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The ECOSENSE forest: A distributed sensor and data management system for real-time monitoring of ecosystem processes and stresses

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Abstract. Forests provide crucial ecosystem services, but are vulnerable to climate-related physical and biological stresses, such as droughts, pests and pathogens. The rapid climate change currently observed increases the pressure on forest ecosystems, with already drastic consequences, e.g., widespread tree mortality across Central Europe. However, we fall short of understanding underlying process dynamics and their impacts on the Earth system. To better understand and predict forest ecosystem dynamics and the associated energy, carbon and water fluxes, detailed knowledge of ecosystem structure, processes and functioning under constantly varying conditions and across different spatial and temporal scales is needed. The ECOSENSE project brings together engineers, environmental and data scientists to establish novel environmental monitoring approaches and to capture distributed forest carbon and water flux dynamics in space and time with a wide range of established measurement technologies and newly developed sensors. Here, we describe the required infrastructure – called ECOSENSE forest – with regard to physical structures, power supply, communication network and data management, that supports such novel environmental sensor networks. We established a comprehensive monitoring system in this ECOSENSE forest, spanning from below-ground to above-canopy with three large scaffold-towers in different plots. More than 670 commercial and 430 self-built sensors monitor over 90 distinct parameters, fluxes, or processes generating upwards of 4,500 time series that capture soil, tree and atmosphere processes with high spatial and temporal resolution. In particular, our design objective is to provide a stable, flexible and secure forest research infrastructure with power, communication and data management using low-cost and commercially available components that meet the needs of various research disciplines. Our considerations and experiences provide impulses and practical solutions for establishing robust, low-cost distributed field research infrastructures and thus increase data continuity and resilience to disruptions at remote locations. The ECOSENSE forest may thus serve as a blueprint for future projects with similar goals and challenges.

1 Introduction

Resilient forest ecosystems are highly relevant for society and an integral part of the UN Sustainable Development Goals (FAO and UNEP, 2020). They contribute to a diverse and productive global biosphere (Storch et al., 2020) and provide significant ecosystem services, including climate regulation (Ehbrecht et al., 2021), carbon sequestration (Pan et al., 2024), drinking water (Winter et al., 2025) and flood protection (Mengist and Soromessa, 2019). Many forests are also used for timber and fuel production (Messier et al., 2022), but at the same time, they harbour biodiversity, health and recreational benefits (Eriksson et al., 2012; Mengist and Soromessa, 2019; Storch et al., 2020).

Despite their adaptive capacities, forest ecosystems are sensitive to abiotic and biological stresses such as climate extremes, pests and pathogens. In particular, under the currently observed rapid climate change, forests have been under unprecedented pressure, resulting, for example, in widespread tree mortality in Central Europe (Hartmann et al., 2022; Schiefer et al., 2025; Schuldt et al., 2020), even reaching local tipping points in ecosystem functioning (Haberstroh et al., 2022, 2025). Increased tree mortality already has negative impacts on, e.g., drinking water quality (Winter et al., 2025) and can shift forest ecosystems to become a net carbon source (Haberstroh et al., 2025).

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Forests and their underlying processes are complex ecosystems. Assessing and predicting their dynamics requires detailed information on their structure, processes and functioning under constantly varying influences, i.e., weather, water availability, or biological stresses (De Frenne et al., 2021). Standard forest inventories reveal long-term trends via structural data sampled at multi-year timescales (e.g., George et al., 2022). This temporally and spatially sparse sampling, however, is not suitable to assess the rapid dynamics and impacts of stressors on trees and ecosystems as a result of individual or cumulative weather extremes (Schiefer et al., 2025). While space-based or aerial Earth observation can provide temporally and spatially continuous information on forest conditions, approaches fall short of revealing key processes and abiotic and biotic interactions at the required spatial and physiological detail (International Tree Mortality Network, 2025; Turner et al., 2004; Wang et al., 2010). Flux tower networks, on the other hand, allow for continuous measurement of energy, water and carbon fluxes between forests and the atmosphere (Friend et al., 2007; Gielen et al., 2017), but are incapable of attributing these dynamics to plant functional types, species and individuals.

Plant functional diversity and species-specific responses to environmental stresses such as extreme drought are important controls of ecosystem fluxes (Anderegg et al., 2018; Werner et al., 2021). Moreover, species-specific acclimation and adaptation potential play a key role in ecosystem functioning (Werner et al., 2025). Besides biological controls, small-scale variation in abiotic site conditions, such as plant-available water or microclimate introduce substantial variability in ecosystem dynamics in space and time (De Frenne et al., 2019). Hence, to comprehensively monitor changing forest structure, functioning and diversity and to advance our process understanding of forest carbon and water fluxes, we need novel and distributed observational systems – systems that provide spatially detailed and temporally continuous information on key plant physiological processes at the leaf, tree and ecosystem level, together with information on the variability in soil conditions and canopy microclimates (De Frenne et al., 2025; Mahecha et al., 2024).

We argue that such an in-depth monitoring of key ecosystem processes and fluxes across different spatial and temporal scales can provide a holistic understanding of ecosystem functioning and disturbance. In the Collaborative Research Centre ECOSENSE (SFB 1537), funded by the German Research Foundation, we develop and test novel environmental sensing techniques and apply them to enhance our understanding and modelling of forest functioning and processes (Werner et al., 2024). We consider this fundamental to predict sustainable forest functioning and hence ecosystem services that buffer climate change. Specifically, with a distributed sensor network approach, we study the impact of forest heterogeneity in space and time in response to hydro-climatic extremes and stresses at an unprecedented level of detail (Werner et al., 2024). Currently, we focus on the dynamics of carbon and water fluxes and their driving factors. **Fig. 1** presents a schematic overview of the multitude of ecosystem measurements conducted. These measurements encompass a wide range of variables collected at the ground as well as within and above the crowns from towers or via drones. For further details, see **Sec. 2.6** and **Table 1**.

