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Grant Proposal

ECOSENSE - Multi-scale quantification and modelling of spatio-temporal dynamics of ecosystem processes by smart autonomous sensor networks

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Abstract

Global climate change threatens ecosystem functioning worldwide. Forest ecosystems are particularly important for carbon sequestration, thereby buffering climate change and providing socio-economic services. However, recurrent stresses, such as heat waves, droughts and floods can affect forests with potential cascading effects on their carbon sink capacity, drought resilience and sustainability. Knowledge about the stress impact on the multitude of processes driving soil-plant-atmosphere interactions within these complex forest systems is widely lacking and uncertainty about future changes extremely high. Thus, forecasting forest response to climate change will require a dramatically improved process understanding of carbon and water cycling across various temporal (minutes to seasons) and spatial (leaf to ecosystem) scales covering atmosphere, biosphere, pedosphere and hydrosphere components.

Many relevant processes controlling carbon and water exchange occur at small scales (e.g. rhizosphere, single leaf) with a high spatial and temporal variability, which is poorly constrained. However, interactions and feedback loops can be key players that amplify or dampen a system's response to stress. Moreover, spatial and temporal scaling rules for these non-linear processes in structurally and functionally diverse ecosystems are unknown. Legacy effects, for example, altered response after previous stress and retarded recovery of forests after climate extremes, are not captured in state-of-the-art models. Currently, we are lacking the appropriate and interconnected measurement, data assimilation and modelling tools allowing for a comprehensive, real-time quantification of key processes at high spatio-temporal coverage in heterogeneous environments. Moreover, since climate impacts are highly unpredictable with respect to timing and location, future research will require novel mobile, easily deployable and cost-efficient approaches. ECOSENSE, therefore, assembles expertise from environmental and engineering sciences, both being excellently paired at the University of Freiburg.

Our interdisciplinary research project will investigate all relevant scales in a next-generation ecosystem research assessment (ECOSENSE). Our vision is to detect and forecast critical changes in ecosystem functioning, based on the understanding of hierarchical process interaction. In the first phase, ECOSENSE will explore these process interactions by investigating pools and fluxes of water and carbon, i.e. CO_2 exchange,

isotope discrimination and volatile organic compounds (VOC), as well as stress indicators by remotely and in situ sensed chlorophyll fluorescence.

To address these research tasks, ECOSENSE will develop, implement and test a distributed, autonomous, intelligent sensor network, based on novel microsensors tailored to the specific needs in remote and harsh forest environments. They will measure the spatio-temporal dynamics of ecosystem pools and fluxes in a naturally complex structured forest system with minimal physiological impact. Measured data will be transferred in real-time into a sophisticated database, which will be explored for process analysis, conducted by Artificial Intelligence and close to real-time process-based ecosystem models for now- and forecasting applications. Thereby, ECOSENSE will: i) break new ground for integrative ecosystem research by identifying hierarchies and interactions of abiotic and physiological processes of forest carbon and water exchange, ii) provide a profound understanding of complex ecosystem responses to environmental stressors and iii) enable the prediction of process-based alterations in ecosystem functioning and sustainability.

Our novel ECOSENSE toolkit, tested and validated in controlled climate extreme experiments and our ECOSENSE Forest, will open new horizons for rapid assessment in vast and remote ecosystems. Thereby, ECOSENSE will allow for a unique avenue of data acquisition and, consequently, for unprecedented scale-crossing ecosystem understanding and modelling.

Keywords

ecosystem processes, ecosystem fluxes, ecosystem models, climate change, microsensors, energy-autonomous, intelligent sensor network

Research profile of ECOSENSE

Introduction

The Collaborative Research Centre (CRC) ECOSENSE will quantify, understand and predict forest ecosystem processes in the context of climate change across scales, spatially from root/leaf to forest stands and temporally from seconds to years, capturing fluxes from the hydrosphere, pedosphere, biosphere and atmosphere (Fig. 1).

Key challenges of forest ecosystems are their heterogeneity and unknown non-linear upscaling laws of processes from the leaf to a whole forest ecosystem. ECOSENSE aims to derive these upscaling laws, which requires sensing, analysis and modelling of the heterogeneity with a unique spatio-temporal resolution.

We will enable this holistic approach by new dedicated robust sensing mechanisms and their implementation into a novel and smart sensor network. Our multi-scale models will integrate data across scales, derive and establish new scaling laws, optimise sensing and predict impacts of climate extremes.

ECOSENSE brings together experts from environmental sciences and microsystems engineering. Both research fields are especially strong at the University of Freiburg and unique in this combination. Joining their forces fits excellently into the vision of the University, the green city of Freiburg and the region of the Black Forest. The *Faculty for Environmental Sciences and Natural Resources* – UNR – embraces a 100-year-tradition of forest science and stands for a broad view of ecosystem research across all scales. The *Faculty of Engineering* was founded in 1995 and is growing rapidly. With the Department of Microsystems Engineering – IMTEK – the Faculty of Engineering comprises the largest microsystems research facility in Germany.

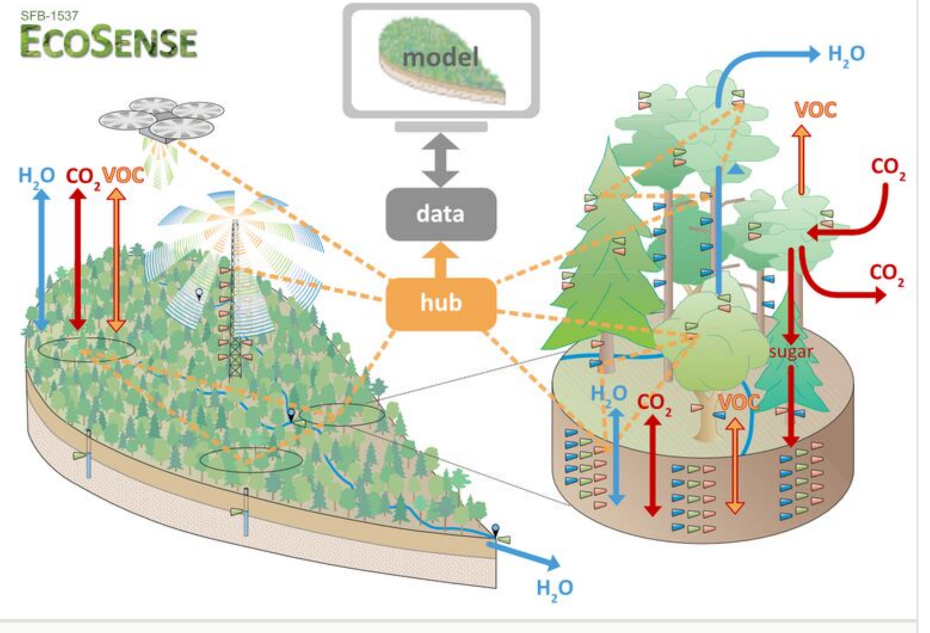

Figure 1. doi

ECOSENSE next-generation ecosystem research assessment.

Our research proposal targets forest ecosystems, as they provide important climate regulatory functions, sequestering roughly 20-25% of global anthropogenic CO_2 emissions each year (Le Quéré et al. 2018, Pugh et al. 2019). Global climate change endangers the sustainability of forest ecosystems with unpredictable and potentially cascading effects on complex physiological processes and interactions within ecosystems (Anderegg et al. 2018). For example, the 2018 heat wave over Europe induced canopy die-back and hydraulic failure in many forests (Schuldt et al. 2020, Walthert et al. 2021). In contrast to managed agricultural systems, response and regeneration times of forest ecosystems are much longer (Williams et al. 2014). Legacy effects, for example, altered response after previous stress (McDowell et al. 2020), are still poorly understood. Identifying tipping points and thresholds of forest functioning will be crucial to ensure effective conservation and mitigation actions. Thus, there is an urgent need to better quantify and predict ecosystem processes in response to climate extremes and characterise the key processes determining forest resilience.

Multiple interactions of biotic and abiotic drivers and complex feedback loops foster spatio-temporal dynamics and heterogeneity in forests from leaf to ecosystem. While it is known that climatic extreme events, such as heat waves, droughts, frosts or beetle attacks, induce stress effects, the observed strong local variability, for example, single tree die-back (Schuldt et al. 2020), is not well understood. Sites/events with a disproportional impact on net carbon and water fluxes, i.e. “hot spots” and “hot moments” (McClain et al. 2003), can have long-lasting impacts on ecosystem functioning, in both a positive or negative manner. For example, over 10% of the annual carbon uptake of diverse ecosystems was observed to take place in the 2% most productive hours (Kannenberg et al. 2020). Inversely, a significant amount of carbon can be lost during heavy rainfalls after dry periods, so-called Birch effects (Unger et al. 2010, Waring and Powers 2016). Moreover, the role of structural and functional heterogeneity of the forest is yet to be explored. Currently, only a few highly equipped sites exist in Germany (e.g. TERENO sites), which are mostly in flat terrain and do not well represent the complexity of our forest ecosystems.

Consequently, ecosystem research faces great challenges to capture relevant processes and their interactions. ECOSENSE will tackle these challenges. We will target the spatio-temporal dynamics of carbon and water pools and fluxes and relate them to the heterogeneous structure of a forest, from the soil to the canopy and the atmosphere. We will use, on the one hand, chlorophyll fluorescence as a sensitive stress indicator (Werner et al. 2002) for hot spots and hot moments, for example, during extreme heat and drought. On the other hand, photosynthetic isotope discrimination and analysis of Volatile Organic Compounds (VOC) will provide insights into plant regulatory responses (Haberstroh et al. 2019, Kreuzwieser et al. 2021), such as water-use efficiency (Werner et al. 2012) and induced stress responses (e.g. after bark beetle attacks).

A thorough quantification is labour-intensive and requires extensive equipment, logistics and computing capacity, which currently presents a major constraint to understand highly dynamic ecosystem processes. This urgent need can be met by novel smart sensor systems tailored to the requirements of remote forest areas (Gabrys 2020). In recent years, smart sensor systems have undergone tremendous development and now provide a key technology for all aspects of automation and Internet of Things (IoT). Miniaturised sensors, communication protocols (Mekki et al. 2019), energy harvesting (Cepnik et al. 2013) and low-power electronics (Wang et al. 2017) have been explored for years for a huge variety of application scenarios in industry (Talari et al. 2017), healthcare (Neves et al. 2008) and smart homes (Stoppa and Chiolerio 2014). Recently, also the integration of deep-learning (DL) for efficient sensor application has come into focus (Guo et al. 2019, Sepasgozar et al. 2020).

However, especially in the harsh and remote environment of a forest, the sensors must be robust and functional over long time spans at least for a vegetation period and preferably for many years. Many opportunities for applying environmental sensing exist and equipment is partly commercially available; however, these devices are typically bulky, heavy, maintenance-intensive, invasive and expensive. Consequently, due to limited resources, the number of sensors deployed in forest ecosystems is low, resulting in sparse spatio-temporal data coverage. This, in turn, leads to huge data gaps for detailed understanding and modelling of complex, multi-scale ecosystem processes. Furthermore, existing solutions lack mobility and are not easily transferable amongst sites or ecosystems. Finally, we still lack miniaturised energy-autonomous sensors suitable for the also energetically harsh conditions present in a forest and equipped with "smartness" to cope with it.

Future sensors for forest ecosystem research must be affordable and easily deployable in large numbers and provide the capability of being widely distributed. They need to be small, minimally invasive, intelligent, energy-autonomous and wirelessly connected in a smart sensor network. Furthermore, they must be robust in terms of temperature, humidity, dirt or biofouling and, finally, if small sensors are lost, they need to be located to retrieve them from the environment. A multitude of such distributed sensors will provide a plethora of data for which deep-learning-based methods enable the deconvolution of the underlying processes driving spatio-temporal heterogeneity. This will then allow the implementation of these processes into existing ecosystem models, which currently address structural and functional heterogeneity based on widely simplified assumptions. The new information about such spatial heterogeneity will, on the one hand, enable the refinement of the model structure and, on the other hand, the optimisation of sensor distribution and activity.

To overcome our: (i) restricted view on processes driving ecosystem functioning, (ii) limitation in suitable sensors and smart network technology and (iii) limitation in models representing spatio-temporal dynamics, ECOSENSE proposes a fully interdisciplinary approach, bridging science and technology across all relevant scales in a next-generation ecosystem research assessment. We will integrate measurements of the hydrosphere, pedosphere, biosphere and atmosphere within one smart, distributed, autonomous and intelligent ecosystem assessment system. The vast amount of data will be integrated in real-time into deep-learning and process-based modelling approaches that will be jointly used for now- and forecasting of carbon and water fluxes at leaf to ecosystem scale.

We hypothesise that only a novel concept of ecosystem analysis, seamlessly combining continuous observations and simulations of each relevant component across scales, will enable the identification of hierarchies and scale coherence of the driving abiotic and physiological processes and environmental triggers. Such a novel concept of integrated sensors, remote sensing, real-time data assimilation and model-based ecosystem analysis will enable us to identify thresholds of ecosystem functioning in response to global climate change and predict future developments.

