping of forest condition to support forest management and policy decisions, and initiate urgent responses to extreme conditions (e.g., short-term fire bans). In the past, ground-based forest observations have already played a key role in the development, calibration, and validation of remote sensing approaches from regional to global scales (e.g., FLUXNET (Baldocchi et al., 2001), U.S. Forest Service's Forest Inventory Analysis Program (Lister et al., 2020)).

Despite the benefits and the potential of their combined use, there are only few cases where remote sensing is integrated into a ground-based forest monitoring network, such as NEON (link), where aerial hyperspectral and lidar surveys are conducted annually for all sites at the peak of the growing season (Kampe et al., 2010). We are not aware of any forest condition nowcasting that presently relies on combined ground and satellite data in an automated way.

In our view, it is essential that a meta-network links data from both perspectives (from the ground and above) in an automated manner (Zuidema and van der Sleen, 2022). This will benefit scientific studies in forest ecology and related fields, as well as research that further develops remote sensing products for an advanced monitoring of forest conditions and complex biological processes that typically span across temporal scales and operate at the regional to global scales.

6. Data storage and processing infrastructure

A particularly important structural element is a data storage and processing infrastructure for the linking methods that includes numerous functions to bridge the gap between automated measurements in the field and timely processed and integrated output. Figure 4 illustrates some of the components and the data flow of such an infrastructure (see also (Zweifel et al., 2021a)). To continuously feed the data processing infrastructure, sensors in the field must be automated and installed together with a data transmission system. The Low Power Wide Area (LPWA) network protocol provides a suitable integrated approach for data acquisition and transmission in near real-time (Wikipedia link). LWPA has been developed for wirelessly connecting battery-powered devices to the internet and meets the key requirements of the Internet of Things (IoT), such as bidirectional communication, end-to-end security, localization services and low power consumption. This is based on LoRa (from "long range") radio communication technology (link Semtech), and LoRaWAN as the higher-level system architecture including the software communication protocol (link LoRa alliance). There is an increasing number of providers which make LoRa accessible in >160 countries (link LoRa alliance).

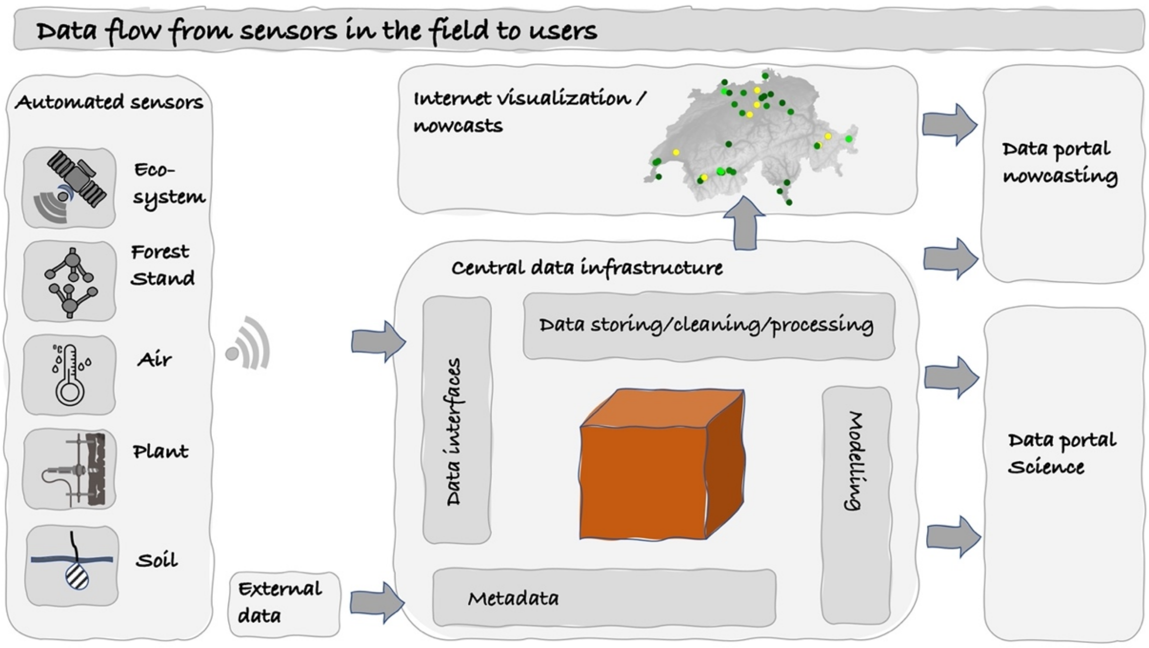


Fig. 4 Data flow diagram, starting on the left with the sensors in the field, with raw data preferably transmitted wirelessly to the central data infrastructure via the required interfaces. Other sources of data are separately fed in. The central data infrastructure stores, controls data quality, cleans and processes data using standardize processing approaches. Further it consists of modeling including forest now- and forecasting. All processing units query an integrated metadata base with e.g., sensor type and location, tree species, preset processing variables, etc. to be functional. The data must be made available at various levels of aggregation and processing through the data portal to websites on the Internet, to stakeholders, and to network partners.

