

Concepts and tools to link remote sensing and ground-based monitoring of European forests

D2.1, Report on forest monitoring network, WP 2, T2.1

Authors: Arthur Gessler (WSL), Dominic Fawcett (WSL), Mirko Lukovic (WSL), Jelle Lever (WSL), Benjamin Brede (GFZ), Aleksi Lehtonen (LUKE), Eduardo García Martínez (LUKE), Emma Bambagioni (UNIFI), Saverio Francini (UNIBO)

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<i>v</i>	<i>Date</i>	<i>Beneficiary</i>	<i>Author</i>
1.0	30/04/2026	WSL	Arthur Gessler

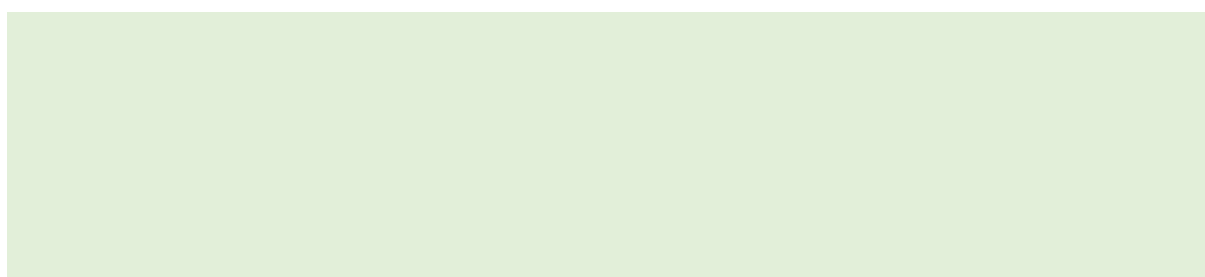
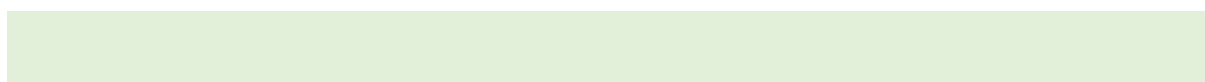


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Abstract

This report presents approaches developed within the FORWARDS project WP2 to bridge ground-based forest monitoring and remote sensing. Advances in proximal methods, including improved dendrometer measurements, meteorological integration, and terrestrial laser scanning, have contributed towards enhanced data quality and comparability. Physiological links between leaf-level traits and drone-based optical data demonstrate that vegetation indices (VIs) can capture drought impacts and recovery at the tree scale. Scaling analyses reveal limitations in applying optical indicators across spatial resolutions and forest types, though relationships between VIs and water availability still show promise at landscape scales. Satellite-based approaches, including temporal autocorrelation, can detect early resilience loss and flag forest areas at risk. Within such targeted risk areas, satellite-based VIs could be directly correlated with plot-scale measurements or integrated within models, for which we demonstrate examples. Machine learning models integrating data from the ground and gridded meteorological data, in future also remote sensing data, can provide complementary wall-to-wall insights, e.g. on tree water deficit. Together, these approaches support identification of forest vulnerability and prioritization of monitoring efforts across Europe.

Main Report

1. Introduction

Forest monitoring is critical for understanding ecosystem functioning, carbon dynamics, and the impacts of climate extremes, particularly drought, which is increasing in frequency and severity under climate change (Hammond et al., 2022). Drought-induced tree stress and mortality have been documented across many biomes and represent a major uncertainty in predicting future forest resilience and carbon sequestration potential (Adams et al., 2017). Monitoring systems must therefore capture both early physiological stress and long-term structural decline across spatial scales.

Traditional ground-based forest monitoring provides detailed physiological and ecological information, including measurements of leaf water potential, pigment concentrations, growth, and crown condition, which are mechanistically linked to drought vulnerability and tree health (Bartlett et al., 2016; Choat et al., 2018). However, these approaches are inherently limited by spatial sparsity and logistical constraints.