Identification of knowledge gaps

Forests provide important ecosystem services due to their high ecological and socio-economic value, but climate extremes have enhanced tree mortality worldwide (Anderegg et al. 2019). Therefore, increasing the resilience and resistance of our forests to climate change is a major challenge. However, strong local differences of the stress impacts on our forest systems during extreme climatic events, such as local tree die-back during the 2018 drought in Germany (Schuldt et al. 2020), are not yet understood, but point towards the complex interplay between pedosphere (soils), hydrology, atmosphere and biosphere. These processes can amplify or buffer stress impacts on ecosystems through a cascade of biotic (e.g. competition and facilitation, Haberstroh et al. (2021)) and abiotic factors (e.g. soil moisture, air temperature and humidity). However, knowledge on the underlying mechanisms enabling informed predictions on a spatially resolved scale is lacking.

It has been recognised that structural heterogeneity in forests can be an important factor for ecosystem stability and resilience against disturbances, such as storms (Bauhus et al. 2017, Ratcliffe et al. 2017). Generally, positive relationships have been found amongst species richness, ecosystem functioning and resilience to stress (Díaz and Cabido 2001, Grossiord 2020). More recently, there is also increasing evidence that spatial heterogeneity in communities may confer important aspects of functional stability, promoting facilitative interactions amongst species. For example, it has been shown that the sensitivity to changes in climate is dependent not only on the intensity of stress and soil type, but also, importantly, on the dynamics of individual-level competition within plant canopies (Aguirre-Gutiérrez et al. 2019), microclimatic conditions within the forest (Zellweger et al. 2020) and their interplay (Werner et al. 2021). Thus, these interactions can modulate ecosystem sensitivity, which is generally not incorporated in traditional models (Levine et al. 2016). Moreover, spatial heterogeneity is increasingly recognised as an important driver at the macro- and micro-scale. In soils, probably the most heterogeneous parts of the biosphere, it has been shown that hot spots and hot moments are important drivers of soil processes (Kuzyakov and Gavrichkova 2010, Miguez-Macho and Fan 2021). Even though the importance of these processes has been identified, we lack affordable and operational non-invasive measurement techniques to cover the relevant scales in complex forest ecosystems.

Essential processes in forests driving evapotranspiration and the carbon sink/source capacity are soil-plant-atmosphere CO_2 and H_2O exchange, which are thereby relevant to buffering or accelerating climate change (Bonan 2008). Moreover, forest ecosystems influence global climate and atmospheric chemistry by the release of volatile organic compounds (VOCs) into the atmosphere (Sindelarova et al. 2014), by impacting atmospheric chemistry and secondary organic aerosol formation (Fuentes et al. 2000). Typically, the scale of process function differs from the scale of process impact. Total ecosystem fluxes are not simply the sum of local processes that can substantially vary at small scale (e.g. soil microbe, fine root or leaf scale). However, process description is highly simplified in models: in extreme cases, single-leaf measurements are scaled up through big-leaf models to the ecosystem scale (assuming that the entire forest responds similarly to a single leaf (e.g. Farquhar et al. (1980)). In more sophisticated models, variability within the canopy species diversity is considered, but not the variability due to different tree sizes or the relationship between single tree canopies. In addition, also processes of plant-soil feedbacks are either neglected or not dynamically represented, specifically the interactions amongst root systems, soil organism activity and abiotic soil conditions, which strongly influence plant performance, ultimately driving ecosystem processes (Pugnaire et al. 2019). How to include processes for which we have limited process understanding is an emerging research field (Reichstein et al. 2019): deep learning can be used both as part of ecosystem models or as a bias-correcting step after the model (Zhao et al. 2019).

Obviously, to date, little is known of how these interactions quantitatively scale to ecosystem fluxes and even less about their potential changes under environmental or climate change. Hence, in spite of the increasing awareness of the relevance of small-scale processes, feedbacks and their interactions, we are currently unable to sufficiently quantify and evaluate their contribution to total ecosystem fluxes. This shortcoming is largely due to a lack of suitably-sized sensors, explicitly tailored to the measurement tasks in forests, which should be connected to a widely distributed sensor network capturing state variables and fluxes rapidly, locally and non-invasively. Moreover, we even lack knowledge on efficient sampling strategies: how often do we have to measure? How many sensors are needed at which spatial distribution? The answers will not only depend on the processes, but also on their spatio-temporal dynamics.

This is particularly relevant as hot spots and hot moments develop dynamically in space in time. A drought event or heat waves can be such a hot moment, with a disproportionate effect on net water and carbon balance (Ciais et al. 2005). Similar effects can be caused by locally restricted events, i.e. hot spots, such as local late frost injuries or beetle attacks of susceptible trees. Little is known on how hot spots and hot moments influence ecosystem fluxes as their impact can persist through time by locally altering plants' performance and resilience. These legacy effects are not well understood either, but may gain importance with increasing frequency and intensity of climatic extreme events. Neither these legacy effects nor the structural and functional heterogeneity within forests is currently represented in existing models due to missing data and incomplete process knowledge.

Therefore, large networks of distributed micro-sensors are mandatory to capture these spatio-temporal stress indicators and flux dynamics from the micro- (mm/s) to macro- (km/years) scales. They need to be combined with intelligent data acquisition and evaluation to feed, in a timely manner, deep-learning tools and process models for immediate assessment, as well as scenario analysis.

Sensor networks should be flexible in up- or down regulating measurement frequencies and require efficient handling of large data packets. Mature forest sites present a particular challenge, as canopy access is limited, energy supply and communication of sensors is out of reach of centralised grid solutions and seasons cause tremendous physical stress on in-situ technical systems. This is why tall forest stands are often restricted to point measurements at canopy towers (Pepin and Körner 2002), which are, however, unable to cover representative areas of the ecosystem.

Despite the manifold of existing IoT (Internet of Things) sensors and sensor networks, significant knowledge gaps remain for the application of wireless sensor networks in forests representing a specific kind of harsh environment. A recent review from Ullo and

Sinha (Ullo and Sinha 2021) argues that, in the field of remote sensing and agriculture, there is still a research need for new robust sensing methods and sensor systems. Particularly, this argument holds for forests, which stand for other timescales and hardly accessible areas.

A robust wireless network has been already installed for animal tracking in the rain forests of Borneo (Sethi et al. 2018), however, without environmental sensors. Several forest sensor networks have been explored for the specific task of fire detection (Lloret et al. 2009) and research in this direction is ongoing, for example, considering energy efficiency (Vikram et al. 2020) or data fusion (Varela et al. 2020). However, the need for fire detection arises typically in dry and hot regions. For a comprehensive assessment of Central European ecosystems as planned in ECOSENSE, other research tasks emerge, such as changes in ecosystem competition and facilitation under cold or heat spells, droughts or floods and other disturbing events. Given that large numbers of miniaturised sensor nodes need to be deployed, they should not interfere with the ecosystem, i.e. with leaves, stems, roots and water and gas fluxes. For example, leaf sensors should avoid shading, be lightweight, enable natural gas exchange and be energy-autonomous, as cables and batteries are inefficient, expensive and maintenance-intensive. It is still an open question which existing sensing principle can be miniaturised with sufficient sensitivity and selectivity. Whenever miniaturisation is not possible, new sensing mechanisms are mandatory and need to be explored. Furthermore, it is not yet known how the sensor size, number and way of deployment will guarantee an undisturbed metabolic function of ecosystem components. Additionally, the robustness of sensors is essential in terms of temperature cycles, UV exposure and fouling processes. How can we guarantee to maintain sensitivity over long periods, in soil or air? Furthermore, the overall energy demand is completely uncertain. We do not know whether distributed solar energy harvesting in the shaded forest or thermoelectric energy harvesting in the relatively stable temperature conditions in soils, will be sufficient. We even do not know the meaning of “sufficient” for our network regarding the frequency of sensing with regard to the actual energy supply condition. This is superposed by the variable need for data under rapidly changing environmental conditions and the avoidance of redundant data accumulation under stable conditions.

Finally, a data- and energy-efficient operation of the network can only be achieved by a continuous interplay and feedback between technical advances and scientific process descriptions and modelling of ecosystem functions.

So far, ecosystem sensing and modelling are not well connected since data availability has time lags of months to years, particularly for classical monitoring programmes, such as Fluxnet and TERENO. Thus, ECOSENSE is breaking new ground in: i) sensing, ii) real-time data assimilation and modelling and iii) combining both for now- and forecasting.

Research programme, goals and long-term perspectives

The central aim of ECOSENSE is to enable a novel dimension of ecosystem process sensing, understanding and modelling. We consider this fundamental to predict sustainable forest functioning, this being the most important ecosystem service that buffers climate change with high socio-economic value in Germany and elsewhere.

We argue that a holistic understanding of ecosystem functioning can only be achieved with in-depth understanding of spatial and temporal dynamics of relevant ecosystem processes across scales.

Heterogeneity and functional diversity of complex forest systems and their interactions and feedbacks are key factors able to buffer or accelerate stress impacts after extreme events.

We identify four topics, which are currently not appropriately addressed, but are of utmost importance to quantify and predict complex ecosystem processes:

- scaling of key processes considering their spatio-temporal heterogeneity and dynamics, hot spots and hot moments and their contributions to ecosystem fluxes;
- developing sensing technology and efficient sensor network communication for providing sufficient spatio-temporal resolution of relevant processes;
- designing size and gridding of sensor networks to capture important dynamics of ecosystem processes from leaf to ecosystem scale;
- big data processing, analysis and assimilation and multi-scale ecosystem modelling considering non-linear scaling laws for improved ecosystem analysis and prediction.

Accordingly, ECOSENSE will address four main research aims as illustrated in Fig. 2.

- a transferable, verified multi-scale ecosystem model extended for spatio-temporal dynamics and scaling;
- an in-depth scientific understanding of the ecosystems studied in ECOSENSE;
- a modular and energy-autonomous sensing system, which will allow rapid deployment in remote areas to evaluate ecosystem processes affected by climate extremes.

These aims will be approached step-wise over 12 years throughout the three funding phases of the CRC.

To achieve our aims, expert scientists of this interdisciplinary CRC will implement a comprehensive research programme, which approaches the challenges in close, mutual cooperation and from two central aspects: from a technical and from an ecological point of view.

To this end, we will explore, develop and implement an intelligent distributed micro-sensor network autonomously measuring fluxes from soil to vegetation and atmosphere.

Consequently, we will address the miniaturisation of established sensing principles for enhanced spatio-temporal resolution and drive the research and implementation of new sensing principles in ecosystem monitoring.

We will assess relevant ecosystem processes covering scales from root/leaf to forest stands and, temporally, from seconds to years, capturing fluxes from the hydrosphere, pedosphere, biosphere and atmosphere. In the first phase, ECOSENSE will focus on water and carbon fluxes, namely H_2O, CO_2 and VOCs and their carbon isotopes, as the most prominent drivers and chlorophyll fluorescence as a well-established stress marker. These data will be evaluated in the light of detailed information of forest structure and microclimate, tree and soil nutrition and soil physical properties, which will be assessed by a thorough characterisation of the ECOSENSE Forest.

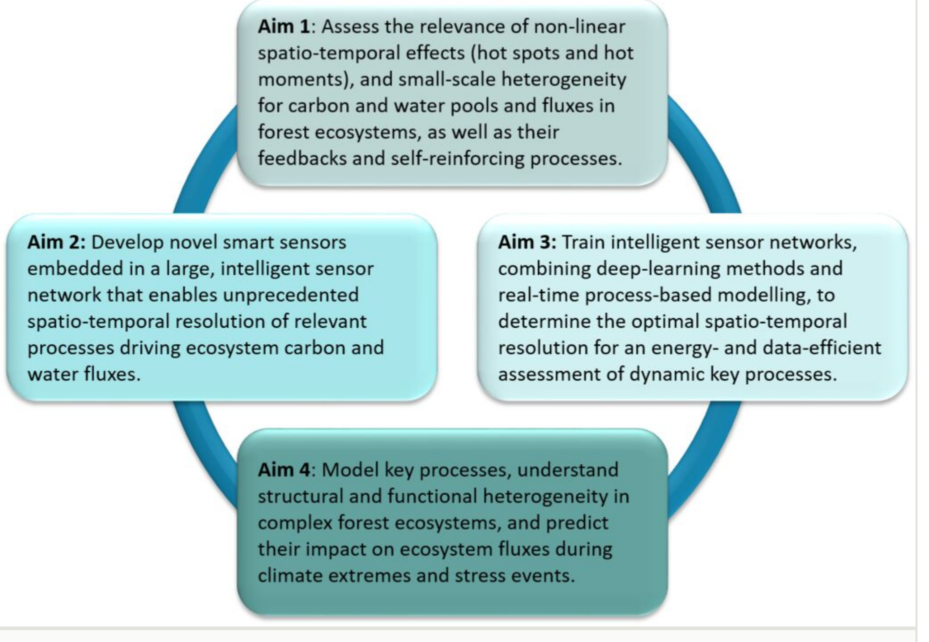

Figure 2. doi

ECOSENSE research aims.