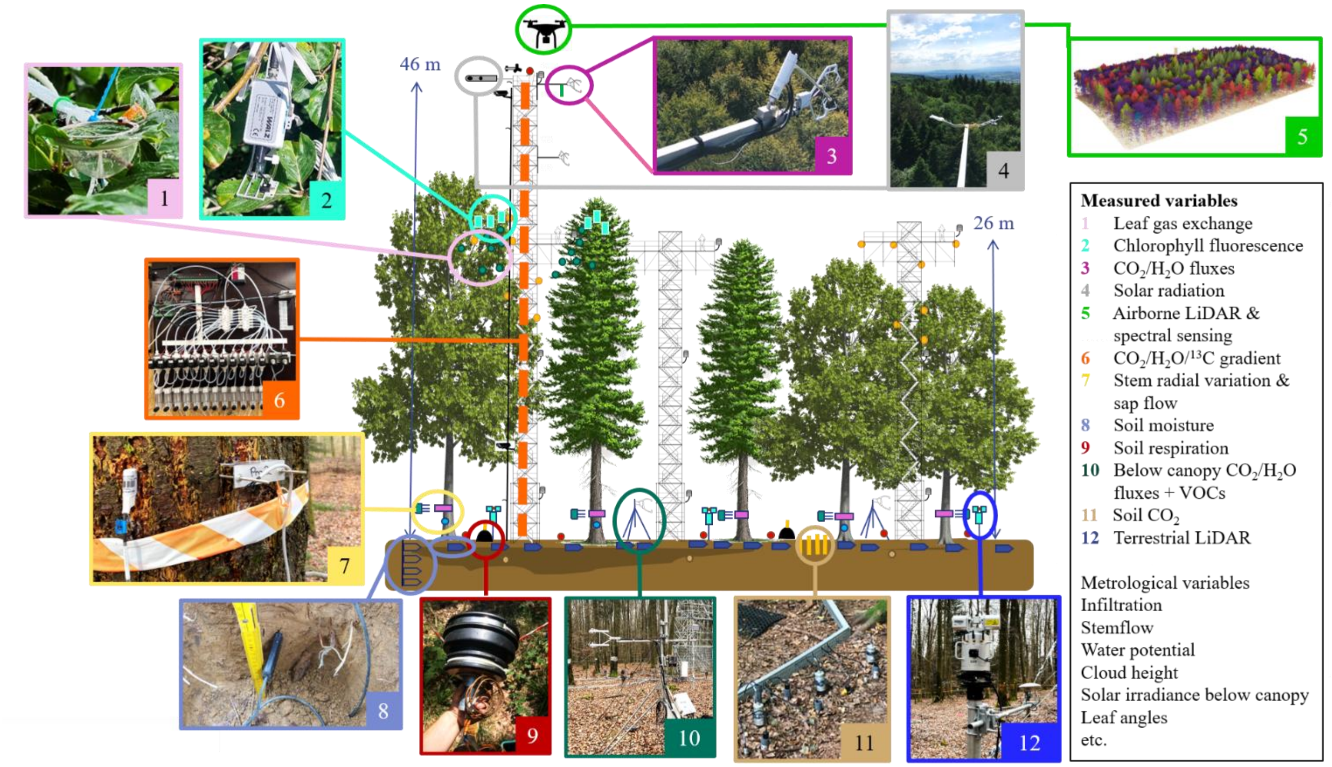

Figure 1: Simplified schematic of the environmental monitoring network.

ECOSENSE brings together engineers, environmental and data scientists. Utilising this high level of interdisciplinarity, we aim to establish an efficient and scalable monitoring set-up that captures key components of forest carbon and water fluxes. Data from newly developed sensors can then be validated with established measurement devices and the resulting unprecedented abundance of collected data is used to 1) enable integrated data-driven modelling for process revelation and 2) evaluate assumptions of physiology-oriented models regarding spatial and temporal distribution of process activity. This not only enhances mechanistic understanding but also provides the means for scenario analysis as well as extrapolation to other sites, species and forest structures. The overarching long-term goal of ECOSENSE is thus to use a scientific framework that integrates cutting-edge hardware technologies with data management and analytics to transfer new mechanistic knowledge into comprehensive and transferable modelling and forecasting systems. Developing and deploying such a sensor network in forest ecosystems, however, entails many challenges, which translate to the following six design criteria for distributed forest sensing networks:

1. The structural complexity of forests and the resulting process heterogeneity, even within a single tree, requires **a large number of small, lightweight and spatially distributed sensors** that measure fluxes, stresses and processes at an exceptional level of detail. The sensors need to be easily distributable, scalable and affordable so they can be deployed in representative quantities on tree leaves and branches, in the soil or on light structures.

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2. Sensor networks need to **measure continuously from minutes to decades to capture the rare nature of climate extremes and their spatial variability**. The resolution and continuity of such data streams are typically challenged by power for sensing, storing and transmitting data. Hence, a sensor network system in a forest requires intelligent, resilient and distributed power management and data transmission.
3. Forest sensor networks need to sample in soils, trees, on leaves and in the atmosphere to provide **concurrent data across the different ecosystem compartments** with enough repetitions to account for spatial and temporal variability.
4. Sensor networks require sufficient robustness to **endure challenging and rough environmental conditions** (rain, heat, humid and freezing conditions, tree motions, partially with high acceleration and damage caused by animals), as these situations provide the most valuable scientific insights into ecological disturbances and tipping points.
5. Ideally, data from sensor networks are provided in **near real-time for rapid analysis** to allow for data completeness, (remote) maintenance and assistance, including the planning of special observation campaigns with additional manual measurements or intelligent sampling.
6. **Effective data management** is required to ensure that the vast and diverse datasets generated by forest sensor networks are centrally stored, standardised in format and accompanied by consistent quality flags and metadata. This enables cross-comparison, the application of deep-learning algorithms and the integration into ecosystem models. It also ensures long-term availability and (re-)usability.

Within the ECOSENSE project, we have embraced these design criteria to develop, test and deploy novel environmental sensors in a prototype forest observatory, called the ECOSENSE forest, located in southwest Germany. Here, we present an overview of the hardware, sensor, power and communication infrastructure that supports our vision of integrated forest sensor networks. We discuss the needs, challenges and implementation of the ECOSENSE forest sensing and data management infrastructure. The concepts, infrastructure and technologies presented are transferable to other environmental and ecological forest observatories and may serve as a blueprint for a novel forest sensing network.

2 Field site infrastructure

The following section provides a short description of the ECOSENSE forest – its geographical setting, followed by details on power supply, communication infrastructure and the established monitoring system, with a focus on newly developed sensors or self-built and less-common measurement systems. For specific details on deployed hardware and software, see **Table S1** in the supplements. It summarises essential infrastructure components, including manufacturer and model numbers and also provides additional information, further thoughts and comments from our own practical experience. Devices that are listed in **Table S1** and also named in the text are marked with $^+$.

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2.1 ECOSENSE forest structure and site conditions

Our experimental site, the ECOSENSE forest, is a mixed temperate forest ecosystem located in the municipality of Ettenheim, Germany at the foothills of the Black Forest (reference point mixed plot tower: 7.87821731° E, 48.26852173° N, WGS-84, height 521 m a.s.l.). The climate is classified as Cfb (temperate air temperature, no dry season, warm summer) in the current Köppen-Geiger climate map (Beck et al., 2023). Mean annual precipitation sum and air temperature at the closest official weather stations are 911 mm (station Ettenheim/Ettenheimmünster 2.71 km to the south, 214 m a.s.l.), respectively (DWD, 2023, reference period 1991–2020) and 11.0 °C (station Lahr 11.37 km to the northwest, 156 m a.s.l.). The managed (low-impact) forest ecosystem is dominated by European beech (*Fagus sylvatica* L.), interspersed with Norway spruce (*Picea abies* L.), English oak (*Quercus robur* L.), European silver fir (*Abies alba* MILL.), Douglas fir (*Pseudotsuga menziesii* MIRBEL) and Scots pine trees (*Pinus sylvestris* L.). Two representative soil profiles were analysed according to IUSS Working Group WRB (2022): In the southern part of the area a Dystric Stagnic Cambisol (loamic) derived from carbonate-free quaternary loess over strongly weathered mesozoic shell-limestone is found. Below 40 cm redoximorphic features occur from seasonal water logging. In the northern part a Dystric Skeletic Cambisol (siltic, humic) was identified, derived from carbonate-free quaternary loess over colored/platy sandstone. Below 40 cm a strong platy structure and a high stone content occurs. Both profiles are strongly acidified with a pH (KCl) between 3.5 and 4.5. The forest floor is thin, consisting mostly of OL and shows a patchy OF layer.

2.2 Measurement plots and scaffold towers

In the ECOSENSE forest, we established three intensive measurement plots, of which one is dominated by European beech (“beech plot”), one by Douglas Fir (“Douglas fir plot”) and one contains a mix of the two species (“mixed plot”). Within each of these plots, we installed three scaffold towers that allow access to the tree canopies for sensor installation, manual measurements, e.g., of leaf gas exchange and destructive sampling (**Fig. 2**). For this purpose, towers were equipped with canopy-access platforms in 24–26 m height. The tower located in the mixed plot extends above the treetops to a total height of 46 m and accommodates an eddy covariance system for continuous measurements of net ecosystem CO_2 and H_2O fluxes over the forest (Sulzer et al., 2025) as well as other sensors and instruments capturing environmental variables (see **Sec. 2.6** for more details). The three towers were placed in an arrangement so that the Douglas fir plot and the beech plot are located within the long-term turbulent footprint (measurement area) of the eddy covariance system at the mixed plot. The scaffolding towers were constructed in April 2024. To keep the impact on forest soil, i.e., amount of sealed surface area, as low as possible, we opted for small concrete foundations (in the size of tower base areas, depth 0.80 m) and micropiles (eight per tower, in two different distances from the tower) as anchors for tower guy wires providing static stability. We also operate a weather station at a nearby clearing (see **Fig. 3**). An additional measurement plot with Silver firs (supplied with power but not connected to the communication network) is located 245 m southeast and downhill from the beech plot.