Remote sensing offers a scalable alternative by enabling repeated, spatially continuous observations of vegetation condition. Optical satellite data have been widely applied in disturbance detection and drought monitoring (Cohen et al., 2018; Goetz et al., 2006). However, conventional greenness-based metrics primarily detect changes in leaf area or canopy structure, which typically occur later in the stress trajectory (Buras et al., 2021; Forzieri et al., 2022; Gazol et al., 2018). This limits their effectiveness for early detection of physiological drought stress.

Recent advances in both, remote sensing and ground-based monitoring methods, pave the way for bridging between plot and landscape scale. New sensor networks and processing pipelines greatly improve the temporal frequency of assessing structure and water status at plot-level (Zweifel et al., 2021) while hyperspectral and high-resolution remote sensing now allow detection of subtle spectral changes associated with plant physiological processes before visible canopy decline (Houborg et al., 2015; Zarco-Tejada et al., 2019). Nonetheless, scaling remains challenging due to canopy structural heterogeneity and species composition effects influencing spectral signals (Hilker et al., 2010; Kattenborn et al., 2024; Ripullone et al., 2011).

This report presents an overview of efforts towards integrating proximal plot-scale and remote sensing measurements, including technologies, methods and insights with a focus on studies associated with the FORWARDS project.

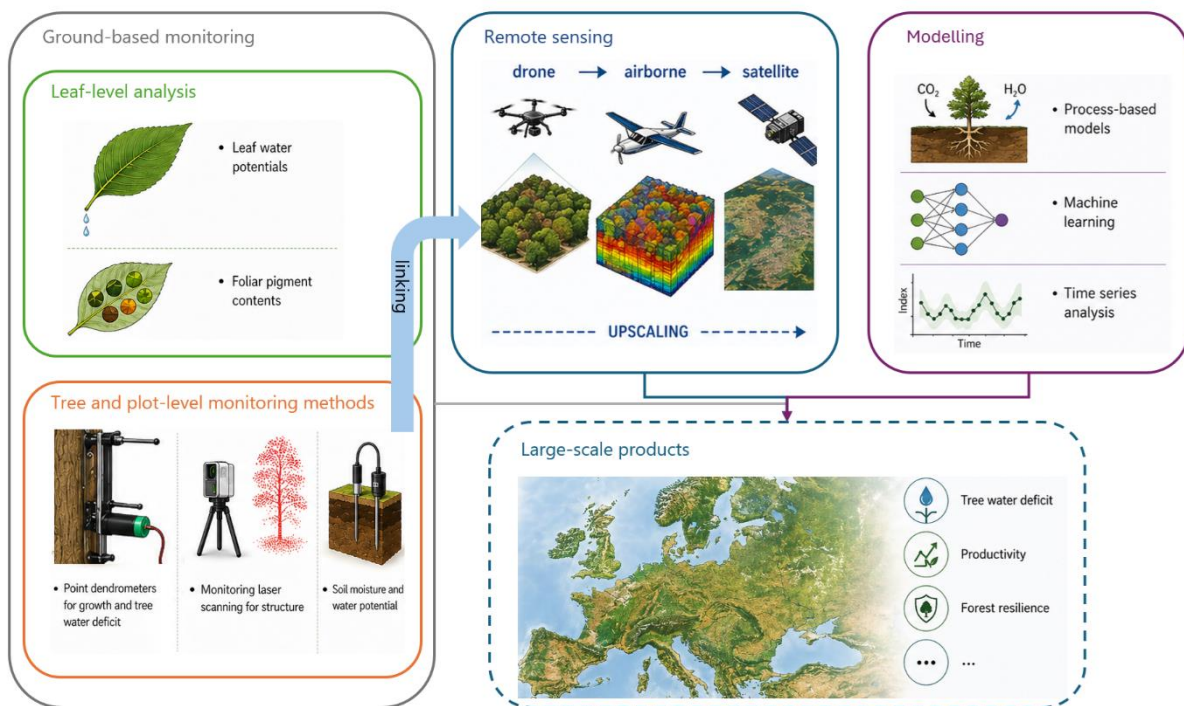


FIGURE 1: SCHEMATIC OVERVIEW OF HOW FORWARDS WP2 SEEKS TO LINK GROUND-BASED MONITORING AT LEAF, TREE AND PLOT LEVEL WITH REMOTE SENSING DATA TO EVENTUALLY GENERATE WALL-TO-WALL MAPS OF INDICATORS OF FOREST CONDITION AT NATIONAL AND EUROPEAN SCALES. ILLUSTRATIONS FOR THE DIAGRAM WERE GENERATED WITH CHATGPT-5.