Data interfaces need to allow for any type of data stream from different sources to be processed and forwarded to the heart of the infrastructure, the central data processing platform. This platform not only houses the data from different processing and integration layers but must also have an integrated meta-database. Such a meta-database contains information about locations, sensors, measurement objects, methods, specific calibration, and processing parameters, and many more functionalities.

In larger meta-networks, it may be advisable to have multiple data storage and processing units that perform specific tasks but are always interoperable (Fig. 2, see also the approaches of e.g., dataone, link). According to system analysis concepts, decentralized processing units facilitate operability and increase the stability of the entire network.

Further it is crucial that the various recipients of data and generated information have suitable access that is as barrier-free as possible via a data portal and the respective interfaces. Internet pages displaying nowcasts must be served automatically with updates and research partners must be able to access the stored (raw and processed) data automatically or manually. In addition to technical solutions, it is advisable to develop a suitable and fair data policy for all parties involved and beyond (de Lima et al., 2022).

4. Discussion and Conclusions

4.1. From separated sites to a network

Aristotle, a philosopher of ancient Greece, stated that the whole is greater than the sum of its parts. This historical statement is supported by scientific theories of systems analysis (e.g., (Barrier, 2003) based on an understanding of biological systems (e.g., (Maturana and Varela, 1992; Vester, 2007)) and applied to human-made systems, particularly in business (e.g., (Lundvall, 2007). In this sense, there is great untapped potential in linking existing infrastructures, methods, and research approaches, including those in forest sciences, to benefit from emerging synergies (Fig. 2). It is increasingly important to understand and show how our Earth’s climate is shaped by forests, how climate shapes the forests, how forests are connected to other (natural and artificial) systems, and how much we can learn about entire forest ecosystems from individual tree responses (Nature, 2022; Sass-Klaassen et al., 2016; Zuidema and van der Sleen, 2022). We, as beneficiaries of forests globally, must learn to use forests in a sustainable manner that preserves their broad functionality (Achim et al., 2022). Most importantly, to achieve this understanding, we need long-term observational infrastructure that is spatiotemporally well replicated and includes as many perspectives as possible (Anderegg et al., 2022; Besson et al., 2022). A novel meta-network should allow us to study forests from the soil to the canopy, including their microclimate. It must also provide nowcasts on forest condition to inform and support the public and decision makers in a timely manner.

We therefore call for linking the existing forest observation infrastructures and thinking about how to integrate more disciplines into a larger whole that serves to complete the picture of understanding forest ecosystems. In this way, an optimized monitoring network will emerge that promotes scientific discovery and services for society, drawing on a range of disciplines including plant physiology, ecology, geology, hydrology, microbiology, soil science, meteorology, remote sensing, socio-ecology, and many others. This optimized network may be composed of autonomously managed sub-networks (using very different linking methods) whose own dynamic developments are preserved without losing their connection to the whole.

4.2. Key to an optimized network

This vision is quite far from our current situation, but considering some key aspects, we are convinced that it is feasible with some coordinated effort. First, we determined that forest research must consist of methodologically diverse sites and subnetworks. This is the only way to account for the myriad aspects and questions that must be considered to understand forest ecosystems on a global, but also on a regional scale. This means that we do not have to start from scratch with building new networks, but rather link the existing infrastructure more efficiently. In our view, this is also the most practical way to build an optimized network, because many forest infrastructures have accumulated so much knowledge and valuable long-term data sets that it would not be wise to discard all of this in favor of a new infrastructure. So, we are also making a real virtue out of necessity.