Finally, the overarching long-term outcome of ECOSENSE will be a scientific framework of hardware, methods and workflows to transfer ecosystem sensing and modelling into other (forested) ecosystems. This Forest ECOSENSE Toolkit (Fig. 3) builds on:

We will start with a limited number of commercially available sensors, to initiate ECOSENSE's systems research right from the start. They will be substituted step-by-step with the new distributed sensors and sensor systems once they are ready for field deployment. Sensing and measuring principal and key tree responses to extreme environments will be first tested in the newly-founded "Ecosphere Experimental Platform (EcoExPo)" of the UNR on the campus of the Faculty of Engineering. Subsequently, they will be transferred to our joint field site, the ECOSENSE Forest, in the state forest of Ettenheim near Freiburg. The ECOSENSE Forest represents a well-grown mixed needle and broadleaf forest at the foothills of the Black Forest. Given the complexity and challenges, both in developing the intelligent sensor network and the deconvolution of ecological processes across all relevant scales, we will start this CRC, as stated, focusing on carbon and water fluxes, while taking forest structure, soil characteristics and nutrient contents into account. Moreover, our vision is that the system can be expanded to include further factors/elements such as nutrients fluxes, other trace gases and biotic interactions in the future.

These research activities are jointly implemented into the ECOSENSE research network comprising three Research Areas as shown in Fig. 4:

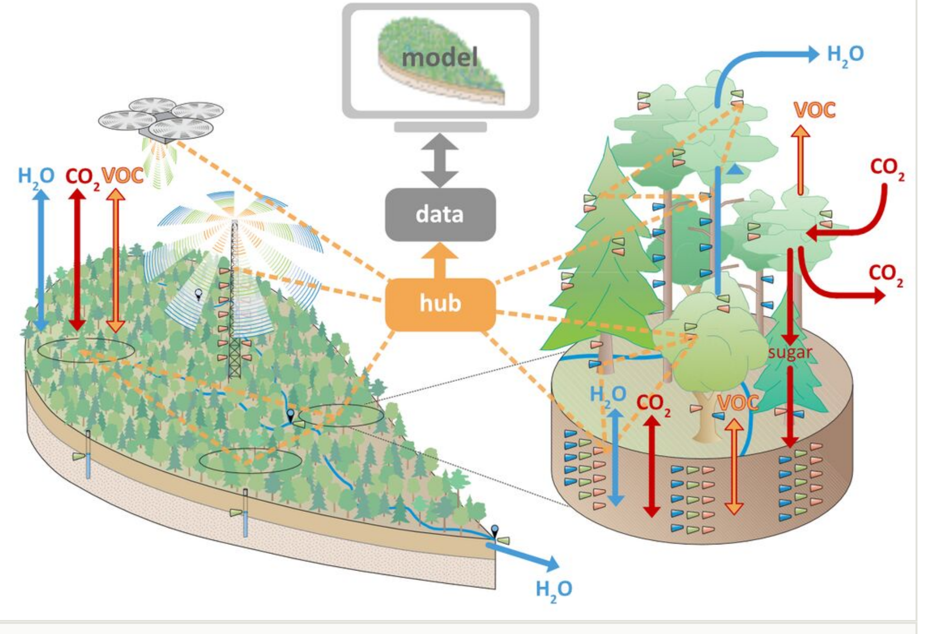

Figure 3. doi

Structure of the ECOSENSE Toolkit. Left graph section of a forest ecosystem with selected stands (black circles) and an eddy covariance tower. The right graph shows an enlarged stand in the forest ecosystem with different tree communities – for example, pure versus mixed forest stands. Triangles stand for envisaged micro-sensors: measuring soil moisture, CO_2 content and soil temperature. Within the canopy at the leaves, gas exchange, VOC and chlorophyll fluorescence (green and red triangles), at the branches water and carbon fluxes combined with the stem water and phloem sap flow (blue triangles) will be measured. In addition and to complete the picture, eddy covariance technology provides net ecosystem carbon (including VOC) and water fluxes while remote assessment of fluorescence signals by UAV acquires information on canopy vitality. Measured data will be transferred in real-time into a sophisticated database via a central hub. It will be explored for process analysis, utilising deep-learning approaches for implementation of a comprehensive model for now and forecasting applications.

Area A: the assessment of H_2O, CO_2 and VOC fluxes and their isotopes from soil, trees, to atmosphere;

Area B: the assessment of stress indicators through chlorophyll fluorescence from individual leaves to forest stands;

Area C: sensor network implementation, materials for environmental robustness, efficient data management, deep-learning and modelling.

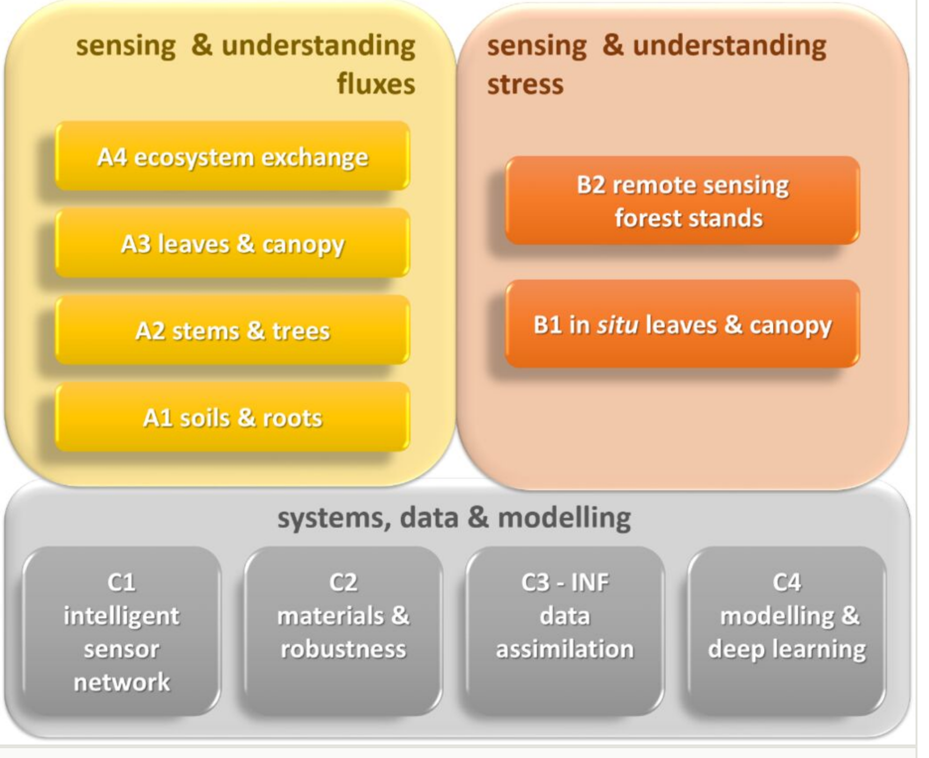

Figure 4. doi

Structure of the ECOSENSE research network comprising three Areas: Area A focuses on the measurement of ecosystem processes, namely CO_2, VOC and H_2O fluxes; Area B focuses on chlorophyll fluorescence as the stress marker; Area C builds the common foundation including sensor network communication, resistance, data assimilation and deep-learning and process modelling.

The outstanding characteristic of ECOSENSE is the consequent entanglement of both disciplines in almost every project. Therefore, the CRC has a unique structure: The three Research Areas are divided into ten projects (Fig. 4), of which the projects in Area A and Area B each comprise subprojects from the technological and from the ecological side, while Area C addresses overarching research tasks. This results in a total amount of 18 scientific subprojects and includes 23 doctoral and postdoctoral funded researchers, as outlined below. The structure reflects the close cooperation, which ensures a highly dynamic knowledge exchange, joint development of novel approaches and strongly fosters cross-disciplinary team building. It will be further enforced by the joint experimental platforms (EcoExPo and ECOSENSE Forest, Z1), a common ECOSENSE research training group (RTG) and cross-disciplinary workshops and communication (Z2).

In the following, we will provide an overview of the Areas and projects in a nutshell. Fig. 5 shows the circle of interacting and data exchanging projects and illustrates the interlinkage of the technical (blue) and ecological (green) subprojects spanning from pedosphere through biosphere to atmosphere. Thereby, Area A focuses on water and carbon pools and fluxes, Area B on stress indicators (Chlorophyll Fluorescence, ChlF). The fluxes of VOC measured in A3 and A4 are also stress indicators and thus reach into Area B. Area C covers cross-spanning projects, as all sensors will require low power electronics and communication from C1 and environmental robustness from C2. Finally, C3-INF collects all data from Areas A and B and the interdependence of Area A and Area B data is analysed and modelled in C4.

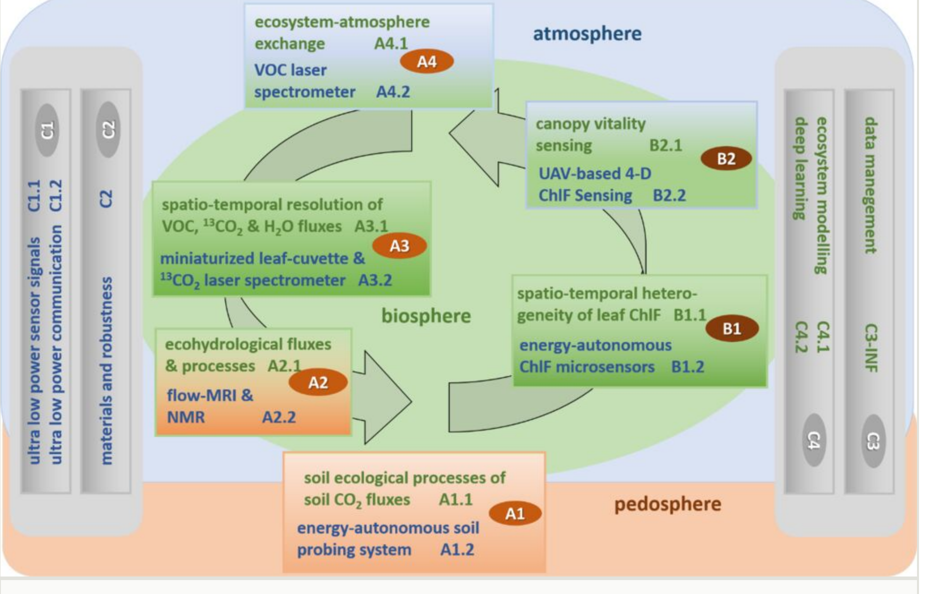

Figure 5. doi

The ECOSENSE project network that interacts from pedosphere through biosphere into the atmosphere accompanied by cross-spanning C projects. Each project of Areas A and B consists of a subproject of environmental science (green) and technical engineering (blue). Area C is cross-spanning projects (grey).

Research Area A - H_2O, CO_2 and VOC fluxes along the different ecosystem compartments and scales

Underlying plant and soil processes such as photosynthesis, respiration, ecohydrological H_2O fluxes, as well as soil-plant and plant-atmosphere interactions, will be emphasised (Fig. 5). Process-based understanding of pools and H_2O, CO_2 and VOC fluxes will allow

CO_2-flux to be partitioned into: (i) ecosystem respiration (Re) and photosynthesis (gross primary production, GPP), (ii) the contribution of different functional units within a plant (leaves, stem, roots) and soils (heterotrophic and autotrophic respiration); and (iii) above-ground and below-ground processes and evaluate hot spots and hot moments within the mixed forest. Furthermore, Research Area A aims at the partitioning of VOC fluxes within the canopy, between species and its significance for the ecosystem VOC flux.

A1 will assess the spatio-temporal heterogeneity in soil fluxes and microclimatic/edaphic conditions to evaluate the importance of rhizosphere and microbial sources and identify hot spots and hot moments in microbial and tree root functioning and their interactions (A1.1). To this end, we will develop novel soil probes measuring CO_2 and temperature, which can be installed with high spatial coverage in a measuring grid. They will be energy-autonomous through thermo-electric and solar energy harvesting and, thus, perfectly fulfil a “deploy-and forget” strategy (A1.2).

A2 addresses ecohydrological fluxes and processes in heterogeneous forest patches investigating dynamics and spatial patterns in root water uptake, tree sap flow and phloem carbon isotopes, its feedbacks on spatio-temporal soil moisture variability and heterogeneity and how this, in turn, affects tree water use efficiency and phloem sugar transport. We aim to trace water and carbon fluxes in trees and sharpen our picture of biotic controls (A2.1). Here, we will develop a fully novel methodology through compact Magnetic Resonance Imaging (MRI)/Nuclear Magnetic Resonance (NMR) sensors, based on permanent magnets attached to small-sized branches. They will allow for in situ imaging of the H_2O fluxes without interfering with the branch and NMR analysis of xylem and phloem sap flows (A2.2). Continuous in situ phloem sap NMR measurements will allow a new dimension of quantifying integrated carbon transport in trees.

The goal of A3 is to capture spatial and temporal dynamics in photosynthetic carbon isotope discrimination, stomatal conductance and leaf H_2O and VOC fluxes within and amongst tree crowns in a mixed forest ecosystem. Environmental impact on photosynthetic CO_2 fixation can be decoded by ^{13}C-isotope discrimination, determining hot spots and hot moments of photosynthetic C fixation, C respiration and VOC emissions (A3.1). Micro gas cuvettes will be developed and deployed in large numbers to monitor the 3D-variability within the canopy. Equipped with an integrated open-close mechanism, they will be connected to multiple small, low-cost carbon isotope laser spectrometers, which will also measure leaf H_2O fluxes. As the laser spectrometers cannot be miniaturised to a similar extent as the leaf cuvettes, they will be placed at a central position and connected by tubing (A3.2).