2. Advances in automated proximal monitoring of tree water and structure dynamics

A major challenge in linking ground-based measurements with satellite observations lies in mismatches in temporal resolution and process sensitivity. Physiological processes such as stomatal regulation and water potential dynamics operate on short timescales (Brodribb et al., 2017), whereas satellite observations can be used to integrate signals over longer periods of time or represent temporal snapshots which are however difficult to align with proximal field measurements.

Automated, high-frequency proximal monitoring systems provide an intermediate observational layer that captures continuous physiological and structural responses at the tree and plot level. These methods enable detection of sub-daily dynamics in growth and water status directly related to drought stress (Peters et al., 2025).

High-frequency measurements are particularly valuable for interpreting optical remote sensing signals influenced by rapid physiological processes such as stomatal regulation and changes in photochemistry (Garbulsky et al., 2011). Continuous proximal observations help disentangle whether spectral changes are driven by short-term physiological regulation or longer-term structural decline.

Furthermore, proximal monitoring supports validation and calibration of remote sensing products across scales, enabling links between physiological processes and canopy reflectance (Pierrat et al., 2025; Xu et al., 2020).

2.1 Point dendrometer time-series and gap filling

High-resolution environmental monitoring networks are essential for understanding ecosystem processes but are susceptible to data loss from wireless transmission failures, hardware malfunctions, and adverse weather conditions. To address this and increase the suitability of these measurement networks for integration with remote sensing data, we developed a multi-tier deep learning pipeline for gap-filling and virtual reconstruction of correlated environmental signals (time series) recorded at 10-minute resolution across a network of 92 Swiss forest monitoring sites (TreeNet/LWF). The pipeline processes five co-located variables - air temperature, relative humidity (*Figure 2*), soil temperature, soil water potential, and stem radius (dendrometer signal) (*Figure 3*)- in a fixed cascade: each stage produces a gap-filled output (level 3 – L3 data) that serves as an additional input feature for downstream stages, systematically exploiting inter-variable physiological correlations.

For each variable, gaps are handled by a five-tier strategy that scales model complexity to gap severity. Tiers 1-4 fill gaps in sensors with physical measurements: Tier 1 applies linear interpolation for gaps up to 30 minutes; Tiers 2 and 3 employ a Bidirectional Temporal Convolutional Network (BiTCN) with multi-head self-attention for gaps up to 35 days, reconstructing the target from bilateral context and gridded meteorological covariates; Tier 4 uses a Meteo Regression TCN model with learnable per-sensor embeddings for gaps exceeding 35 days. Tier 5 generates complete synthetic time series ("virtual sensors") at sites lacking a specific instrument, using either a BiTCN conditioned via Feature-wise Linear Modulation (FiLM) on static geographical and ecological site descriptors, or, depending on the physical property, a two-stage statistical model combining a site-level Ridge regression for mean bias correction with a LightGBM model for weather-driven detrended residuals, followed by physics-based 10-minute disaggregation using the (Buck, 1981) saturation vapour pressure formula. Bidirectional processing and self-attention allow the model to integrate long-range temporal dependencies from both past and future observations surrounding a gap. Training uses a sensor-disjoint 90/10 inner train/validation split to prevent the FiLM conditioning layers from memorising per-sensor corrections and to ensure generalisation to unseen sites.

So far, in production, the temperature model (13 channels) fills 49,330 gaps across 87 sensors with a 99.8 % fill rate (holdout MAE: 0.83 deg C, $R^2=0.88$). The humidity model (14 channels) fills 54,669 gaps across 96 sensors and reconstructs 26 virtual sensors at sites without hygrometers (Tier 5 LightGBM holdout: daily MAE = 4.55 %RH, 10-minute MAE = 6.31 %RH). The pipeline architecture is generic and applicable to any multi-variate environmental monitoring network with correlated time series recorded at fixed spatial locations.