Second, if we consider what makes a system of any kind and how it increases its intrinsic knowledge gain, it is first and foremost the connection between the parts (Fig. 2). We have found that standardized and quality assured linking methods, additionally inserted into existing infrastructures that were previously incompatible with each other, can take on the role of these essential connections without the need to homogenize all the methods of different sites. The linking of different methods should cover the pedosphere, biosphere, and atmosphere, but should be as simple as possible to acquire, install, and operate. For our vision to be feasible, it is important to keep the barrier to the adoption of linking methods as low as possible, so that the additional effort required to link infrastructures remains attractive and leads to a win-win situation for all potential users, including partners with budget constraints. To obtain timely information on forest condition, some of the linking methods will need to be automated, including data transmission to a central database.

Third, a monitoring system needs an information center to function properly. This is where data are collected and processed. Without this center, the system would not be able to collect or output data in a timely manner. The complexity of such a data center can quickly become very large and its functionality also requires optimization or fragmentation of data storage into different sub-centers (Fig. 2). It may make sense, for example, to process data from automated linking methods in one central location, while data from non-automated sources or supersites are distributed and exchanged less frequently but on a regular basis.

Fourth, it is imperative that data from remote sensing are implemented into this data center. The specific view from above provides another dimension of forest condition and contextual data with a high and unbiased spatial coverage and thus a greater potential for upscaling in contrast to ground-based measurements (Kwok, 2018). The satellite-based information should preferably be uploaded in the form of automatically created proxies that condense the amount of data to the essentials. Despite the large potential of satellite-based data alone, we are convinced that the combination of both, ground-based monitoring and remote sensing technology, is key to advance understanding of forest ecosystems. The birds eye perspective of remote sensing has limited sensitivity for the large vertical dynamic of forest ecosystems (Damm et al., 2020) and can only serve as an indicator of dynamics in the different forest layers, from the crown of the dominant trees to the understory vegetation, to the processes in the soil. Particularly the discovery of physiological processes requires sophisticated multi-scale measurements along the vertical gradient of a forest. However, the potential to use satellite remote sensing to gain insights over large areas is undisputed (Kwok, 2018). In addition, new remote sensing proxies are continuously being developed through new technologies, ranging from information about leaf area (Fang et al., 2019; He et al., 2020), photosynthetic activity (Gamon et al., 2016; Porcar-Castell et al., 2021), biomass stock (Frappart et al., 2020), radial stem growth of trees (Eitel et al., 2020), to vegetation water content (Konings et al., 2021) and many more. The information collected by ground monitoring networks serves as an invaluable data source for validating and calibrating these proxies.

In this context, it is also important to address the increasingly potent analysis methods that allow patterns to be detected in ever larger amounts of data (sometimes referred to as 'big data'). Artificial intelligence methods such as neural networks, can be trained to identify, for example, tree species or damaged crowns from a satellite-based multispectral image of a forest (Reichstein et al., 2019). In general, the rapid development of machine learning methods is enabling entirely new models and perspectives for big data analysis, including data-cleaning and gap-filling (Lukovic et al., 2022), and the treatment of heterogeneous data sets with different data structures (Bodesheim et al., 2022; Munteanu et al., 2022). This technology, together with the linking methods of a meta-network, could also be the backbone for the interpolation of the many other variables measured in the various infrastructures. The standardized linking methods thereby form the homogeneous data grid along which other variables measured at only a few points can be interpolated and scaled. Today, machine learning algorithms are opening up increasingly powerful possibilities that could also allow us to apply supersite insights more broadly. For example, eddy covariance-based net ecosystem productivity (NEP) could be related to linking methods that measure stem growth, VPD, and soil water, which would allow for the extrapolation of NEP across all points in the meta-network. Using data from linking methods in a meta-network, machine learning could even help partially overcome the limitation of only being able to relate standardized data.

4.3. Nowcasting - a link between retrospective analysis and predictions

Our vision is to use forest networks for scientific data additionally also for a nowcasting and forecasting system. To be able to classify and understand current forest processes, we need long-term information as a basis for assessing the current condition and, of course, timely data to produce realistic forest response signals. Actual and adequate quantifications of forest responses to extreme (and normal) conditions should become as self-evident as weather forecasts (Dietze et al., 2018). The proposed structure of a meta-network has all the prerequisites to achieve these goals and to ensure the necessary data flow. Finding meaningful, easily maintained, and automated variables that link infrastructures is central to this (see Table S2).