Finally, to bridge the gap between the relatively small scale of an individual tree and a forest stand, A4 will assess ecosystem-atmosphere exchange by eddy covariance measurements of H_2O, CO_2 and its isoflux ($\delta^{13}CO_2$), to separate fluxes into components (ecosystem respiration and photosynthesis (gross primary production, GPP) at an integrated scale. Further VOC uptake and release by our forests will be measured, linking to important ecosystem functions, which are strongly sensitive to environmental changes (A4.1). Here, we will develop, for the first time, an optical spectroscopic sensing technology, to measure VOCs using tunable laser absorption spectroscopy (TLAS) along a concentration gradient at the tower (A4.1b) and connected to single-leaf cuvettes, as developed in A3.2.

Research Area B - Active chlorophyll fluorescence measurements as a sensitive stress parameter addressing the relevance of microclimatic heterogeneity

In Research Area B, we aim for a full picture of chlorophyll fluorescence (ChlF), as a sensitive parameter to trace effects on environmental changes and biotic and abiotic stresses on the photosynthetic efficiency, ranging from leaf-based networks up to canopy and forest stand. This Research Area will identify hot spots and hot moments of the heterogeneous 3D structure of the forest canopy and enable us to relate the underlying process to small-scale microclimatic changes, for example, incident light, temperature and humidity at the leaf surface, as well as to macro–scale stress events.

B1 will capture heterogeneity in leaf-level ChlF and associated microclimate in a novel dimension of a spatial network within and amongst tree canopies, to efficiently identify hot spots and hot moments of stress-induced changes of photosynthetic efficiency (B1.1). To this end, we will develop novel wireless, energy-autonomous ChlF sensors, using flexible, multifunctional (microclimate) and highly integrated microsensor probes (B1.2). A new kind of leaf sensor (< 1 cm^2) to be deployed, covering multiple positions within the canopies, will strongly profit from the advantages of microsystem technology: they will have the highest degree of miniaturisation, to ensure the least interference with leaves and they will need to be mass produced. These sensors will act as independent sensor nodes, due to solar energy harvesting enabling them to communicate their data wirelessly and can be installed at the beginning of the season on the leaves in a deploy-and-forget strategy.

To bridge the gap from single leaves and trees to even larger forest stands, B2 will use remote assessments of active ChlF via an unmanned aerial vehicle (UAV) to generate detailed repeated spatial maps to visualise and assess tree vitality, identify hot spots within the forests and transfer the sample based findings into area wide monitoring (B2.1). In doing so, we will further develop the models for chlorophyll fluorescence assessment, based on UAV-carried remote sensing devices, calibrated against the tree leaf measurements. We will develop a strongly miniaturised, highly integrated lightweight UAV-based active ChlF sensing instrument using LiDAR techniques with an efficient new scanning paradigm. It will allow for largely extended flight campaigns with high spatial resolution (B2.2). Thereby, the calibration of the UAV-borne data will directly profit from the leaf sensor network of B1.

Research Area C - Intelligent sensor network, robustness, data management, ecosystem model and deep-learning

This Research Area builds up the full chain from data acquisition, through an intelligent, energy-autonomous and robust sensor network, over comprehensive and quality-assured database to process-based and deep-learning model assessment and forecasting. The key challenges addressed are: (i) to develop sensors operating and communicating reliably under field conditions, with fluctuating input of ambient energy and exposure to weathering and biofouling; (ii) a real-time collation of sensor data into a central database in order to make it accessible to our new process-based and deep-learning models.

C1 will perform research on specific needs for all distributed sensors (from Areas A and B) creating a number of innovations for embedded autonomous sensor systems. All sensors will be equipped with ultra-low power electronics and communication capabilities (C1.1) to go beyond their pure sensing function and to enable them to be used as active and intelligent sensor nodes in our ECOSENSE network. Self-test features and energy awareness will be incorporated to improve a sensor node's performance over time. Wireless communication between individual sensor nodes and central sensor hubs will be provided in multiple ways (C1.2), by using newly-established communication networks (e.g. narrow-band Internet-of-Things or NB-IoT), as well as for specially tailored low-power local radio (e.g. LoRa). The energy supply of such widely distributed sensor nodes has to happen either via energy harvesting from thermal, solar or mechanical ambient energy or via passive remote sensing approaches similar to today's RFID technology. Our long-term goal is to achieve a maintenance free, reliably working network.

C2 will investigate how sensor nodes, being in direct contact to the environment as soil probes and leaf sensors, can be designed to be long-lasting and stable by preventing fouling processes, such as the accumulation of dirt or bacterial growth. This requires tailored surface structures and anti-fouling coatings, whose specification strongly depends on sensor location. In soil, they are exposed to long wet phases, while in air, they are exposed to large temperature and humidity variations or simply to the accumulation of dirt. Furthermore, trade-offs have to be found between, for example, being insect and bacteria repellent, while at the same time, not out-gassing unwanted VOCs.

C3-INF will generate, manage, adapt and extend a joint database for all project data, securing homogenised formats, storage, selection and accessibility by all groups. As ECOSENSE relies on data interoperability within and between its projects, as well as with the scientific research community, the challenge lies in managing easy data access using existing data formats where appropriate and creating new research data formats where necessary. To achieve this, C3-INF will overcome the burdens of data management policies by providing a central platform based on AQUARIUS (Aquatic Informatics, Vancouver) and additional tools for joint data storage, management and backup of all ECOSENSE projects. C3-INF will further provide services for data interoperability and exchange, for shared data analysis tasks (e.g. data quality control) and for managing project workflows.

C4 will develop process-based model simulations and deep-learning tools for data analysis to interact with and optimise the sensor-based monitoring, as well as to deepen our understanding of impacts of spatio-temporal heterogeneity and dynamics for total ecosystem water and carbon exchange. An existing 2D process-based model will be extended, calibrated and run in a now- and forecasting 3D mode, covering spatio-temporal heterogeneity of small-scale processes and integrating new scaling laws for non-linear interactions (C4.1). Using deep-learning algorithms, the plethora of data will be efficiently evaluated to distinguish between important and redundant data. The aim is to, on the one hand, provide sufficient spatio-temporal resolution, thus allowing for a reliable ecosystem modelling and, on the other hand, save sensor node energy and reduce redundant data accumulation (C4.2). Thereby, deep-learning and process simulations interact with the sensor network in two directions; i.e. i) data assimilation from the sensor network into the model systems and ii) adjustment and optimisation of the measuring design based on simulated outputs and predictions.

Z-projects and RTG – Common infrastructure, administration and Research Training Group (RTG)

The research of ECOSENSE is also accompanied by two Z-projects. They include our infrastructure, i.e. joint research platforms (Z1) and an administrative coordination project (Z2). Furthermore, we consider it important to offer a dedicated Research Training Group (RTG) for the doctoral researchers of our highly interdisciplinary CRC programme.

In our joint research platforms, Z1 we will take the ECOSENSE sensor network from the laboratory into a test-bed for experimental climate simulations in our new campus research facility and to the real world, our ECOSENSE Forest, a well grown mixed forest near Freiburg.

EcoExPo (Ecosphere Experimental Platform)

To test the newly-developed sensors and equipment, as well as novel ecological hypotheses, we will conduct pilot studies at the newly-founded Ecosphere Experimental Platform (EcoExPo, *Eva Mayr-Stihl Umwelttechnikum*) of the UNR, located directly on the Technical University Campus of the University of Freiburg. It comprises a greenhouse, outdoor experimental fields with large-scale weighing lysimeter fields, rainout shelter with different vegetation and soils, as well as an indoor experimental facility with four Ecotron units for controlled climate change experiments and simulation of environmental stresses.

The outdoor experimental platform with several large-scale weighing lysimeters and different rainout shelters will allow us to test sensors and hypotheses in different soil types and with rain exclusion or flooding experiments under natural fluctuations of environmental conditions. In order to support ECOSENSE directly and more realistically, we will extract large-scale soil monoliths for the lysimeters (2 m diameter and 1.5 m depth) directly in the ECOSENSE Forest from the three sites including young beech and Douglas fir trees (up to 8 m). These monoliths including the trees in the centre allow direct observations in the soil and trees. We will have the possibility to cover each lysimeter with a mobile Ecotron (Fig. 6) to allow specific environmental and climate conditions including different air temperatures, air humidity, atmospheric CO_2 concentrations and rainfall amounts. An Ecotron allows comprehensive investigations of several important plant and ecosystem functions, fluxes and processes under controlled environmental conditions. The four Ecotron units (with four lysimeter subunits each) will be equipped with environmental sensors (such as above- and belowground moisture, temperature), incident light (PAR), soil temperature and air temperatures and humidity as well as watering regimes can be fully controlled. Above and belowground compartments will allow continuous measurement of carbon (CO_2 and VOC) and water fluxes and their respective isotopic composition through an automatic sampling system connected to carbon and water isotope laser spectrometers (Picarro). Additionally, automatic VOC measurement will be possible by linking the PTR-TOF-MS of the Werner group during measurement campaigns to the sampling streams. Belowground compartments include smaller-scale portable lysimeters (surface area up to 1 m^2), which can be moved from the greenhouse, outdoor lysimeter fields to Ecotrons or other test environments. The mobile lysimeter allows planting various trees or other vegetation to the typical soil of the ECOSENSE Forest or other soil types of interest.

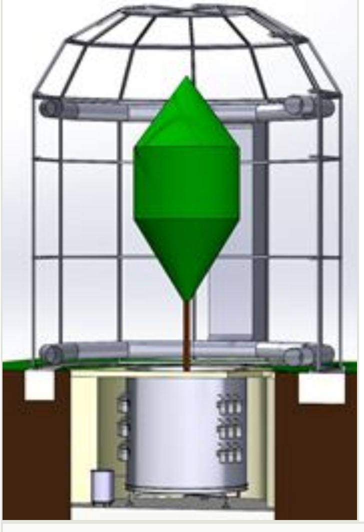

Figure 6. doi

Sketch of the planned lysimeter site including the mobile Ecotron showing the situation as envisioned with a beech tree in the lysimeter.

ECOSENSE Forest

A well-suited forested area (Fig. 7) has been selected and permission granted by local authorities. The area is located in the municipal forest of the city of Ettenheim, approximately 45 minutes' drive north of Freiburg and easily accessible by forest roads (Fig. 8). The forest is nested in the hilly transition between the upper Rhine Valley and the Black Forest providing a mixed forest system, dominated by beech with patches of spruce, oak, fir, Douglas fir and pine trees of different ages in mixed and pure patches. The Ettenheim forest site is a managed forest, with a low-impact sustainable management strategy. Three stands were selected for the first phase of ECOSENSE with pure beech, mixed beech-Douglas fir and pure Douglas fir trees, suitable for investigating the hypotheses on spatio-temporal heterogeneity (Fig. 9). The orographic location of the forest on an extensive plateau was selected to fulfil the requirements for an eddy covariance (EC) tower and two canopy access towers. The requirements for EC measurements are met with relatively flat or uniformly sloped terrain (< 5°). The forest provides similar roughness in the fetch of the prevailing wind directions up to 1-1.5 km. In addition, there are many forest patches on the same plateau with different composition and ages that can be used in the next phases of the project. The Mayor of Ettenheim and the local forester support ECOSENSE and will provide long-term access (12 years) and adjust management of the forest surrounding our sites in order to provide the best environment possible.

Figure 7. doi

ECOSENSE Forest Field Site: The area is located in the state forest of Ettenheim, approximately 40 minutes north of Freiburg and easily accessible by forest tracks already in place. It is nested in the hilly transition between the upper Rhine Valley and the Black Forest, providing a mixed forest system, dominated by beech and spruce of different aged mixed and pure patches.

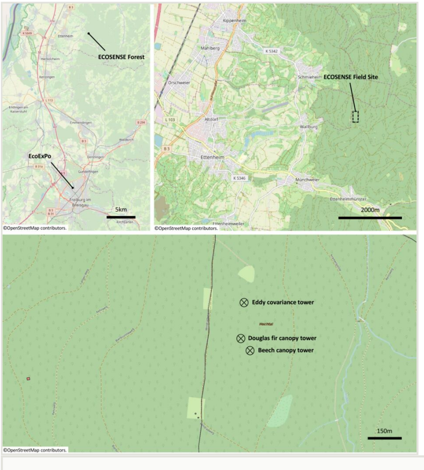

Figure 8. doi

Location of ECOSENSE Forest near the city of Ettenheim and the EcoExPo in Freiburg. The map on the right shows the exact location of the ECOSENSE field site related to Ettenheim, while the lower map shows the topographic situation of the field site and the location of the three towers.