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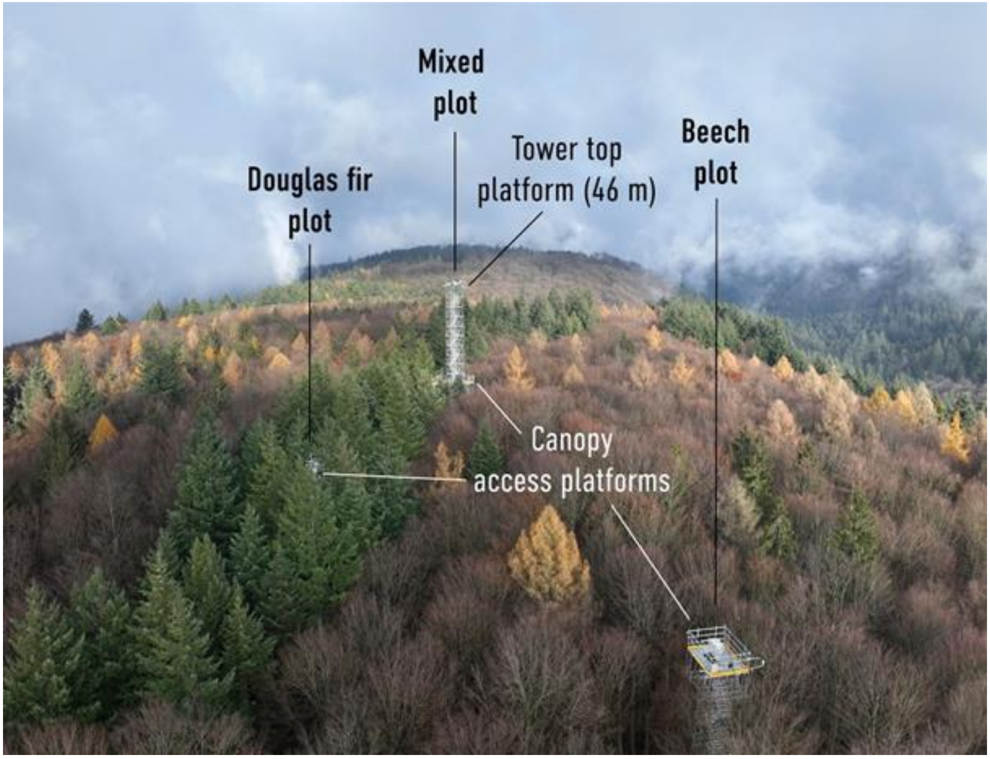

Figure 2: Unmanned Aerial Vehicle (UAV) image of the ECOSENSE forest facing north. The three measurement plots are each equipped with a tower platform providing canopy access. The tower at the mixed plot extends above the treetops (total height: 46 m) and is used for above-canopy flux measurements. The wintertime photo from Dec 2024 illustrates the contrasting tree coverage with dominantly coniferous Douglas firs, leafless European beech trees and European larch with yellow foliage. Image credit: M. Gassilloud

2.3 Measurement container

Central to our field site infrastructure is a custom-built measurement container (2 m x 4.8 m), mounted on a trailer chassis. It functions as the backbone for power distribution and network connectivity in the field, which will be described in detail in the following sections (see **Sec. 2.4** and **Sec. 2.5**). It also houses gas analysers that are not rated for outdoor use. Since some instruments only function at moderate temperatures and additionally produce considerable heat during operation, the container is ventilated and equipped with a redundant air conditioning system: if one unit fails, the second takes over automatically to maintain cool and stable indoor conditions and avoid overheating of expensive and sensible devices. The interior of the container is insulated with closed-cell rubber foam[+] and covered with wooden panelling. This allows for the easy installation of shelves, lighting and additional hardware. The container's sheet metal construction provides inherent protection against lightning strikes. In addition to instruments and IT hardware, the container stores tools, first aid supplies, a defibrillator and work benches for preparing samples and performing small tasks. Pressurised gas cylinders are stored in a separate, lockable metal shed next to the measurement container.

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2.4 Power supply

To provide power to the ECOSENSE forest, we tap into the municipal power grid at a high-voltage transformer (20 kV) via a three-phase transformer located around 700 m from the measurement container. Within the container, a three-phase (400 V) power line is routed in and split into multiple fused circuits, effectively distributing power across separate 230 V lines. Individual circuits are additionally protected with fault-current circuit breakers (RCDs) and their respective power consumptions are monitored with power meters[+]. Those also allow for remote surveillance and shutdown of (parts of) the power supply. Additionally, we use DC-RCDs to protect from DC failures. The entire system is equipped with surge protection, which diverts lightning and other events to ground or short-circuits them. Critical infrastructure and sensitive measuring devices run on uninterruptible power supply units (UPS) within the container to reduce the risk of damage during (short) power failure or current spikes.

For safety reasons, we decided to only provide 230 V AC power within the measurement container, reduce voltage there via AC/DC-converters[+] and distribute power across the ECOSENSE forest at protective extra-low voltage (< 50 V DC, DIN norm VDE 0100-410:2018-10). For this, fused power lines[+] in cable conduits[+] were laid to each of the measurement plots. There, voltages are further converted by DC/DC-converters[+], usually to 24 V or 12 V, as required by measurement devices and data loggers. The various power lines are galvanically isolated to avoid failure of the entire electricity network in case of, e.g., malfunctional devices or external factors like lightning strikes. We emphasise that it has proven useful that each device connected to the power infrastructure is individually and appropriately fused to avoid negative mutual influence in case of broken equipment or human errors in operations among researchers of different projects. An overview of power supply, distribution and access points across the ECOSENSE forest can be found in **Fig. 3**.

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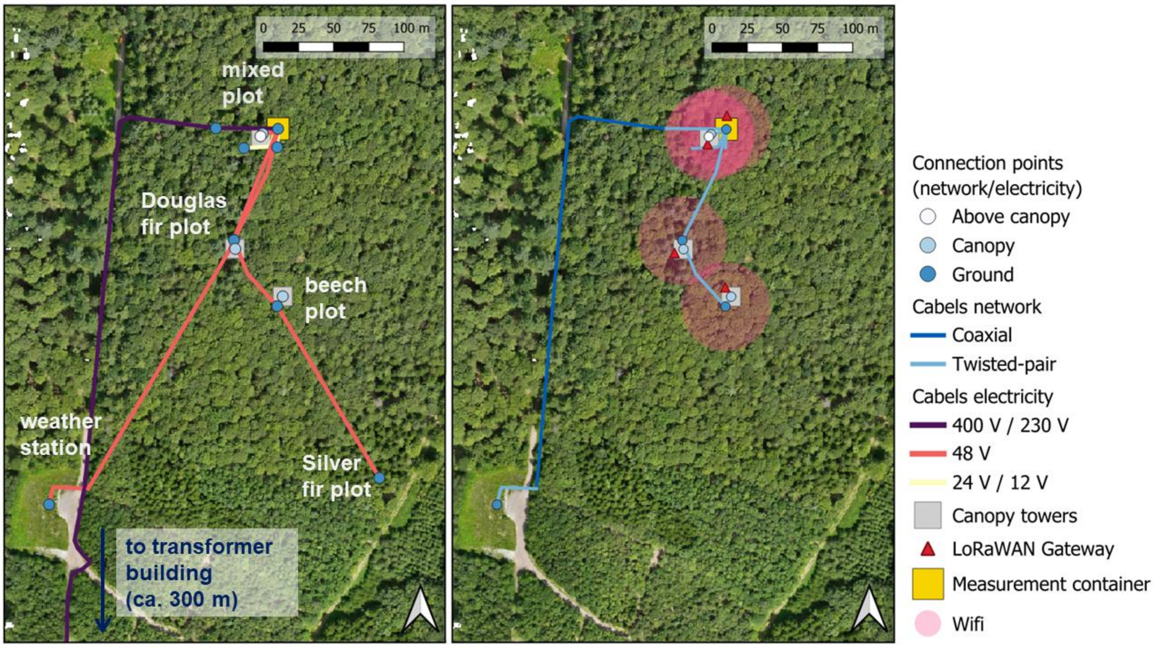