However, we also note that further efforts are needed to develop meaningful forest nowcast signals beyond the retrospective data analysis that is still common and important. To date, little has been done in this direction, mostly based on continuous stem radius and sap flow data from trees, or based solely on satellite data, as in the case of the French Biomass Carbon Monitor, a platform that measures the role of forests in carbon sequestration through changes in biomass (link). Another example is TreeNet (link), a mainly Swiss consortium that calculates daily nowcasts for stem growth and water deficit of trees compared to long-term averages of individuals. The TreeNet infrastructure (Zweifel et al., 2021a) could thus serve as a prototype for how to implement the proposed meta-network. TreeNet links a handful of supersites and about 50 minisites, connecting various forest monitoring groups that have not previously collaborated on this scale. It has a fully automated data processing infrastructure, including the forest nowcasting models mentioned earlier. The automated, standardized linking methods are precision point dendrometers on trees (biosphere), air temperature and humidity sensors in the atmosphere, and soil water potential and soil temperature sensors in the soil (pedosphere). The network is thus able to provide timely information to a variety of non-scientific stakeholders but has also proven to provide data for highly regarded ecophysiological research (Etzold et al., 2022; Walthert et al., 2021; Zweifel et al., 2020; Zweifel et al., 2021b). However, this network currently lacks the automated merging of remotely sensed and ground-based data. TreeNet is focused on ecophysiological questions. Other research foci (e.g., biodiversity, ecological communities) also require other linking methods (Besson et al., 2022), so it makes sense that there will continue to be meta-networks of different sizes and content that overlap. The difference from today, however, should be that the data streams are interconnected.

4.4. Conclusions

This white paper is a call for networking existing forest observation infrastructures to further improve science and build a system that is capable of producing forest nowcasts. We recommend implementing the simplest, quality-assured, most standardized linking methods possible on existing forest research sites that result in a meta-network with maximum potential knowledge output with minimum effort and resources. Whenever possible, linking methods should be automated. Such a meta-network has the greatest potential for capturing forest ecosystem dynamics, if it is fed in parallel with data from above (remote sensing) and below (field observations), and if the data are automated, both transmitted in near real-time and analyzed in an information center. The concept invites established networks to think outside the box and offers isolated minisites the opportunity to join a larger network at a reasonable cost. In addition, it opens up novel opportunities to integrate poorly connected areas into current ecological forest research. In addition, we call for the development of improved nowcasting models for forests that provide not only (valuable) raw data for scientists, but also meaningful, easy-to-understand aggregated signals on forest condition. Such an optimized infrastructure could make a crucial contribution to the understanding, protection, and use of forests for scientists, forest stakeholders (forest managers and policy makers), and the public.

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5. Supplementary Material

5.1. Table S1

Table S1. Collection of forest measurement sites and networks
(Site/network need sto involve ground-based monitoring)

Name code	Name	Link	Type[1] [IN/MO/Exp]	Data base update[2] [no/D/Y/M/d/h]	Data availablity[3] [A/B/C/no]
baytreenet	Baytreenet	https://baytreenet.de	MO	h	C
BCNM	Barro Colorado Nature Monument, Panama	https://stri.si.edu/facility/barro-colorado	MO	h	C
BIFor FACE	Birmingham Institute of Forest Research FACE	https://www.birmingham.ac.uk/research/bifor/face/index.aspx	EX	?	no
CSFE	Climate Smart Forestry Experiment		MO/Exp	d	C
CTFS-ForestGEO	CTFS-ForestGEO	https://github.com/forestgeo/Site-Data	IN	no	no
DendDrought/DendroGlobal	Automated dendrometer data collections		DC	no	no
DendroNetwork	Real-time biomonitoring of forest ecosystems	http://dendronet.cz	MO	h	C
eLTER	Integrated European Long-Term Ecosystem, critical zone and socio-ecological research	https://elter-ri.eu/	MO	no	D
FluxNet	FluxNet	https://fluxnet.org/	MO	h	A
ForestGeo	Forest Global Earth Observatory	https://forestgeo.si.edu	MO	?	C
ForestPlots	ForestPlots	https://forestplots.net	MO	d	B
IAP	Intercantonal Forest Observation network of IAP	https://www.iap.ch/	MO	Y	C
ICOS	Integrated Carbon Observation System	https://www.icos-cp.eu	MO	h	A
ICP-Forests	International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests	http://icp-forests.net/	MO	Y	C
ISMN	International Soil Moisture Network	https://ismn.geo.tuwien.ac.at/en/	MO	h	A
ITRDB	International Tree-Ring Data Bank	https://www.ncei.noaa.gov/products/paleoclimatology/tree-ring	DC	no	B
Loetschental Transect	The Lötschental tree-growth monitoring transect	https://www.wsl.ch/en/tree-ring-research/the-loetschental-tree-growth-monitoring-transect.html	DC	no	C
LTER	Long Term Ecological Research	https://lternet.edu/	MO	no	C
LWF	Long-term Forest Ecosystem Research	https://www.lwf.ch	MO	Y	C
NEON	National Ecological Observatory Network	https://www.neonscience.org	MO	Y	A
netCTF	Network for Monitoring Canopy Temperature of Forests	https://gtr.ukri.org/projects?ref=NE%2FV008366%2F1	MO/Exp	Y	no
NFI	National Forest Inventories	http://enfin.info/	IN	Y, D	C
NGEE-Tropics	Next generation ecosystem experiments	https://ngee-tropics.lbl.gov	MO	?	C
Phenocam	PhenoCam: an ecosystem phenology camera network	https://phenocam.nau.edu/	MO	d	A
Rainfor	Amazon Forest Inventory Network	https://rainfor.org/en/	IN	Y, D	C
Sapfluxnet	SAPFLUXNET Project	https://sapfluxnet.creaf.cat/	DC	no	B
Smartforests	Smartforests Canada	https://smartforest.uqam.ca/	MO	?	C
TERENO	Terestrial Environmental Observatories	https://www.tereno.net	MO	Y	C
TERN	Ecosystem Research Infrastructure	https://www.tern.org.au	MO/Exp	Y	C
TreeNet	The biological drought and growth indicator network	https://treenet.info	MO	h	B
TreeWatch	Tree Water and Carbon monitoring Network	https://treewatch.net/	MO	h	C
Tropi-Dry	Environmental Monitoring Super Site Santa Rosa	https://www.tropi-dry.org/super-site/	Exp	?	C
TRY	Plant trait database	https://www.try-db.org/TryWeb/Home.php	DC	no	B