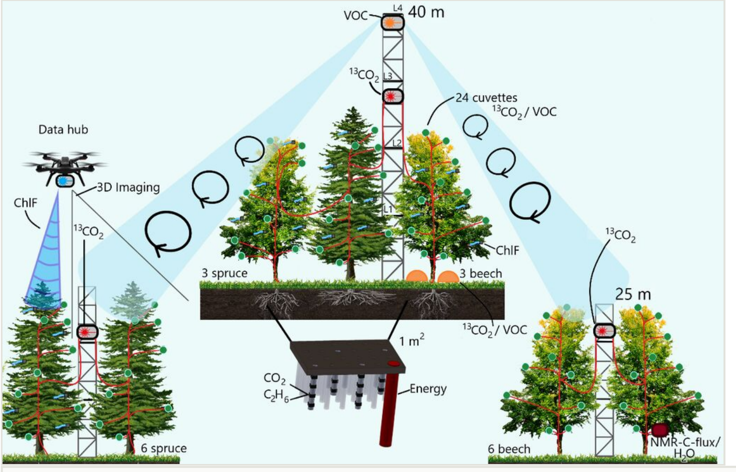

Figure 9. doi

Sensor network at ECOSENSE Forest: sensors are distributed in mixed and pure tree groups from soil through stems, leaves and canopies to the atmosphere.

The field site is located on Triassic sedimentary rock. The plateau area, which comprises the selected stands, has relative homogeneous geological and pedological conditions of “Plattensandstein-Formation”, a sandstone with layers of clay and some smaller outcrops of the “Rotton Formation”. The soils are Cambisols with a silty loam to loamy clay texture, carbonate free and well developed to a depth between 60 to 120 cm. The field capacity is between 230 and 350 mm with average permeability and low stone content. The plateau is drained by four creeks in steep valleys in different directions. The elevation ranges between 450 to 520 m a.s.l. A recently funded DFG project (Christiane Werner, Natalie Orlowski, Markus Weiler) already established the first sensor network near the selected field site examining ecohydrological processes and tree interaction in the mixed spruce-beech forest.

Finally, Z2 ensures internal and external communication, fosters the collaboration within and between the projects, monitors and controls the timeline of the work in progress and the quality of the scientific content, supports publication processes and controls for good scientific practice.

ECOSENSE is strongly interdisciplinary and we want to encourage our young scientist members, namely doctoral and postdoctoral researchers, to cross the borders of their field and to develop a broader perspective. We are planning for an integrated research training group (RTG) which, on the one hand, uses existing doctoral researcher programmes of the University, but, on the other hand, is complemented by ECOSENSE specific measures. Thereby, we will train them in all important aspects and skills of the various disciplines and Research Areas involved in ECOSENSE and support them towards scientific independence already at an early career state, to develop their own scientific network and visibility in the international research community and to provide them with excellent career perspectives.

To wrap up the research programme, we summarise in Table 1 our research goals on a shorter, a medium and a longer perspective, i.e. on a 4 year, 8 year and 12 year timescale, representing the three proposed phases of ECOSENSE.

Table 1.

The short, medium and long-term goals of ECOSENSE

Phase 1: Years 1 to 4 **Sensing principles, network foundations, relevant ecosystem functioning parameters**
● Establishment of a joint research platforms including three eddy covariance towers at the ECOSENSE Forest; ● Characterisation of the ecosystem structure and assessment of basic parameters; ● Measurement of fluxes and pools of H_2O, $^{13}CO_2$, VOC and their isotopes as well as of stress parameters with existing sensor types at selected sites from soil, tree, canopy and atmosphere; ● Evaluating new sensor principles and measurement approaches, miniaturisation of sensors; ● Evaluating sensor nodes with low-power electronics, communication and energy awareness; ● Implementation of deep-learning algorithms as well as setup, initialisation and first evaluations of the ecosystem model ● Successive transfer of new sensors from the lab into research platforms and extension of spatial coverage; ● First results on the importance of key processes and heterogeneity, at different compartments and scales (soil, trees, atmosphere) for ecosystem stress resilience and functioning.
Phase 2: Years 5 to 8 **Sensor network upscaling, closed-loop data acquisition, towards understanding heterogeneity**
● Enhancing resolution, selectivity, sensitivity and data rate; ● Sensor optimisation in terms of materials, robustness and function; ● UAV-based sensor system for active chlorophyll fluorescence measurements; ● Towards large numbers: parallelisation of sensor nodes, processes for large numbers; ● Towards a “deploy and forget strategy”: enhancing autonomy, sustainable materials; ● Large data network with enhanced spatial coverage of the forest; ● Evaluation of spatio-temporal variability, feedback and interaction within the forest and its role for sustainable ecosystem functioning; ● Application of deep-learning and feed-back for targetted selection of relevant data, evaluation of non-linear scaling laws.
Phase 3: Years 9 to 12 **Fully autonomous network, “deploy-and-forget” sensor nodes, full ecosystem model validation**
● Fully biocompatible and sustainable sensor nodes enabling “deploy-and-forget”; ● Full UAV-based sensor system for active spatial chlorophyll fluorescence measurements coupled with hyperspectral image data; ● Energy-autonomous, independent, self-learning, self-calibrating, self-organised network; ● Identification of required spatial and temporal scales to capture relevant processes, interactions and feed-backs driving ecosystem functioning; ● Understanding ecosystem functions across all scales, verified non-linear scaling-laws, identification of key processes, enhancing or buffering stress impacts, resilience and sustainability of forests.

Starting from the second phase, we will evaluate the possibility to derive side projects for a transfer of the developed concepts and solutions into commercially available sensor products, either via the foundation of start-up companies or in cooperation with industrial partners (e.g. within the transfer opportunities of the DFG). We aim to provide the scientific community and governmental institutions with robust, long-lasting and low-cost sensors to be deployed and operated with minimal effort (“deploy and forget”) and to be designed and fabricated in an environmentally compatible manner.

The ECOSENSE project composition resulting from the research programme described above is summarised and illustrated in Fig. 10, which lists all project and subproject titles, as well as the associated PIs (in green: partners from the environmental sciences, in blue from the technological sciences). Research Areas A and B are the building blocks to assess ecosystem pools and fluxes and stress effects, while in Area C, the ecosystem model, data assimilation and deep-learning span the roof across all projects, whereas the integrated intelligent sensor network will interlink all sensor projects at all levels. The basis of ECOSENSE is the common infrastructure comprising the joint experimental platforms (EcoExPo and ECOSENSE Forest), joint data management and modelling and all Z-activities.

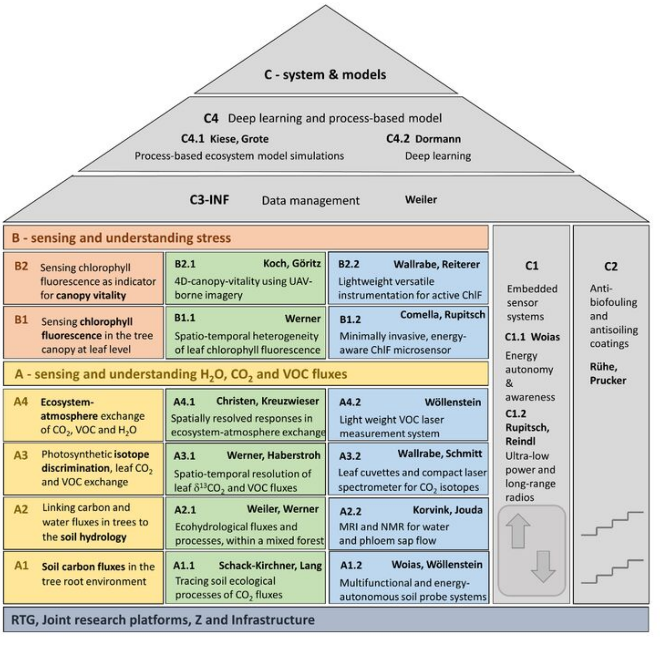

Figure 10. doi

ECOSENSE project network covering the three Research Areas (A fluxes, B stress, C overarching projects) and partners from UNR (green) and IMTEK/INATECH/KIT (blue).

Most of our PIs are members of the Faculty of Engineering or Faculty of Environment and Natural Resources (University of Freiburg) located within close vicinity (< 5 km). Karlsruhe

Institute of Technology (KIT) provides complementary expertise, with established long-term collaborations and associations to the University of Freiburg. ECOSENSE will further profit from the involvement of some colleagues of the Fraunhofer Institute for Physical Measurement Techniques in Freiburg, also located on the campus of the Faculty of Engineering.

Scientific positioning of ECOSENSE within its general research area

Research Area A – sensing and understanding ecosystem C and H_2O fluxes

Forests represent one of the most important components of the global C cycle as they are a major sink of atmospheric CO_2 (Bonan 2008) and provide ca. 50% of terrestrial net primary production (Stephenson et al. 2014). However, the carbon sink strength of forest ecosystems is highly sensitive to environmental change (Friedlingstein et al. 2020), with unpredictable and potentially cascading effects on complex physiological processes and interactions within ecosystems (Anderegg et al. 2018, Werner et al. 2021). In agricultural systems, short-term intervention through pest control, irrigation or improved stress-resilience of crops allows the mitigation of climate impacts to some extent (Jansson et al. 2021). In contrast, effects on diverse, highly structured forests are more complex with long response times and legacy effects (Williams et al. 2014, McDowell et al. 2020), which are still poorly understood. Our knowledge on dynamics in CO_2 and H_2O exchange of terrestrial ecosystems results from integrated eddy covariance (EC) measurements (Reichstein et al. 2007). However, they often neglect the diversity and variability of structural and functional process-based information within ecosystems, as most EC sites measure even-aged homogeneous forests in flat terrain. Further, EC measurements generally do not resolve the underlying plant physiological and soil processes of photosynthesis and transpiration or heterotrophic and autotropic respiration. Moreover, they mostly focus on horizontally homogeneous and structurally simple ecosystems, not able to disentangle the role of ecosystem fragmentation and heterogeneity (Grote et al. 2011). However, to predict and forecast future behaviour and increase sustainability of forest ecosystems under different management practices, as well as under a changing environment, it is essential to properly resolve underlying processes, separate fluxes between ecosystem compartments (e.g. soil, roots, stem, leaves, atmosphere) and different species. In this regard, stable isotopes provide an efficient tool to partition ecosystem carbon (Werner et al. 2006) and H_2O (Dubbert et al. 2014, Dubbert et al. 2019) fluxes and deconvolute the underlying drivers and processes (Unger et al. 2010, Volkmann et al. 2016a).

> *However further research is needed to implement isotope fluxes on eddy-covariance sites and, in particular, integrate information of spatial and temporal heterogeneity in mixed forest ecosystems. We are only at the beginning to explore the role of interactions between structural and functional diversity and microclimate for forest (Singh and Zimmerman 1992) stress resistance (Anderegg et al. 2018, Werner et al. 2021). Moreover, the role of hot spots and hot moments (McClain et al. 2003), i.e.*

sites/events with a disproportional impact on net carbon and water fluxes, for example, during/after climatic extreme events which can have long-lasting impacts on ecosystem functioning, are yet to be explored.

Forest ecosystems do further play an important role in the global climate system by releasing biogenic volatile organic compounds (BVOCs) into the atmosphere (Guenther et al. 2012). Biogenic VOC fluxes from vegetation exceed anthropogenic emissions of VOC by far (Singh and Zimmerman 1992, Lathière et al. 2006). The vegetation re-emits ca. 1–2% of photosynthetically fixed carbon back into the atmosphere mainly as isoprene and monoterpenes (Šimpraga et al. 2019) dominating the global BVOC flux (Arneth et al. 2008, Guenther et al. 2012). Emitted into the troposphere, highly reactive BVOCs strongly impact atmospheric chemistry by formation and degradation of, for example, tropospheric ozone and formation of secondary organic aerosols (Fuentes et al. 2000, Fiore et al. 2012). Therefore, it is essential to achieve a deep understanding of the processes determining ecosystem VOC fluxes, i.e. leaf VOC biosynthesis and soil VOC exchange (Arneth et al. 2010). Today, the uncertainty of global and regional BVOC emissions is still high (see Fu et al. (2019)). The impact of environmental stresses, such as droughts, on VOC exchange is not fully understood and, therefore, not satisfyingly integrated into models (Bonn et al. 2019, Otu-Larbi et al. 2020; MEGAN 2.4, Guenther *et al*. unpublished). A lack of process-based knowledge on emissions is the main uncertainty for accurate present and future predictions.

Hence, detailed information on spatial and temporal variation in VOC emissions is one important knowledge gap for future forecasts regarding ecosystem stress response and in respect of atmospheric chemistry and global change. Continuous measurement of ecosystem VOC fluxes, which would allow for identifying hot moments, are still scarce, even in temperate forests. Even less is known on how different ecosystem components contribute to total ecosystem VOC balance. Identifying hot spots of VOCs and their relevance for total ecosystem fluxes in a spatially heterogeneous forest has, to our knowledge, never been attempted (A4).