Figure 3: Map of power (left) and communication network infrastructure (right) in the ECOSENSE forest. Image credit: M. Gassilloud

2.5 Communication network and remote control

Due to limited mobile phone network coverage in the ECOSENSE forest, we decided to install a satellite-based internet access point[+]. The receiving device was installed on top of the 46 m above-canopy tower (mixed plot). From there, an Ethernet cable[+] connects to the main network switch[+] inside the measurement container. The whole network in the ECOSENSE forest is directly connected to the network of the University of Freiburg via a VPN (virtual private network) tunnel. This approach facilitates easier access to research data, management systems and underlying servers (see **Sec. 3**), some of which are only accessible within the university network. Additionally, static IP addresses within a defined address pool can be manually assigned to devices in the ECOSENSE forest. This makes servers, computers and data loggers remotely accessible from the university network or through the university's VPN client. These are centrally managed by the ECOSENSE technicians. The remaining IP addresses available (253 addresses in total) are assigned dynamically to devices connecting to the network on site. The gateway[+], which establishes the connection via VPN tunnel, hosts a firewall. To restrict and track access from the outside, the University of Freiburg hosts a MAC filter, meaning only computers/servers with pre-registered MAC addresses can connect to the ECOSENSE forest directly. Another possibility for remote access is through the university's VPN client, which requires a login with a personalised user ID. This allows us to protect the ECOSENSE forest network against attacks from outside and inside.

From the main network switch, the network spans to various other switches[+], located at the three plots at ground level, on the tower platforms and at the weather station (see **Fig. 3**). For the most part, we laid patch cables for connections. Only for the

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long distance (> 450 m) from the main tower to the clearing with the weather station, we used a coaxial cable that was buried in a tube underground, together with the main power cable. For all important network nodes, intelligent and controllable managed layer-two network switches[+] were procured to facilitate remote troubleshooting and allow for remote restart and restriction of data transfer over specific ports. To minimise the risk of surge damage, e.g., in case of lightning strikes, we included surge protectors[+] at important network junctions and in front of sensitive and expensive devices, in particular protecting the main network switch and the server[+] inside the measurement container.

In addition to connection via Ethernet ports, we installed various Wi-Fi access points[+] covering the three main plots (compare **Fig. 3**). In case an Ethernet cable is damaged or the connection is otherwise faulty, the Wi-Fi network automatically takes over part of the network traffic, offering redundancy and thus increasing network stability.

For newly developed sensors, we provide LoRaWAN (Long Range Wide Area Network) as a local data transmission protocol. The PoE (Power over Ethernet) powered LoRaWAN gateways are installed on top of the measurement container and on each tower platform to increase transmission reliability and redundancy. In Europe, LoRa gateways typically operate at 433.05–434.79 MHz (ISM band EU433) or 863–870 MHz (ISM band EU863). Due to its energy efficiency during transmissions LoRa provides an advantage for sensors that are autonomous or miniaturised. The gateways send their data via the network in the ECOSENSE forest to "The Things Network", from where the measurements are then pushed to the server inside the measurement container.

Prospectively, network interconnection between plots should be changed to fibre-optic cables, as the amount of data transported is larger than expected, in particular due to sensors with a high temporal resolution or image-based sensors, that were in part not included in the initial project plan. This would also expand network capacity for future technical developments and collaborations that will likely further increase data traffic within the ECOSENSE forest.

2.6 Environmental monitoring setup

We established a comprehensive monitoring system in the ECOSENSE forest across multiple scales, i.e., from leaf to stand level. More than 670 commercial and 430 self-built sensors monitor over 90 distinct parameters, fluxes, or processes generating upwards of 4,500 time series that capture soil, tree and atmospheric processes with high spatial and temporal resolution. With this large amount of data collected at different scales, we aim to improve upscaling approaches and modelling of ecosystem processes and stresses (see **Sec. 4.1**).

The following inventory (**Table 1**) provides an overview of the main measured processes and fluxes, based on ecosystem compartments in the ECOSENSE forest. Fluxes and processes shown in **bold** are measured by novel sensors, i.e., those developed within the ECOSENSE project.

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Table 1: Inventory of measured variables in the ECOSENSE forest.

Layer	Measured variables
Above-canopy platform	Air temperature, atmospheric pressure, H_2O/CO_2 mixing ratios, global (shortwave) irradiance, diffuse irradiance, normal direct shortwave irradiance, longwave hemispherical irradiance, shortwave reflectance, longwave emission and reflection, evapotranspiration, H_2O flux, CO_2 flux, lightning strikes and distance, phenology, precipitation, reflectance and sun-induced fluorescence, relative humidity, sensible heat flux, snow and rain rate, up- and downwelling photosynthetically active radiation (PAR), visibility, wind direction, wind speed
Tower platforms in the tree canopy	Air temperature, leaf inclination angle distributions, atmospheric H_2O/CO_2 mixing ratios, precipitation, relative humidity
Clearing	Air temperature, precipitation, relative humidity, up- and downwelling long- and shortwave radiation, wind direction, wind velocity, cloud base height, cloud cover, mixed-layer heights
Tree leaves	**Chlorophyll fluorescence, leaf relative humidity, leaf temperature, PAR,** water potential, leaf gas exchange: CO_2 and its carbon isotopes, H_2O, volatile organic compounds (VOCs)
Tree stems	Sap flux, stem flow, **stem radial variation**, stem water potential
Below-canopy	Air temperature, atmospheric H_2O/CO_2 mixing ratios, atmospheric pressure, CO_2 flux, evapotranspiration, H_2O flux, latent heat flux, relative humidity, sensible heat flux, shortwave irradiance, phenology, **precipitation throughfall,** soil CO_2, soil and litter VOCs, **soil water infiltration,** Plant Area Index (via permanent terrestrial LiDAR (Light Detection and Ranging)), Leaf Area Index (LAI) (via digital hemispherical photographs)
Below-ground	Soil heat flux, soil water content, soil temperature, soil water potential, CO_2 mixing ratio in soil air (ppm)
Campaign-based	Ambient VOC mixing ratios, VOC fluxes with relaxed eddy accumulation (REA) system, vertical gradient of VOC mixing ratios, stem and leaf VOC fluxes, soil VOC exchange, vegetational change (drone-based LiDAR and spectral sensing), soil respiration, respiratory quotient in soil, leaf water potential

A central feature of the ECOSENSE project is the high spatial resolution of forest measurements, enabled by the deployment of a wide range of sensing technologies. Both commercially available instruments and newly developed sensors were implemented to capture environmental processes across multiple spatial scales. The monitoring system was designed to cover macroscopic (> 10 cm), mesoscopic (< 10 cm and > 1 cm) and microscopic (< 1 cm) dimensions. Macroscopic sensors were primarily installed on the ground and within tree stems, mesoscopic devices extended measurements into branches and twigs and miniaturised lightweight sensors were attached directly to individual leaves.

In the following, we briefly describe a selection of notable sensors, measurements and systems, from above-canopy to ground-based. We refer to **Table S2** in the supplements for a complete list of all deployed devices, including manufacturers, model numbers, quantities and other useful information, such as associations with larger systems. Devices listed there and mentioned in the text are marked with #.