[1] IN: inventory, MO: monitoring, Exp: Experimentation, DC: Data collection
[2] no: no regular data update, h: hourly or higher, d: daily, M: monthly, Y: yearly, D: Decade
[3] A: near real-time data base (open access), B: historic data (open access), C: data on request, D: no

Name code	Data display (nrt)	Nowcasts	Supersites	Microsites	Experimentation	Remote data	Fig. 1	References
baytreenet	yes	no						
BCNM	yes	no	x		x	x		
BIFor FACE	no	no	x		x			MacKenzie et al. 2021
CSFE	no	no	x	x	x	x		Vos et al. 2023 (in press)
CTFS-ForestGEO	no	no	x	x				
dDrought/DendroGl	no	no	x	x			x	Salomon et al 2022
DendroNetwork	yes	no	x	x	x	x		Krejza et al. 2021
eLTER	no	no						
FluxNet	yes	no					x	
ForestGeo	no	no	x	x			x	
ForestPlots	no	no	x	x				DeLima et al. 2022
IAP	no	no		x	x			Braun et al. 2021
ICOS	yes	no	x			x		Heiskanen et al. 2021
ICP-Forests	yes	no	x	x		x	x	Lorenz and Fischer 2013
ISMN	yes	no	x	x				
ITRDB	no	no		x			x	
oetschental Transe	no	no	x					
LTER	no	no	x	x	x			Mollenhauer et al. 2018
LWF	yes	no	x	x				Schaub et al. 2011
NEON	yes	no	x	x		x	x	Schimel et al. 2007
netCTF	no	no		x				
NFI	no	no						
NGEE-Tropics	no	no	x	x	x			
Phenocam	yes	no				x		
Rainfor	no	no						
Sapfluxnet	no	no	x	x	x		x	Poyatos et al. 2021
Smartforests	no	no						Pappas et al. 2022
TERENO	yes	no	x	x				Brauer, A., et al., (2022),; Heinrich et al., (2018)
TERN	no	no	x					
TreeNet	yes	yes	x	x	x		x	Zweifel et al 2021
TreeWatch	yes	no	x	x				Steppe et al. 2016
Tropi-Dry	no	no	x		x	x		
TRY	no	no		x				Kattge et. al. 2020

5.2. Tables S2

Table S2. List of potential automated linking methods

Qualifiers for automated use over years

very good	good	ok	difficult	very difficult

Atmosphere		Tech feasibility	Reliability	Energy consumpt	Data transfer	Data proc	Invasiveness	Acceptance	Cost
Sensor/method	**Variable measured**								
Air temperature sensor	Air temperature	very good	very good	very good	very good	very good	very good	very good	very good
Relative humidity sensor	Relative humidity	very good	very good	very good	very good	very good	very good	very good	very good
Radiation sensor	Radiation	very good	very good	very good	very good	very good	very good	very good	very good
PAR sensor	PAR	very good	very good	very good	very good	very good	very good	very good	very good
Anemometer	Wind speed/direction	very good	very good	very good	very good	very good	very good	very good	very good
Precipitation measurement devi	Precipitation	good	good	very good	very good	very good	very good	very good	very good
Throughfall sensor	Throughfall	good	good	very good	very good	very good	very good	very good	very good