Moreover, a deeper process-understanding of VOC emissions, even for well-studied isoprene, is needed (Sharkey and Monson 2017, Yáñez-Serrano et al. 2019). Different species can emit VOC either from storage structures and/or by *de novo* production as protection against heat, high light or biotic stress. Still, little is known on the driving metabolic processes under natural conditions or in response to multiple microclimatic, macroclimatic and biotic interactions. By combining continuous VOC measurements and leaf carbon isotope discrimination as an integral measure of water-use efficiency, a novel process understanding of driving metabolic regulation can be achieved (Ghirardo et al. 2010, Werner et al. 2020, Kreuzwieser et al. 2021). Moreover, it has recently been shown that analysing the C isotope signatures of VOCs (by GCMS-C-IRMS, Haberstroh et al. (2019)) can reveal metabolic branching points in VOC production pathways and will open the door to link information on tree physiology with VOC emission and provide deeper insight into the relative contribution of individual species at the ecosystem level. Nowadays, measurements of leaf $^{13}CO_2$ and VOC emissions at a high spatial and temporal resolution is strongly restricted by several factors:

Emission rates obtained from cuvette measurements are, to some degree, artificial because atmospheric conditions inside the cuvettes often differ in light, leaf temperature and gas concentrations from the natural environment (Fig. 11) and long-term employment induces artefacts like accelerated leaf ageing. This hampers progress to properly link top-down (EC measurements) with bottom-up (leaf cuvette) approaches and to understand flux dynamics at small spatial and temporal scales. While $^{13}CO_2$ laser spectrometers are now field-deployable (requiring electricity and shelter), measuring multiple locations in natural forests is limited due to high cost of instruments. For continuous VOC measurements, currently only mass spectrometry is available, with even much higher costs and power requirements. These large and sensitive analysers are not deployable in harsh environments without (air-conditioned) huts. Thus novel, compact, cost-efficient, maintenance-free laser spectrometers for $^{13}CO_2$ and selected VOC (i.e. isoprene) will open new horizons for continuous field measurements (A3, A4).

Figure 11. doi

Left: Example of a gas cuvette currently used resulting in covering the whole leaf with inevitable changes in microclimate during CO_2, VOC and H_2O flux measurements (Photo Erik Daber). Right: Active leaf cuvette switching a ventilation gap and pores: normally open design – A3.

As pointed out above, hot spots and hot moments can have an important positive or negative impact on net carbon and water fluxes (Kannenberg et al. 2020), but processes driving the persistence of hot spots are still poorly understood. Additionally, there is increasing evidence that spatial heterogeneity in communities may confer important aspects of functional stability and promoting facilitative interactions amongst species (Aguirre-Gutiérrez et al. 2019). For example, soil-tree interaction of species with diverse root systems and hydraulic strategies drive spatial heterogeneity in ecosystems due to important interactions and feedbacks amongst species competing for water (Haberstroh et al. 2021) or facilitating hydraulic redistribution of water in soils via their root system. Thus, tree-soil interactions are key players influencing both water transport and storage in the subsurface, feedback to the atmosphere through transpiration and soil-microbial interactions in the rhizosphere. Trees can increase or decrease soil moisture variability by various mechanisms and at different scales, such as rainfall redistribution by, for example, interception, stem flow, preferential flow along roots and root water uptake or redistribution (Bachmair et al. 2009, Dubbert et al. 2019, Sprenger et al. 2019). In general, the generated spatial patterns are very persistent in time (Keim et al. 2005), which causes a dynamic spatial heterogeneity of transpiration (Renner et al. 2016).

> *However, little is known on these potential self-reinforcing processes - How these processes facilitate tree transpiration or soil moisture heterogeneity has ever hardly been quantified and only a few modelling studies exist (e.g. Guswa (2012), Guswa and Spence (2012)). Thus forest-generated soil moisture patterns will control the variability of partitioning between transpiration/plant available water and also subsurface water flow paths and groundwater recharge in a forested landscape (Tromp-van Meerveld and Weiler 2008).*

The plasticity of each tree species to adapt their water uptake strategies (Hund et al. 2009, Volkmann et al. 2016b, Dubbert et al. 2019) strongly controls tree sap flow, transpiration and the ability to explore water sources in competition with neighbouring trees (Haberstroh et al. 2021) even under stress. This inversely determines their CO_2 uptake rate, production, transport and distribution of carbohydrates, which are loaded into the phloem. The phloem sugar flux within the tree depends on the source-sink-relationship, stress impacts and environmental factors (Lemoine et al. 2013). The response to these environmental parameters is reflected in changes in the stable carbon isotope ratios of phloem sugars. It presents an integrative parameter of canopy photosynthetic discrimination (Rascher et al. 2010), which is tightly related to water use efficiency (Werner et al. 2012), but must be sampled destructively and analysed in the lab.

> *Given these analytical restrictions, total carbohydrate fluxes from source to sinks at the tree level are not well understood. Currently, there is no analytical system to continuously and non-destructively measure dynamic changes in phloem sugar flux under natural conditions.*

In a laboratory setting, Nuclear Magnetic Resonance (NMR) undoubtedly is the most specific non-invasive chemical sensor system available, with tremendous versatility in measurement modalities. Apart from spectroscopy, NMR can reveal fluid dynamic properties and fluxes, multicomponent diffusion down to the nanoscale and can reveal all transport variables with chemical specificity. The xylem and phloem which are the main transport pathways in a plant are very sensitive to conventional invasive physiological experiments (Windt et al. 2011). Therefore, being non-invasive and non-destructive are key features of magnetic resonance spectroscopy (NMR) and imaging (MRI) that make them particularly suitable for measuring the flow dynamics in plants and trees. High field (7T which corresponds to 300 MHz 1H Larmor frequency) MR micro-imaging allowed obtaining maps of the water flow in castor bean seedlings (Köckenberger et al. (1997), Fig. 12). Moreover, the achieved high resolution (47 µm x 47 µm in-plane resolution in a 1 mm slice) allowed the distinction between xylem and phloem flows. Although higher fields are favourable for NMR due to their high signal noise ratio (SNR) (the requirements that are needed for studying the metabolomics (Deborde et al. 2017), measurements at low fields (

Van As et al. 1994, Homan et al. 2007, Windt et al. 2009, Windt et al. 2011) proved successful and accurate in obtaining information about xylem and phloem sap flow, changes in diurnal water status, growth in the trunk of the plant and the amount and physical state of water in the plant.

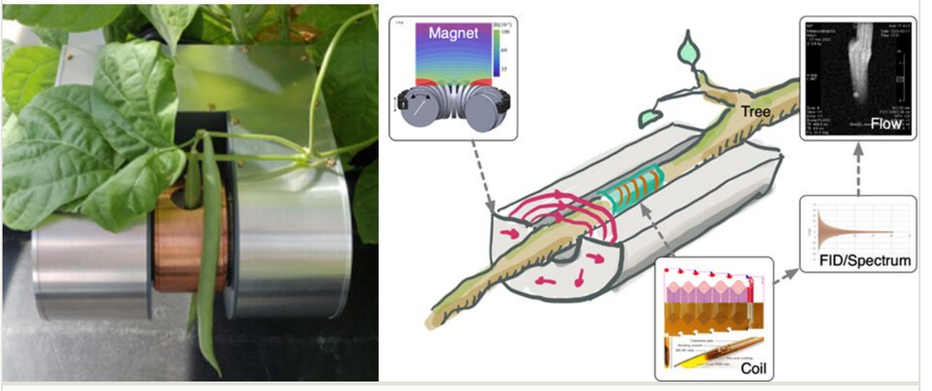

Figure 12. doi

Left: "A portable NMR sensor to measure dynamic changes in the amount of water in living stems or fruit and its potential to measure sap flow" (Windt and Blümler 2015). Right: Conceptual scheme of the workflow showing the different packages of the project including hardware (NMR magnet and NMR sensors), methodology (signal and image processing) and information extraction (sap flow and concentration) – A2.

> *An open question is whether the laboratory NMR setting can be extended to the forest environment and what the limit of detection would be. To answer this question, novel advances in the hardware and methodology of NMR need to be implemented, such as high-sensitivity low-field NMR detectors (Silva et al. 2019, Silva et al. 2020), advanced signal processing techniques (Jouda et al. 2015, Jouda et al. 2019) and signal amplification solutions (Jouda et al. 2017, Spengler et al. 2017) (A2).*

Roughly 30% of the carbon fixed in photosynthesis is transported through the phloem belowground. Partially, the assimilated carbon is exuded by tree roots and their mycorrhiza associations feeding microbes in the rhizosphere and promoting microbial activity (Kuzyakov et al. 2000). The emission of CO_2 from soils into the atmosphere is at the centre of current scientific debate, being key to climate change and its mitigation (Sánchez-Cañete et al. 2018). The net CO_2 emission from soils is commonly termed soil respiration resulting from the respiration of the rhizosphere (roots and microorganisms) and free-living microorganisms in the soil decomposing soil organic matter. Soil respiration is highly dynamic (Unger et al. 2010) and it has been shown that, in soils, probably the most heterogeneous parts of the biosphere, hot spots and hot moments are important drivers of soil processes (Kuzyakov et al. 2000).

High-resolution techniques to assess the response of microorganisms and plant roots to changing environmental conditions and elucidate how this response is related to plant induced processes, such as photosynthesis or transpiration are mostly applied in the laboratory. For ecosystem studies, methodological problems, such as disturbance of soil, costly equipment, energy demand, bulky sampling chambers as well as the immense infrastructure inclusive Teflon tubes (Fig. 13), impair the analysis of plant-induced, microbial and abiotic soil processes.

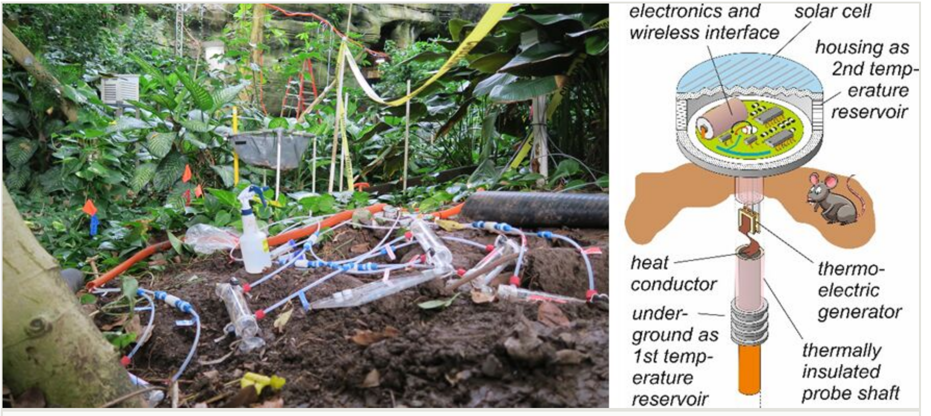

Figure 13. doi

Left: Soil gas flux measurements with chambers connected by Teflon tubes implemented in disturbed soil (Photo Erik Daber). Right: Schematic set-up of the energy harvesting sub-units planned for use with the soil probe – A1.

For the exploration of CO_2 sources and production, high spatial resolution of CO_2 measurements is required rather than limited point measurement of emissions at the soil surface integrating over hours to days and meters (Courtois et al. 2019). The development of methods which enable CO_2 concentration measurements in undisturbed soils at high spatial and temporal resolution would enable completely new insights into belowground ecosystem processes and are at the same time essential for reliable CO_2 flux estimates on ecosystem scales (A1). To this end, energy-autonomous ground soil probes are required which are able to measure relevant parameters of ground soil in a required depth profile and with a required temporal resolution and can be employed at high spatial coverage.

The state of the art in energy-autonomous ground soil probes is limited, with only some research progress for applications in agriculture systems (Adamchuk et al. 2004). In general, such devices are not available for true environmental monitoring and not being developed with the concepts mentioned. Concerning the energy supply for remotely deployed and operated probes, very recent studies are available on thermoelectric energy harvesting in ground soil, however, not in combination with ground soil monitoring sensors (Huang et al. 2019).

The research described above demonstrates the principal feasibility of this technique. However, concepts are not optimised for soil monitoring with minimal ground intrusion, modular system design and easy deployment and servicing from above-ground. The sensor systems integrated into a soil probe should be smart in their advanced signal *processing capabilities, should allow for wireless communication and be fully energy-autonomous. Operation must be possible in remote areas and with zero maintenance access, within ECOSENSE under the severe and highly variable environmental conditions found in a forest environment (A1).*

Research Area B: Sensing and understanding of stress - state-of-the-art and research challenges

Sun- and pulse-induced chlorophyll fluorescence (ChlF) measurements are elegant methods to assess how changes in environmental conditions, biotic and abiotic stresses affect the photosynthetic activity of the forest, which is a key indicator for ecosystem functioning. ChlF captures the efficiency of light energy conversion in photosynthetic reactions of leaves, which is a highly sensitive indicator of the functional status of vegetation prior to visible signs of stress, such as loss of chlorophyll content or leaf area. However, while ChlF provides a sensitive tracer due to its rapid response to macro- and microclimatic conditions, it is associated with high heterogeneity due to variations in environmental conditions in structurally diverse, tall grown forests.

Leaf-level ChlF measurements provide a direct monitor of the physiological state of the vegetation and have widely been used as a very sensitive probe of photosynthetic reactions under stress (Björkman and Demmig 1987, Werner and Correia 1996, Kalaji et al. 2016). Active ChlF does allow the determination of the maximum efficiency of photosynthetic energy conversion, which is one of the most reliable parameters of stress effects, such as photoinhibition under natural conditions (Werner et al. 2002, Kalaji et al. 2016). Combining ChlF measurements in the light and dark allows to disentangle short-term response from long-term stress (i.e. chronic photoinhibition, Werner et al. (2002)), which have emerged as central parameters to detect stress effects on vegetation and ecosystem function. However, to date, the use of both parameters in large scale monitoring systems is delimited by the number of affordable sensors, energy requirement and requested manpower for operation. Moreover, while crops and grasslands allow ground-based monitoring, forests provide much larger challenges due to difficulties in accessing tree crowns, only possible by tree climbers or restricted by the presence of a tower (Fig. 14) and, hence, in monitoring large areas in heterogeneous terrains, which requires energy-autonomous sensing networks (C1).