Monthly airborne LiDAR scans conducted via drone overflights generate geospatial point clouds used to monitor the forest's structure (Gassilloud et al., 2025). To further characterise vegetation structure, permanent terrestrial laser scanners# on the ground provide a daily estimate of the plant area index (Calders et al., 2023). Monthly digital hemispheric photographs# are used to estimate the LAI (Zhang et al., 2005). Both indices represent the amount of plant surface area – either total or leaf-

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specific – and play a key role in influencing ecosystem processes while providing insight into a changing vegetation structure. Complementing these structural measurements, canopy and below-canopy phenology is tracked with two phenocams# mounted on the mixed plot tower (Brown et al., 2016).

The same tower platform also hosts a high-resolution, non-imaging spectrometer system# for continuous and spectrally resolved measurements of vegetation reflectance and sun-induced chlorophyll-a fluorescence above the canopy. In addition, the top platform supports an above-canopy eddy covariance system# that continuously measures wind fluctuations, air temperature fluctuations and density changes of CO_2 and H_2O and on-site calculates ecosystem sensible heat, CO_2 and H_2O fluxes. Approximately 10 m below, a relaxed eddy accumulation (REA)# system (Kunz et al., 2025; Sarkar et al., 2020) is installed to measure VOC fluxes in campaign mode, complemented by soil VOC fluxes (Kreuzwieser et al., 2025). At canopy height (approximately 26 m) a network of 26 leaf-angle cameras# (Kattenborn et al., 2022, 2024; Kremer et al., 2025) monitors leaf movement to investigate radiative transfer, relationships with water supply and related physiological plant stress. Leaf gas exchange, leaf $\delta^{13}C$ discrimination and biogenic VOC (BVOC) emissions from 24 leaf enclosures located in the sun and shade canopies of European beech and Douglas fir trees are continuously monitored using a gas sampling system comprising a zero-air supply and automated switching, measurement and flushing units (Werner et al., 2021). Six cavicams# (Brodribb et al., 2016) measure branch shrinking and swelling, enabling continuous monitoring of xylem water potential. Along the tower profile, a custom-built gas sampling system draws air from 12 inlets at different heights for sequential on-site measurements of CO_2 and H_2O concentrations. With this data we calculate CO_2 storage below and inside the canopy used to correct above-canopy eddy covariance measurements (Foken et al., 2012). Inside the measurement container, the air sampled along the height gradient can also be directed to other analysers usually connected to the leaf gas exchange system mentioned above, e.g., to a carbon isotope and gas concentration analyser# and a proton-transfer-reaction time-of-flight mass spectrometer# to determine $\delta^{13}C$ values and VOC concentrations, respectively. At ground level, eddy covariance measurements are conducted beneath the canopy (Douglas fir and beech plots) (Paul-Limoges et al., 2017). An additional REA system is deployed in the Douglas fir plot. This distributed network enables atmospheric quantification of CO_2 and H_2O fluxes across different forest strata. In addition to the measurement plots, three intensive soil measurement plots were established near the Douglas fir and mixed towers. At these plots, soil CO_2 efflux is estimated using the gradient method (Maier and Schack-Kirchner, 2014), which applies moisture-specific gas diffusivity to determine fluxes at increasing radial distances from three selected tree stems. To continuously monitor soil CO_2 dynamics, one of the intensive plots was equipped with low-cost soil CO_2 sensors enclosed by specially manufactured gas-permeable membranes, while the other two plots were equipped with established soil CO_2 sensors. Alongside these measurements, an extensive sensor network was deployed across the site to monitor ecosystem functioning at multiple spatial and temporal scales. The most represented sensors at the site include 507 soil moisture probes# distributed across multiple soil depths to quantify infiltration and water availability, 58 sap flux sensors# to assess tree-level water use and 20 soil CO_2 sensors# to monitor carbon cycling and related processes such as soil CO_2-efflux and water retention. Precipitation is recorded using 20 tipping-bucket gauges# and 13 air temperature and humidity sensors# provide reference data and microclimatic/vertical differences.

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In addition to the commercial instruments, a suite of newly developed sensors was deployed to expand measurement capabilities and overcome persistent challenges in environmental monitoring (details in the following paragraph). Rainfall redistribution in the forest is measured by **5 throughfall trough systems**# below the canopy and **12 stemflow collar systems**# around selected trees. Spread in a stratified sampling pattern across the ECOSENSE forest, **60 self-developed infiltration samplers** measure infiltration of both canopy throughfall and stemflow from the forest floor into the soil (Dedden and Weiler, 2025). A total of **33 self-built dendrometers**# were installed to record stem radial variation and growth dynamics (Dumberger et al., 2025). Furthermore, **newly developed leaf-scale sensors**# (Wallrabe et al., 2025) were implemented. These consist of three complementary modules that can function as part of a system but can also be deployed independently: (i) a minimally invasive gas sampling cuvette (ECOvette#) for CO_2, $\delta^{13}C$, H_2O and VOC fluxes, connected via tubing to a centralised gas analyser (Frey et al., 2025b), (ii) a sensor module measuring leaf and ambient temperature (Frey et al., 2025a), relative humidity and PAR (Klüppel et al., 2025) and (iii) a chlorophyll fluorescence sensor (Baghbani et al., 2025). They are operated by **newly developed microcontroller platforms** that enable unified control (Shinde et al., 2025) and data transmission via the LoRaWAN network+ (Bäumker et al., 2019). There are currently **22 chlorophyll fluorescence sensors#, 27 ECOvettes#** and another **22 self-built needle-cuvettes#** installed on Douglas fir trees distributed across the forest. All of these are equipped with **PAR and temperature sensors#.** Cuvettes additionally measure air humidity inside and outside the leaf enclosure.

The functioning of all above-described environmental sensors is regularly challenged by high variability in relative humidity, intensive rainfall and storms, fog (condensation), air temperatures below 0 °C in the winter months, high air temperatures and UV irradiation during the summer months, tree motion and the presence of animals and insects. Under these conditions, all sensors and electronics need to be robust and suitable for long-term and continuous measurements or regular campaigns. We therefore discuss some challenges encountered and the lessons learned from operating the sensor network in the ECOSENSE forest. To ensure water resistance and enhance long-term durability, sensor boards were coated with Plastic70. The electrical contacts remained uncoated for maintenance and reflashing of microcontrollers. Parylene C was used to prevent gas diffusion of newly developed leaf cuvettes. Within the ECOSENSE project, we additionally work on novel, nanostructured perfluoroacrylate-based coatings preventing biofouling and soiling on sensitive sensor surfaces. The exposure to wind and resulting tree motions are particularly challenging for measurement devices attached to branches and leaves, as it can induce vibrations and sudden displacements at high speeds and accelerations. To mitigate this, sufficient slack was left in the power cables and gas sampling tubes connected to affected sensors, allowing them to absorb wind-induced forces. In addition, predetermined breaking points were incorporated into both cables and tubing to reduce the risk of damage. A range of sensors attached to branches and leaves operate on batteries instead of wind-prone power cables, but this introduces other challenges: batteries are difficult to replace in the canopy and add weight that stresses leaves and twigs, counteracting our lightweight design approach. To enhance overall system resilience, we therefore work towards energy autonomy. Wind, however, not only affects sensors but also our towers. We found that they move with unexpected variability under windy conditions. Therefore, in spring 2025, we added tube insulation as tower padding to minimise the impact of towers on surrounding trees and in particular sample branches. Another source of equipment malfunction arises from various animals present in the forest, such

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as voles, birds, wild boars, snails and insects. Issues arose, e.g., from insects feeding on leaves equipped with cuvettes and voles gnawing on sensors and cables or nesting inside infiltration sampler systems. Combined measures of increased physical barriers and chemical repellents, such as metal grids in the soil, cable channels with steel wool and chilli spray on cable insulation, proved effective. Overall, regular maintenance and repair remain tasks whose time expenditure should not be underestimated and should be considered in project planning.

3 From measurements to data

The research data life cycle of the various, heterogeneous data streams originating from all instruments can be structured into a hierarchical data acquisition framework (**Fig. 4**). The framework resembles a funnel, starting broad with diverse sensors measuring numerous environmental variables across the ecosystem and gradually narrowing as data are transmitted, unified and processed. Ultimately, all streams converge into centralised servers and databases, ensuring structured, consistent and accessible datasets for scientific analysis and long-term archiving.