Biosphere		Technical feasibi	Reliability	Energy consumpt	Data transfer	Data processin	Invasiveness	Acceptance	Cost
Sensor/method	**Variable measured**								
Red/farRed sensor	Red/farRed	very good	very good	very good	very good	very good	very good	good	good
Point dendrometer	Stem radius	very good	very good	very good	very good	good	good	good	ok
Sap flow sensors	Sap flow	good	good	difficult	very good	good	good	good	ok
Satellite remote sensing	carotenoids content, GPP, phenology	very good	good	very good	ok	ok	very good	good	ok
Infrared sensor	Leaf temperature	ok	ok	good	good	good	good	good	good
Phenocam	Canopy pictures	difficult	ok	ok	difficult	ok	good	difficult	ok
Hemiview sensor	LAI	difficult	good	good	difficult	difficult	very good	good	ok
AE sensor	Acoustic emissions (drought stress)	difficult	good	good	good	difficult	very good	good	difficult
FDR/TDR sensor	Xylem water content	good	very good	very good	very good	very good	very difficult	good	very good
Lidar measurements	Canopy structure/biomass	difficult	very good	ok	difficult	very difficult	very good	good	very difficult
NDIR CO2 sensors	Xylem [CO2]	ok	difficult	difficult	very good	good	very difficult	very difficult	ok
Root camera/Minirhizotron	Fine root pictures	ok	difficult	ok	very difficult	very difficult	ok	ok	very difficult
Eddy covariance	CO2/H2O/VOC exchange	very difficult	good	difficult	difficult	difficult	good	difficult	very difficult
Infra red gas analyzer	Stem CO2 efflux	very difficult	difficult	difficult	good	good	ok	difficult	difficult
Stem pressure sensor/ psychror	stem pressure	very difficult	difficult	very good	very good	good	ok	good	ok
Leaf pressure sensor	Leaf pressure	very difficult	difficult	very good	very good	good	very good	good	good

Pedosphere		Technical feasibi	Reliability	Energy consumpt	Data transfer	Data processin	Invasiveness	Acceptance	Cost
Sensor/method	**Variable measured**								
Soil water potential sensor	Soil water potential	very good	very good	very good	very good	very good	very good	very good	very good
Soil temperature sensor	Soil temperature	very good	very good	very good	very good	very good	very good	very good	very good
Soil moisture/water content sen:	Soil moisture	very good	very good	very good	very good	very good	very good	very good	very good
Soil sounds	Audio records	good	good	good	difficult	difficult	very good	good	good
Infra red gas analyzer	Soil CO2 efflux	very difficult	difficult	difficult	good	good	ok	difficult	difficult

5.3. Table S3

Table S3. List of potential non-automated linking methods

Qualifiers for frequent application over years

very good	good	ok	difficult	very difficult

Atmosphere		Technical feasibility	Reliability	Data processing	Invasiveness	Acceptance	Cost
Sensor/method	**Variable measured**						
Rain water collection	Chemical compounds						
Long-term weather data analysis	Annual temperature, precipitation, etc						

Biosphere		Technical feasibility	Reliability	Data processing	Invasiveness	Acceptance	Cost
Sensor/method	**Variable measured**						
Tree height measurement	Tree height						
Tree stem diameter at breast height measurement	Tree stem diameter						
Species determination	Plant species						
Leaf collection/analyses	Chemical compounds						
Litter traps	specific leaf area/biomass turnover						
Health status determination	Health status						
Wood cores	Tree age/wood density						
microcores (wood)	Xylogenesis						
Band dendrometers	stem circumfence increase						
Hemispherical pictures	Leaf area index						
xylem water collection	chemical compounds						
Gas-exchange chambers	Leaf and stem gas exchange						
Scholander pressure bomb	Leaf or branch water potential						
Drones/planes with LIDAR/PRI etc	Canopy structure/Leaf water content/etc						

Pedosphere		Technical feasibility	Reliability	Data processing	Invasiveness	Acceptance	Cost
Sensor/method	**Variable measured**						
soil texture determination/digging profile	soil traits						
soil water collection/analysis	nitrogen deposition/chemical compounds						