To guarantee a high spatio-temporal resolution of ChlF measurements, sensors are to be deployed in high numbers to capture the in heterogeneous light environment in tree canopies up to the top. They need to be highlyminiaturised to avoid negative influence on the microenvironment of the leaf and be energy-autonomous and equipped with means of wireless communication. Only then, they provide maintenance-free sensors, which fulfil our requirements of a deploy-and-forget-strategy. As they are fabricated by microtechnology in mostly parallel processes, they are low-cost and affordable in high numbers (B1).

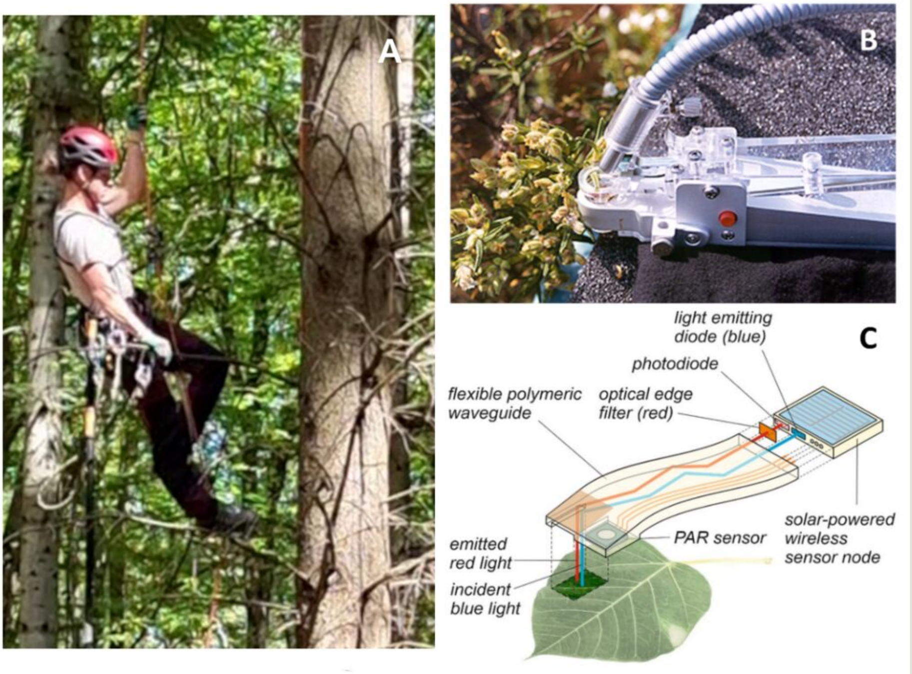

Figure 14. doi

A: Tree climbing to measure ChlF with a portable system. B: PAM-2000 ChlF measuring probe (Photo C. Werner). C: Conceptual drawing of the novel ChlF sensor system with a flexible polymeric waveguide as optical probe head, attached to a leaf – B1.

Remote sensing of ChlF, i.e. from drones, allows an even larger spatial coverage, though at the expense of high temporal resolution. So far, mostly passive solar-induced fluorescence measurements are captured, where ChlF is derived from radiance emitted by vegetation using the absorption bands in surface solar irradiance. With remote sensors, it is usually retrieved with instruments of sub-nm spectral resolution in the narrow window of the O_2 absorption bands or Fraunhofer lines, for example, with Fraunhofer Line Discrimination and spectral fitting methods (Plascyk and Gabriel 1975, Alonso et al. 2008, Cogliati et al. 2015); see review by Mohammed et al. (2019). However, disentangling the many factors that influence the steady state ChlF signal such as environmental conditions, physiological state of plants and light re-absorption/scattering remains challenging. Especially in forest environments, vegetation is particularly complex with respect to species and structural diversity, canopy age and understorey, which complicates the SIF retrieval and its interpretation with regard to photosynthetic activity (Mohammed et al. (2019) and references therein). A collection of ancillary information (such as on environmental conditions, crown shape etc.), measurements with sufficient spatial and temporal resolution as well as multiple fluorescence variables may be required to fully interpret sun-induced ChlF signals and deconvolute underlying physiological reaction to stress (Aasen et al. 2019 Mohammed et al. 2019). Satellite or aircraft sensors for optical forest mapping typically offer a spatial resolution too coarse to resolve individual canopies and overflights remain expensive and restricted to certain heights (Safaei et al. 2022). Unmanned aerial vehicles (UAVs) offer an alternative platform for above crown measurements with higher flexibility in flight timing and heights (Schiefer et al. 2020). Furthermore, measurements can be performed under partly cloudy and even overcast skies, which hinder satellite-based observations. Thus, they can fill temporal gaps in remote sensing time-series studies. However, changing cloud cover resulting in variable illumination conditions (Göritz et al. 2018) can complicate the remote sensing parameter retrieval and needs to be considered in the signal analysis. Nevertheless, UAV-based observations in principle, enable the collection of complementary data at intermediate scale, which is required for closing the modelling gaps between single leaves measurements and remote sensing imagery on regional or even global scales and many advances of sun-induced ChlF sensing on UAVs have been made recently (Vargas et al. 2020).

In contrast to passive SIF measurements, laser-induced fluorescence measurements permit a simultaneous light detection and ranging, which enables an analysis of registered ChlF signals with respect to their position in space. Thus, ChlF signals can be analysed within a spatial framing while facilitating a better connection of airborne ChlF imagery with local in-situ data. Furthermore, an integration of ChlF signals through different layers becomes possible which is of interest for a ChlF mapping and ecosystem assessment at various scales. Opposite to sun-induced ChlF, active ChlF measurements allow for campaigns over the season with less dependence on weather/cloud conditions and are possible even in darkness (Fig. 15). While being a common tool at the leaf scale, laser-induced ChlF measurements on airborne platforms are typically restricted to research systems on aircrafts.

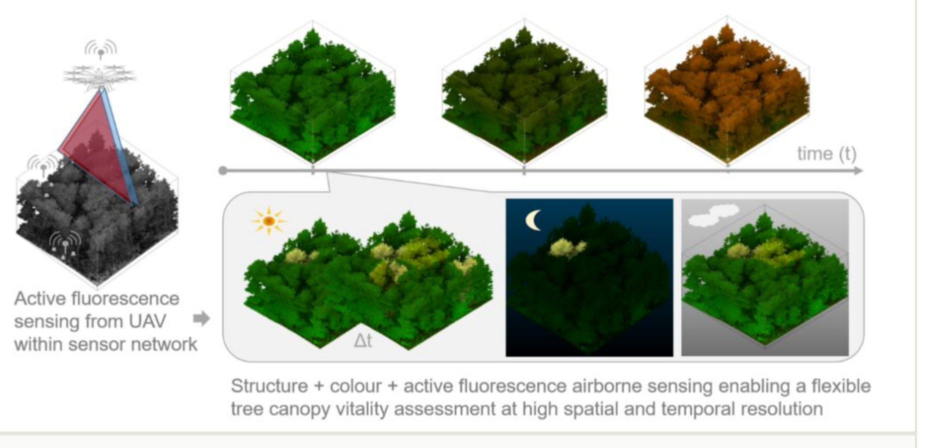

Figure 15. doi

ECOSENSE aims at active ChlF measurement via UVA with high spatio-temporal resolution (left). Campaigns will be run throughout seasons and at various daylight conditions (right) – B2.

- Very strong restrictions apply for UAVs with respect to payload weight and dimension. Due to the low ChlF signal, reliable detection with the help of airborne systems requires very sensitive sensors, accurate calibration and signal correction for interfering effects such as re-absorption and scattering at the leaves or by atmospheric particles. Furthermore, light intensities strong enough to excite fluorescence, but at the same time, low enough to comply with eye safety requirements have to be achieved. Compact instrumentation and methods, which allow for a regular, extensive and spatially resolved above-crown laser-induced ChlF sensing are missing.

Research Area C: Intelligent sensor network, robustness, data management, ecosystem model and deep-learning

Intelligent sensor networks are equipped with steadily increasing intelligence (Sepasgozar et al. 2020), for example, they continuously elaborate on optimising measurement frequency and efficiency. This provides the opportunity to temporally decrease their energy demand, but, on the other hand, requires continuous energy for the adjustment processes. Whereas this does not put specific demands on their energy budgets as long as they are connected to the power grid, challenges still arise when they need to run in an energy-autonomous fashion.

Research is ongoing, for example, for equipment monitoring in industrial environments (Nenninger et al. 2010) or infrastructure monitoring (Zhao et al. 2013). However, a closer look into these studies and products reveals that the proposed energy autonomy of these systems is based on a regular energy supply from the environment, for example, through energy harvesting. The systems will simply cease operation as soon as the available energy is not sufficient, not considering, for example, variable and energy-adapted duty cycles. Energy awareness has, thus, come into focus, but has been covered only by a few studies (Ali et al. 2010, Cammarano et al. 2012). It has also been shown that the implementation of energy prediction schemes can increase the service time of an embedded sensor node by more than 50% (Cammarano et al. 2012). However, there is a risk that using this procedure will lead to an overuse of the harvested energy.

To further support the energy efficiency of the sensor nodes, ultra-low-power operation of integrated circuits for power management, sensor signal processing and RF communication have been investigated. Some convincing devices have been presented as proves-of-concept (Wang et al. 2017), which are, however, not available to embedded system designers. Existing commercial devices, for example, wake-up-receivers (Austria Microsystems Datasheet v1-62 2014) are available, but insufficient for extremely low energy budgets. Amongst others, our own research has addressed this problem with circuits using components-off-the-shelf. Power levels achieved do already match industry's state-of-the-art (Gamm et al. 2010, Woias et al. 2018) with room for improvement and a much easier adaptation to specific applications.

Besides, the energy-efficient implementation of software is not a primary target of developers today, while a multitude of efforts on energy-efficient computing from 40 years ago has been virtually "forgotten". A practical implementation would require a more hardware-related programming of microcontrollers and an optimisation of today's, frequently power-inefficient, code compilers. The revitalisation of this know-how, together with modern hardware platforms and hardware-related programming, reveals an astonishing potential for power saving without sacrificing computing performance (Heller and Woias 2019). Furthermore, an embedded system should be capable of deciding by itself whether and how fast an action is required to save on power-hungry fast computation or on non-relevant wireless communication. Again, the optimisation potential can be realised by approaching an energy-efficient realisation of the required decision-making (Liu et al. 2009).

Radio frequency communication standards for wireless sensors such as ZigBee are optimised for low power consumption in the range of several milliwatts when the radio is active. Within the last years, new communication technologies with particularly large communication distances have been established in the context of low-power wide-area networks (Mekki et al. 2019). Standards like LoRa allow for a communication range of up to 40 km due to low data rates and advanced modulation schemes, while holding power consumption in the range of several 100 µW in duty-cycled receiving mode and several 10 mW for transmitting a packet. Recently, first approaches of synthesising such long-range communication packets by backscattering of ambient RF waves were presented, allowing the transmission of data over a distance of 3 km at a power consumption of only 10 µW (Talla et al. 2017). Still, the implementation requires a specific CMOS design, so that common availability is not given. While all these range metrics are valid for line-of-sight propagation, i.e. without any disturbing objects in the transmission path, the RF communication range reduces significantly in a forest environment, where multi-path propagation and loss of dielectric media are omnipresent. In consequence, reliable communication using the LoRa standard is possible within a radius of approximately 400 m (Sardar et al. 2018). While this is a promising approach, the detrimental influence of dense leaves, wet stems, rainfall or snow represents severe limitations and poses critical challenges on that perspective.

> *Energy efficiency and autonomy are premier requirements for sensor nodes operating under field conditions. While individual and partial solutions for these questions are state-of-the-art, their combination is the challenge addressed in project C1. For radio-communication, the open question is how the existing concepts can be transferred to the harsh environment of a heterogeneous dense forest.*

When sensors are installed in the field for long-term monitoring, they become exposed to demanding environmental conditions, such as water, soil, acid, UV radiation, strongly variable temperatures and cross-contamination with biological objects, for example, insects and microbes. Together with general pollution and dust deposition, this will usually lead to the formation of a biofilm, which will increasingly deteriorate the sensing capability (Fig. 16).

Biofilm formation has been in the focus of intense research for many years; however, up to now, no general solution to the problem has been developed. Many approaches are based on biozides, which are added to a coating and are slowly released with time (Gerigk et al.