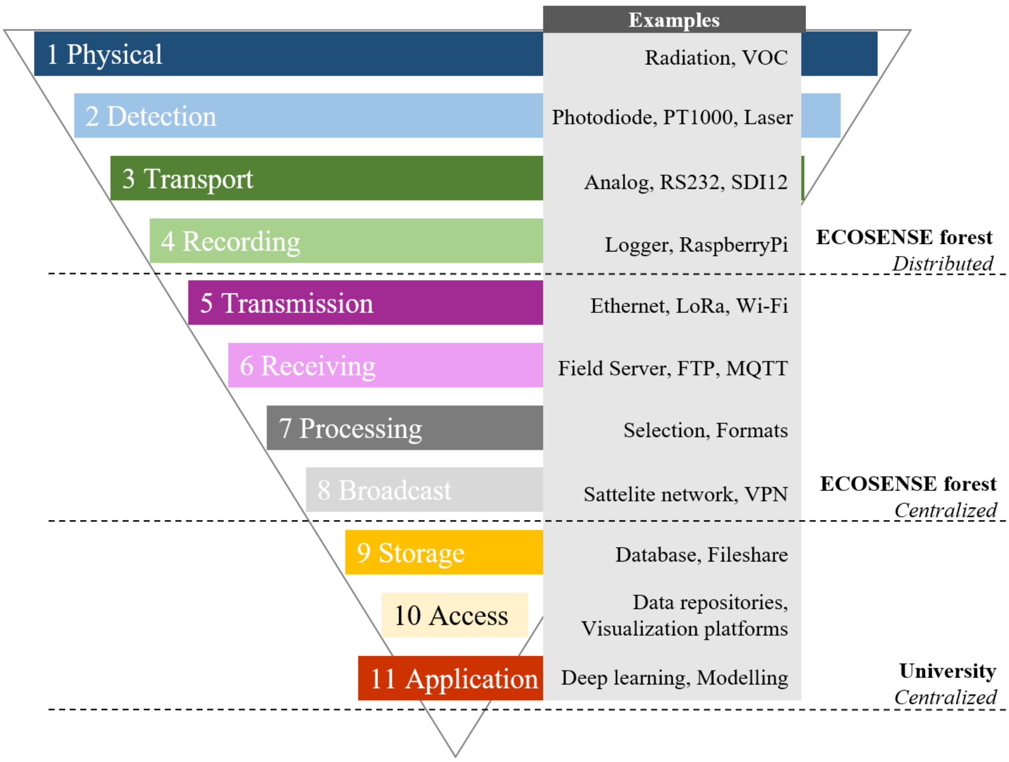

Figure 4: Layer model of the data collection.

The physical layer (1) represents all environmental and ecosystem variables and fluxes measured. Sensors are the detectors (2) that directly measure variables or related proxies and transport the data (3) using different communication protocols (e.g., SDI-

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12, analog, RS232) to recording devices (4), mostly commercial or self-built data loggers. These devices transmit the data (5) via Ethernet, Wi-Fi, or LoRaWAN to various receivers (6), such as the server in the measurement container or "The Things Network". The server offers a range of services (see also **Table S1**), e.g., FTP server (file transfer protocol), HTTP interface (hypertext transfer protocol), MQTT (Message Queueing Telemetry Transport) broker, virtual machines with specialised software, e.g., "NoteRed" for processing. All data streams, with the exception of campaign data, which are typically processed off-site, converge at the FTP server hosted on the server. The server functions as a central hub for initial data handling (7), i.e., parsing and preprocessing data with Python scripts into a unified format to ensure consistency across data sources and reduce data volume. Once formatted, the processed data are then broadcasted to the university network via VPN-secured, satellite-based internet (8). There, time-series data are stored (9) in a specific SQL database ("Aquarius"[+]). Spatial or complex data are temporarily held locally for further processing and made available later on the shared network-attached storage (NAS). The university-based NAS infrastructure functions as a centralised repository, where project members can access (10) data internally – either through file-based access or the SQL database – and interactively explore it using tools such as Grafana (Grafana Labs, 2025, compare **Fig. 5**). While pure data access is currently restricted to project members, derived data products (see **Sec. 4**) may already be available. Completed datasets are published in open repositories to ensure open-source accessibility for the wider research community. Meanwhile, the acquired data are actively employed (11) for scientific analyses, including ecosystem model evaluation, model forcing and training of deep learning algorithms (see **Sec. 4**).

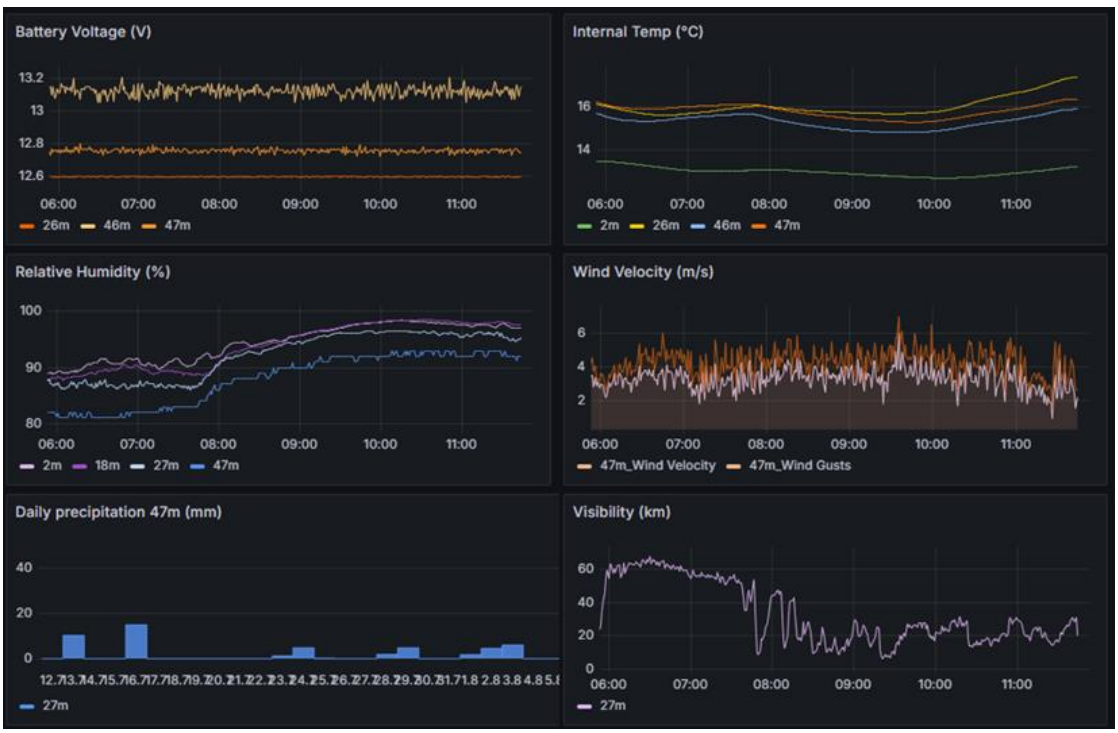

Figure 5: Screenshot of Grafana dashboard showing data from weather stations installed on above-canopy tower.