1998, Vorkamp et al. 2014, Silva et al. 2020). Such approaches are commonly used in very harsh environmental conditions, for example, in marine environments (e.g. protection of ship hulls). A continuous leaching of poisonous compounds into the environment, however, is not desirable and will influence the ecosystem to be monitored. Alternative approaches are for example, the addition of polyethylenglycol chains to the surfaces developed by Grunze and coworkers (Wang et al. 1997, Kingshott and Griesser 1999); however, for such compounds, long-term stability is a serious issue, which has essentially led to abandonment of this approach in outdoor applications, even though it is standard for medical applications. A third strategy which has been employed in controlled laboratory environments is the generation of either a topological (formation of needle-like nanostructures) or chemical pattern on the surfaces. Here, the key idea is to make the surfaces “uncomfortable” for adhering biological cells, either by piercing the cell walls with sharp needle-like structures or by establishing a hydrophilic/hydrophobic pattern on the target surface (Bennett et al. 2009, Weinman et al. 2010, Lejars et al. 2012) which renders cell adhesion difficult. Both strategies have not led to long-term success under real-life conditions: nanostructures at surfaces are mechanically fragile; even low forces will cause mechanical damage to the surfaces and shear off some of the nanostructures. Additionally, the deposition of dust or other contaminants, such as oils will strongly mitigate the effect as discussed further below. Hydrophilic /hydrophobic contrast also is maintained only for shorter periods of time since highly polar surfaces have a tendency to adsorb ubiquitously available lipids from the environment (“hydrophobic recovery”) (Jokinen et al. 2012), so that the polarity contrast becomes diminished and disappears over time and the anti-adhesive properties become lost with time.

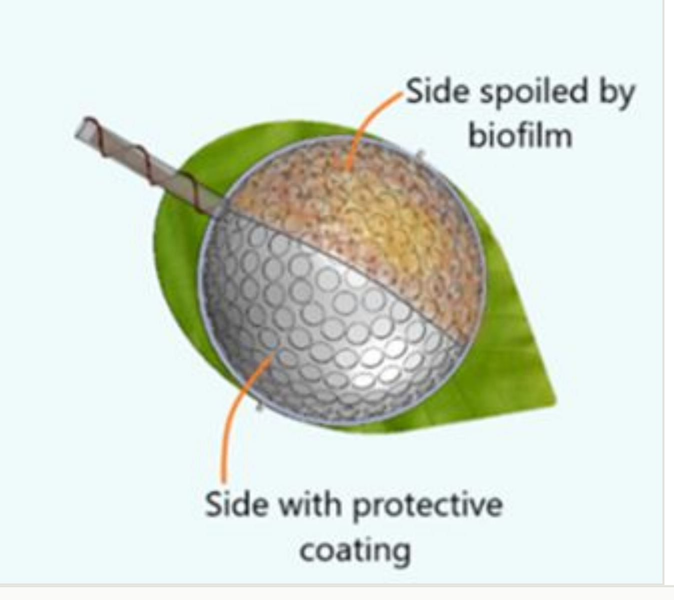

Figure 16. doi

Leaf cuvette as developed in A3, partially protected with anti-biofouling coating from C2.

A concept developed recently is based on the prevention of the adhesion of macromolecular biomolecules and based on “entropic shielding” (Wörz et al. 2012, Pandiyarajan et al. 2013). In this approach, thin hydrogel layers are covalently attached to the surface to be protected. Such hydrogels can swell only in one reaction (Toom) leading to a situation where the polymer chains are strongly stretched. When hydrogels are chosen which have no Coulombic or hydrophobic interactions, any penetration of the hydrogels will lead to additional chain stretching and further reduce the entropy of the system, which leads to a positive free energy of the adhesion process, thus preventing any biomolecule adhesion. So far, such systems have been studied only in bioanalytical or medical environments (interphases) and no exposure to harsh outdoor environments has been tried.

To prevent the adhesion of dust particles on the surfaces of the sensors, a low energy surface coating can be applied. This strongly reduces the surface energy and, thus, the adhesion of any particles. In fact, putting Teflon-like or other highly fluorinated coatings on surfaces is state-of-the-art (McKeen 2013). The trade-off connected to these approaches, however, is that coatings that avoid materials sticking to the surface also have intrinsic difficulties to stick to the sensor. One possible solution is, thus, to generate covalent bonds between the surface and the coating, for example, through the generation of fluorinated self-assembled monolayers (McKeen 2013). Fluorinated polymer layers can be obtained by simply attaching them to the surfaces (grafting to), growing fluorinated chains through a surface-initiated polymerisation (grafting from) or generating the fluorinated layers with the help of surface-attached monomers (grafting through).

An alternative pathway to keep surfaces clean from dust is the so-called “Lotus” effect (Forbes 2008) where wax crystals formed at the leaf surfaces of the Lotus plant lead to the generation of hierarchical surface structures with superhydrophobic properties. Whereas this works fine in more or less controlled environments, in a forest, surfaces will be contaminated with oil (e.g. from spruces) with dust or with proteins or will be damaged by mechanical influences (such as wind or insects) or temperature (including ice coatings) (Hönes and Rühe 2018). In the Lotus plant, such problems are taken care of by shedding damaged leafs and regrowth of new ones, an option not available for artificial materials, such as sensor surfaces.

Biofilm prevention, dust/dirt repellence, UV resistance, avoidance of delamination, long-term film stability - all of these tasks are still to be evaluated and further developed for the harsh forest environment, as the concepts developed so far may not be transferable at all. In addition, measures should not interfere with the environment in a way that sensor signals may be affected/altered.

Most coating methods have been developed for application to planar surfaces (spin coating, dip coating, doctor blading…) or are restricted to monomolecular layers (self-assembled monolayers). We need to extend this concept to robust layers functioning over vegetation periods in a forest. Furthermore, protecting irregular-shaped sensor surfaces, including highly porous surfaces are very challenging.

In environmental science, hardly any research community outside meteorology and hydrology has access to a larger set of spatially-distributed environmental sensors and, in particular, near real-time data availability for modelling approaches is generally lacking. Only very recently, researchers have started to think of multi-sensor data in ecology (Fer et al. 2018), but the statistical assimilation of such data is still in its infancy. One of the obstacles is that ecological processes operate at vastly different temporal and spatial scales, making it difficult to relate, for example, carbon and water fluxes to tree carbon allocation or growth. In addition, forest ecosystems are represented by many different compartments, for example, soil, ground vegetation, stems, roots and canopy, which we need to be understand individually and in interaction, while applications in other fields of science focus on a single or few state variables. In order to connect different compartments and scales, hierarchical theory helps to define the speed and range of processes to be considered (Robinson and Ek 2000, Papyan and Talmon 2018). The key challenges in the analysis of such multi-stream data is thus threefold: (1) the large amounts of raw data that need to be curated and quality-controlled; (2) the large discrepancies in measurement frequency between different sensors; and (3) the continuous updating of data with incoming data ("online learning"). For each of these challenges, solutions have been described (Alber et al. 2019, Brunton and Kutz 2019), particularly for medical imaging (Ge et al. 2018) or speech recognition (Han et al. 2020). Still, fast and open-source solutions that operate in or near real-time are the focus of current research (Wang et al. 2019). Interestingly, while reducing the set of machine-learning tools available to handle such data, multi-scale frequency data also reduce the update frequency of the model towards the slowest processes of interest, with higher frequencies being compressed into sub-layers (Bieker et al. 2019).

> *Deep-learning approaches to big data typically have the luxury of homogenous structure, i.e. constant (Ge et al. 2018) sampling intervals. Assimilating streams of heterogeneous sensor data in real time requires exploration of suitable network structures (C4).*

Ecosystem models are challenged by the disparity between processes, fluxes and states measured in the field and the level of physical, biogeochemical and physiological detail represented in the model. This disparity seriously impedes the evaluation of physiology-oriented ecosystem models and also restricts the application of physiological process-knowledge (derived from laboratory and greenhouse studies) to the complex ecosystem level. On the other hand, several studies have demonstrated systematic errors when modelling terrestrial ecosystem sensitivity to climate variability, indicating that the application of empirical processes for cases which cannot really be backed up with empirical data, are very limited (Piao et al. 2013, Ruiz-Benito et al. 2020).

Regarding the process-oriented description of forest systems, efforts concentrated on growth descriptions for even-aged monocultures until very recently, often paired with a coarse representation of water and nutrient interactions. The reason for this restriction is that expanding to structured and mixed forests requires the representation of individual or plant type interaction, including an advanced description of soil-plant interactions. Such a representation includes a multitude of hierarchically organised processes that are much more difficult to evaluate in a complex forest system.

Development and application of advanced models that cover complex forest structure is essential since heterogeneous forest types are better suited to withstand multiple stressors under changing climate conditions and, hence, represent current and future forestry practice in Europe (e.g. Bauhus et al. (2017)). Only few models with physiological process description representing effects of CO_2, temperature, water and nutrient availability (Medlyn et al. 2011) are trying to represent the competition between differently-sized trees and various tree species in such structured forests, particularly from early stages onwards. Such models are derived either from the competition-based gap models by introducing more processes (e.g. SORTIE: (Coates et al. 2003) or from detailed process-models that increasingly consider individual dimensions (e.g. BALANCE (Grote and Pretzsch 2002); HETEROFOR (Jonard et al. 2020)). Current developments try to further elaborate on combining a process-based environmental responsivity with dynamic consideration of resource competition by neighbouring plants of different sizes or species (Grote et al. 2020).

> *Still, it is challenging to represent the influence of fine-scale environmental changes on plant development, while, at the same time, merging individual developments into an ecosystem dynamic that, in turn, affects environmental influences.*

Due to technical restrictions, until now observational data for example, from FLUXNET/ICOS/TERENO networks were only subsequently used for model parameter estimation and simulation of forest ecosystem dynamics in time delays of up to years (Molina-Herrera et al. 2015, Collalti et al. 2016, Peaucelle et al. 2019). In contrast to meteorological models, ecosystem models are not being updated in time, for example, using Bayesian or Kalman-filter-like approaches (Sun and Sun 2015, Dietze 2017), although these are being used for model calibration (Fer et al. 2018).

> *Linking forest observational data in near real time to ecosystem model and deep learning-based data analysis will enable process advancements and improved now and forecasting of ecosystem states and fluxes which can be further used to re-inform and optimise the sensor data acquisition, which is an emerging and innovative research field, but ,to our knowledge, not yet implemented (C4).*

Management infrastructure

Management of research data and knowledge

Research data management is regarded as critically important to the ECOSENSE project itself, as well as the University of Freiburg. In ECOSENSE, we devote a project (C3-INF) to this topic and refer to the specific data management strategy details there. Here, we only briefly outline the underlying principles.

- Our data management follows the FAIR principles;

● Our data publication strategy is aligned with the DFG-funded NFDIs, specifically NFDI4Biodiversity (overlap-ping with GFBio). Harmonisation between our database (project **C3-INF**) and the NFDI4Biodiversity will be part of the work in the first funding phase;

● Data will be made openly and publicly available within 3 years of collection;

● For sensor construction, we encourage all PIs to follow Open-Source Hardware idea, i.e. releasing detailed construction descriptions for other researchers to copy under a non-commercial licence;

● At the university, research data management activities are being supported by a working group at the computing centre (https://www.rz.uni-freiburg.de/rz/aktuell/rdmg-start/?searchterm=Forschungsdatenmanagement).

Management of the Collaborative Research Centre

ECOSENSE will be jointly managed by two spokespersons having equal rights, with one expert representing the environmental sciences (Christiane Werner) and one the engineering sciences (Ulrike Wallrabe). Together with the spokespersons of our three research areas, the embedded Research Training Group RTG and two representatives from the group of doctoral and postdoctoral researchers, they will form the Board of ECOSENSE which controls and monitors the timely progress and content flow of the project. Furthermore, the Board will be responsible to guide and enable a gender- and diversity-balanced working attitude.

All staff employed in the CRC will be ECOSENSE Members. They will elect all spokespersons of ECOSENSE and an equal opportunity officer. The ECOSENSE Members will furthermore suggest and accept new members in conjunction with the Board. Eventually, they will have the power to accept the finance plan for each year as suggested by the Board.

The doctoral and postdoctoral researchers will implement their own network, the Network of Young Researchers delegate two elected peers to the Board.

The Board will be supported by a coordinator (Nina Stobbe) responsible for finances and the scientific coordination of workshops, retreats and the international ECOSENSE conference to take place in Freiburg, Germany, in summer 2025. The Research Training Group, as well as our joint research infrastructure, will be coordinated by Julian Müller.

We are aware that an intense and open communication within the CRC, but also to the community, is essential for a high quality research output and a strong positive national and international visibility. An intense interdisciplinary cooperation and information flow is already embedded in the unique structure of ECOSENSE, as each project in Research Areas A and B will join partners from different disciplines and the overarching Research Area C will assimilate data from all projects into a common model. One key focal activity will be our joint experimental platform, most importantly our ECOSENSE Forest.

The synergy of the observations of data collected at ECOSENSE Forest will be assured not only by our coordinated data management, but also through various joint workshops, fostering extensive interdisciplinary collaboration. The Board of ECOSENSE will provide the mandatory infrastructure for knowledge exchange (internet platform, ECOSENSE homepage, common data platform) and foster the information flow within the CRC amongst participants.

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Grant title

SFB 1537/1 ECOSENSE

Author contributions

C. Werner and U. Wallrabe contributed equally to this manuscript, share the first authorship and act as co-spokespersons of ECOSENSE.

N. Stobbe and J. Müller supported in the manuscript preparation.

All other co-authors have contributed with their project descriptions.

Conflicts of interest

The authors have declared that no competing interests exist.

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