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The end of the research data life cycle comprises the structured data publication and archiving, ensuring that data remains **F**indable, **A**ccessible, **I**nteroperable and **R**eusable (FAIR, Wilkinson et al., 2016) for future research. This is implemented and supported via the University of Freiburg's publication platform "FreiData" (https://freidata.uni-freiburg.de/), which provides storage, registers digital objects and generates their DOIs. For large remote-sensing datasets, such as aerial imagery and LiDAR point clouds that often exceed several gigabytes, storage and archiving are provided by the domain-specific hubs "deadtrees.earth" (aerial imagery, https://deadtrees.earth/) and "3Dtrees.earth" (LiDAR scans, https://3dtrees.earth/), which are hosted at the University of Freiburg and supported by the National Infrastructure of the Earth System sciences (NFDI4Earth). These platforms also enable rapid access, interactive web visualisation and AI-based data analytics (Möhring et al., 2025; Mosig et al., 2024). In parallel, several data streams recorded in EOCSENSE are ingested in specific databases, including the global PhenoCam Network (https://phenocam.nau.edu/) and the European Fluxes Database (https://www.europe-fluxdata.eu/), contributing to broader coordinated environmental monitoring frameworks.

Having defined the layered architecture – from physical measurement through transport, processing, storage, access, quality control and FAIR publication – we now elaborate how this operates from four end-to-end streams from the forest to data publication. We depict four different flows as data are primarily acquired from those distinct sources: **commercial sensors** which are connected to loggers communicating via Ethernet or Wi-Fi, **novel sensor systems**, built on low-power microcontrollers transmitting data through wireless LoRaWAN nodes and a LoRaWAN gateway linking to "The Things Network", on-site scientific instruments producing **complex data**, such as gradient gas sampling setups and eddy covariance systems that analyse and partially process on-site using dedicated virtual machines, **campaign-based data collection**, where measurements are gathered during field campaigns and stored locally on internal memory devices. These four exemplary data streams, their transmission, broadcasting and application are depicted in **Fig. 6**.

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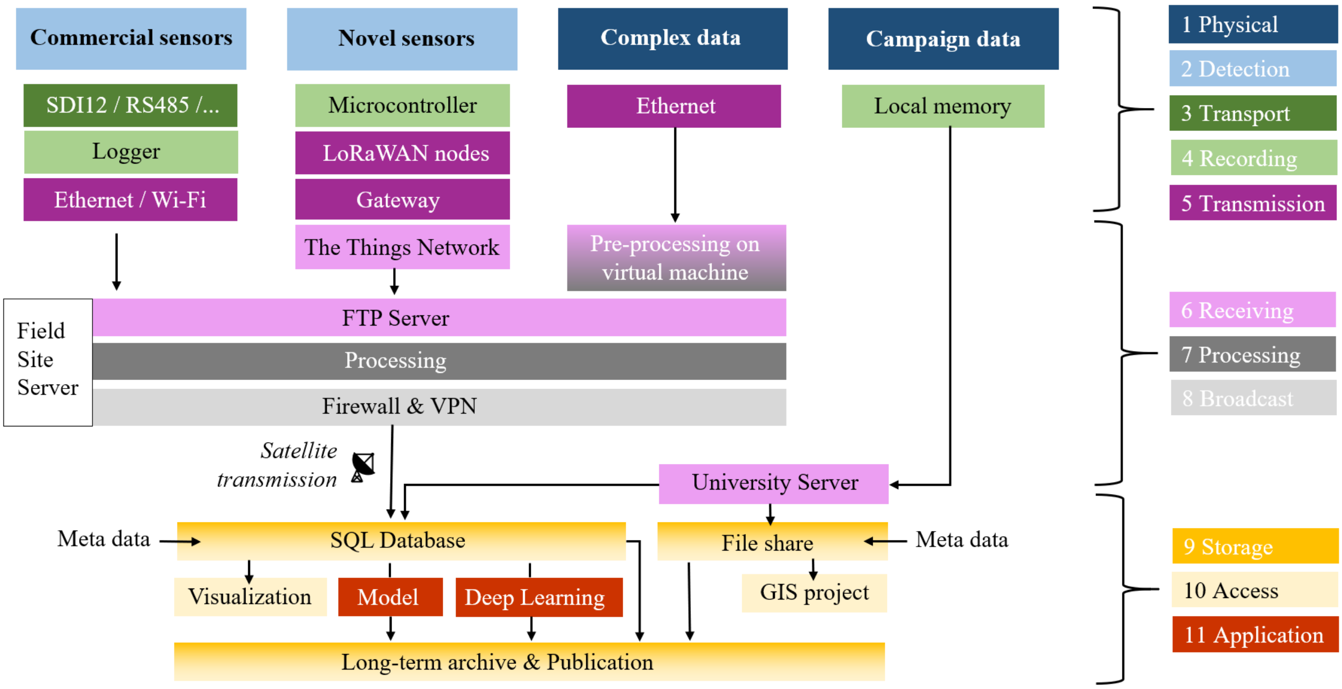

Figure 6: Flowchart data collection in the ECOSENSE forest.

It is worth noting that the current top-down workflow shown in **Fig. 5** and **Fig. 6** is planned to become a loop. One of the key future directions involves feeding outputs from modelling and deep learning processes back into the field operations. For example, insights gained from pattern recognition could trigger adjustments to a sensor's measurement interval or the number of sensors measuring. This adaptive feedback loop would not only enhance the scientific value of the data but would also improve the efficiency and intelligence of the monitoring setup.

As mentioned above, we aim to ensure the FAIR principles for all data collected. Essential components of FAIR data are the systematic documentation and preservation of metadata associated with all spatial and temporal datasets (Wilkinson et al., 2016). Each time series is accompanied by key contextual information, including spatial coordinates, instrument identifier, data ownership, measured parameter, unit of measurement, sampling interval, observation period and time reference. Due to predetermined and unalterable database architecture, it is not possible to integrate all metadata into the active datasets using a standardised schema. Therefore, upon completion of each time series metadata are appended in the form of XML or JSON schema files, in accordance with an appropriate metadata standard, i.e., "DataCite" (Brase, 2009). The specific metadata standard is selected in consultation with the Central Data Facility (CDF) of the University of Freiburg and NFDI4Earth, with the goal of ensuring long-term interoperability and broad usability.

In general, the scientific value and (re-)usability of environmental data depend on the data quality. Real-time monitoring enables early detection of anomalies or sensor malfunctions, minimising data gaps and poor-quality measurements. After data collection, the implementation of quality control procedures is an important aspect within the ECOSENSE project. Rather than

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removing questionable measurements, nearly all observations are retained and assigned a quality flag on a per-data-point basis. Three categories are applied: good, fair and poor. Data flagged as good have passed certain checks and are deemed reliable for analysis. Data flagged as fair may be plausible but come with uncertainties that might require inspection in further analysis, while poor data should be treated with substantial caution and might not be suitable for subsequent analysis. The only values permanently removed from the dataset are those resulting from major technical failures, where it is certain that no valid measurement was obtained. The type of quality control applied depends on the measured parameter, but common approaches include variance analysis, threshold testing and cross-checking with related variables (e.g., substantial increases in soil moisture must be preceded by precipitation). While some of these processes are automated through scripts, much of the evaluation still relies on expert judgement via visual inspection. Ultimately, the goal is to publish all data with quality flags.

4 From data to information

Transforming raw data into meaningful information is a central objective of environmental monitoring and research. This process involves multiple layers of interaction with the data, both in real-time and retrospectively, serving internal and external purposes. At its core, environmental datasets form the foundation for scientific research and publication. They can be analysed for mechanistic relationships and used for comparative studies and long-term ecological analyses, potentially after development or improvement of physiological process-based models that describe these relations.

4.1 Terrestrial ecosystem modelling

The collected data are further used to evaluate models and explain ecosystem responses to environmental changes using data and models. Therefore, it is essential to obtain representative ecological and biophysical knowledge from measurements at small scales, e.g., leaf-level, derive course-effect relationships, put these into functional and process-based relationships and apply rules about how triggers and processes are temporally and spatially related, considering bidirectional interactions and feedback loops (see e.g., Mahecha et al., 2010). Both functional relationships as well as scaling laws have been integrated into physiological-oriented, process-based models such as LandscapeDNDC (Grote et al., 2011a; Haas et al., 2013). This dynamic vegetation model has been initialised, applied and will be further developed with data obtained at the ECOSENSE forest. It has been demonstrated that the model covers full carbon-, nitrogen- and water balances as well as growth responses of various forests (Cameron et al., 2013; Grote et al., 2011b; Mahnken et al., 2022). The intriguing aspect of this model is that it not only considers microclimate in high vertical resolution, but is also capable of representing very small soil- (e.g., N_2O, Cade et al., 2021) and plant-related fluxes (incl. biological volatile organic compounds, Havermann et al., 2022). Such models can serve as an instrument to analyse small scale observations and to use this knowledge to estimate larger-scale impacts of particular environmental influences. Thereby, it is possible to evaluate previous knowledge, estimate unmeasured fluxes (gap-filling), test the plausibility of measurements at different scales, judge the importance of specific findings for the ecosystem response and extrapolate responses beyond observed impacts in scenario analyses. At the same time, measurements will reveal

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mismatches between real-world responses and the model's virtual reality, which is important information to adjust the model's functionality and parameterisation. Confirmatory or deviating results could also guide a reduction and/or intensification/redistribution of sensors in order to increase their efficiency.

4.2 Deep-learning

A complementary approach to the described process modelling is a data-driven analysis of interrelations among measurements. The breakthrough in neural network-based machine learning, typically referred to as deep learning or artificial intelligence (AI), also facilitates using a different form of inputs. When traditional statistical and machine-learning approaches use tabular data, deep learning can mix those with time series, images and even sound and video information (Pichler and Hartig, 2023). However, such flexibility comes at a cost: firstly, the amount of data required to fit deep learning models is substantially larger than for the less flexible traditional regression-like approaches; secondly, the resulting multi-dimensional representation of data in such a network typically remains extremely opaque, despite attempts to deduce the main relationships implicitly encoded (through "explainable AI": Adadi and Berrada, 2018; Briegel et al., 2020; or symbolic regression: Udrescu and Tegmark, 2020). What we get is a representation of the interrelationship of observed data. Since the neural network is ignorant of biology and physics, some of these relationships will be indirect or spurious and this is where the complementarity with the process-based models arises. We can efficiently explore, for specific environmental conditions, how deep-learning models predict the tree or stand response. These data-driven relationships and hypotheses emerging from them can subsequently be tested with physiology-oriented models. Discrepancies between the two approaches can then be investigated in detail. Is the process correctly depicting our biological understanding for this specific situation? Did our process-based understanding lack cardinal components? Or is the lack of auxiliary data the reason why the neural network makes deviating predictions?

4.3 Transforming measurements to a digital twin and virtual reality

To ground model-based analyses in field data, all sensor systems, infrastructure and trees in the 3-hectare core zone of the ECOSENSE experiment are precisely georeferenced using GNSS (Global Navigation Satellite System). Regular terrestrial and drone-based laser scans capture the architecture and seasonal dynamics of every tree, creating a detailed and living 3D structural model of the forest. This dynamic 3D representation together with the sensor-derived data streams form the foundation for the ECOSENSE 3D digital twin, developed in collaboration with the XR Future Forests Lab at the university campus. Using advanced engines like Unity (Unity Technologies, 2025) and Unreal (Epic Games, 2025), the 3D digital twin is brought to life in immersive virtual reality (VR), offering realistic and interactive experiences of the ECOSENSE site (**Fig. 7**). VR opens new dimensions for teaching and outreach. It allows hundreds of students to virtually "walk" through the forest without setting foot on site and can bring ECOSENSE to people around the world. Hidden sensors, buried in the soil or perched high in the canopy, become visible and invisible processes like CO_2 fluxes, sap flux and soil-plant-atmosphere interactions are animated in space and time. As the temporal coverage of the ECOSENSE forest grows, the 3D digital twin will also allow

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users to "time travel" through the site's development and dynamics, enabling an interactive and immersive experience of ecological change across years.

Figure 7: Virtual Reality (VR) representation of the ECOSENSE forest based on the 3D Digital twin. The visualisations are based on the Unreal 3D engine, enabling immersive virtual "walks" through the ECOSENSE site.

4.4 From tree to data stream: field access via QR codes

During the GNSS-assisted inventory of the ECOSENSE site, approximately 1,400 trees not only received precise coordinates and a unique identifier, but also a durable physical tag featuring a scannable QR code and an alphanumeric ID. These QR codes can be accessed with any smartphone or tablet and link directly to the ECOSENSE database (**Fig. 8**). This includes structural properties of that tree as obtained from LiDAR campaigns (e.g., crown volume, height, position) and the sensor-based data streams. Moreover, this system transforms the forest into a living, responsive archive: users in the field can not only instantly retrieve data but they can also input data – whether it is recording a mortality event, updating diameter measurements, or documenting sensor maintenance.

For students and researchers alike, the QR code acts as a gateway into the tree's digital history. Linked metrics like height, crown dimensions, or growth rates provide insight into individual development. Moreover, time series from associated sensors, such as sap flux or soil moisture, can be directly accessed and visualised on mobile devices, contextualising tree responses to environmental conditions. In essence, these QR codes turn each tree into a smart node within the digital twin of ECOSENSE, revealing processes and ecological dynamics in real time or from the past.

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Figure 8: Field access to tree-level data streams. Scanning a QR-coded tag on a tree launches the ECOSENSE Shiny app on a smartphone, retrieving the associated tree information, such as time series from the central database.

4 Conclusion

In response to the growing vulnerability of forest ecosystems to climate-induced stressors, the ECOSENSE forest observatory offers a comprehensive, integrated platform to monitor and better understand ecosystem dynamics. Following our design criteria, the presented infrastructure enables high-resolution sensing, both in space and time, across different ecosystem compartments and scales, with a variety of commercial and novel sensors. We established distributed power and communication systems and a flexible data infrastructure capable of managing, accessing and analysing heterogeneous, large datasets, also remotely. This co-designed environmental observatory demonstrates the potential of integrated monitoring systems to advance environmental research and inform more effective forest management and conservation strategies.

Designed as a transferable blueprint for future observatories, the ECOSENSE forest showcases how modular, multi-sensor networks can be deployed in structurally complex environments. Establishing the infrastructure – including three measurement towers, grid connections, a measurement container and a site-wide communication network – required more than two years. Beyond financial and technical challenges, the organisational and regulatory demands were considerable, involving expert assessments and permits such as ordnance clearance, species protection evaluations and structural analyses of the tower statics.

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These experiences underscore the logistical, administrative and environmental complexities involved in building and operating such advanced ecosystem monitoring platforms. This is particularly true for research projects that are often limited to a few years and thus under considerable time pressure.

Despite these challenges, the ECOSENSE forest provides real-world experience for developing similar observatories. While not a one-fits-all solution, ECOSENSE offers practical insights into the design and implementation of integrated monitoring systems. We hope that the descriptions of this field site can support others in establishing similar infrastructures and foster continued innovation in ecosystem monitoring across different environments and research needs.

Supplements

Table S1: Bill of Material (BoM)

Table S2: Sensor Inventory

Code/Data availability

This study did not involve the generation or analysis of new data and code; hence, data sharing does not apply.

Author contribution

JT, KK and DW prepared the original manuscript with contributions from all co-authors. AC, CD, JF, RG, TK, MS, UW, MW, CW supported the conceptualization of the manuscript. AC, CD, UW, MW, CW, LC, AG, SH, OP JR, SJR, HSK acquired the projects' funding. AC, CD, RG, TK, UW, MW, CQ, AG, JKR, OP, JR, SJR, HSK scientifically supervised the research. KK, DW, JS provided the technical infrastructure and support of the project. JMÜ did the administration. SB, JB, LD, SD, YF, MG, TG, AG, SH, JKL, LK, JKR, HL, SKR, US, TS, CST conducted the research and developments. JT, KK, DW, MS, JMA contributed visualizations. JMA, CSC, JS realized software solutions.

Competing interests

The authors declare that they have no conflict of interest.

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We used AI (ChatGPT) for a final spelling and punctuation check of the manuscript.

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