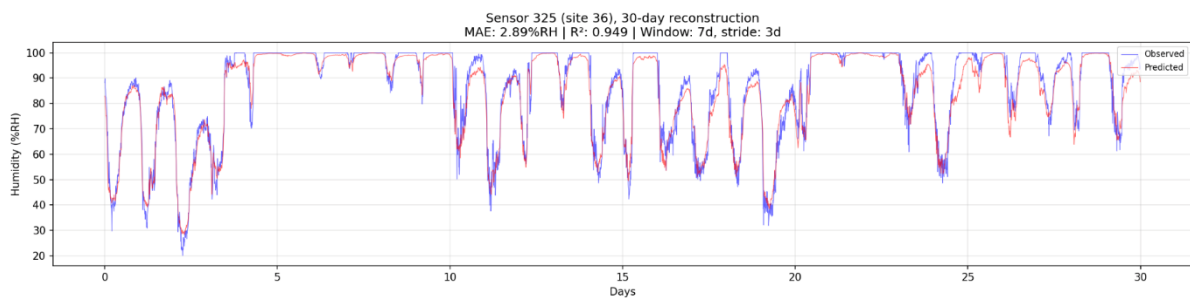


FIGURE 2: TIER 2 PREDICTION OF A 7-DAY GAP IN THE STEM RADIUS USING A MODEL WITH TEMPORAL CONVOLUTION NETWORK ARCHITECTURE. THE CONTEXT IS GIVEN BY THE STEM RADIUS SIGNAL BEFORE AND AFTER THE GAP AND ALSO THE OTHER AVAILABLE BELOW CANOPY SENSORS AND THE GRIDDED DATA. THE GREEN CURVE IS THE GROUND-TRUTH AND THE ORANGE LINE IS THE PREDICTION. IN THIS CASE THE PREDICTION IS SHOWN FOR THE ENTIRE 30-DAY PERIOD.

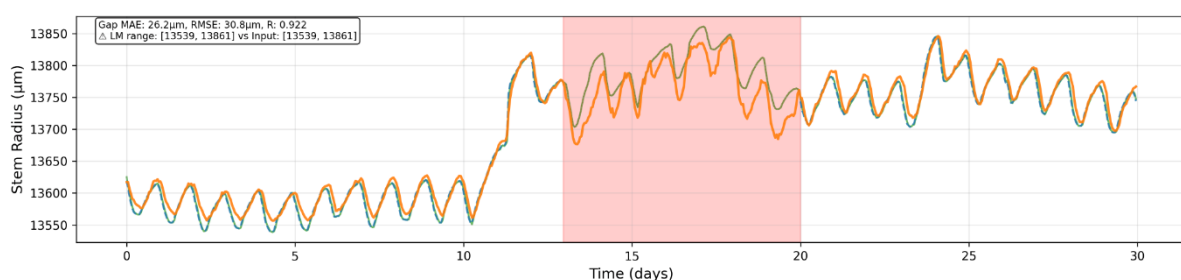


FIGURE 3: TIER 4 GAP PREDICTION OF THE RELATIVE HUMIDITY FOR A PERIOD OF 30 DAYS USING THE METEO REGRESSION TEMPORAL CONVOLUTION NETWORK ARCHITECTURE. THE BLUE CURVE IS THE GROUND-TRUTH AND THE RED CURVE IS THE PREDICTION. THE PREDICTION RELIES ON THE BELOW CANOPY TEMPERATURE MEASURED ON SITE AND THE AVAILABLE GRIDDED METEO DATA.

2.2 Proximal laser scanning for monitoring of canopy structure

2.2.1 Unoccupied Aerial Vehicle Laser Scanning (ULS)

ULS allows the detailed acquisition of forest structure from above, often providing better representations of the upper crown compared to TLS due to occlusion. Occlusion however also limits the level of detail which ULS can provide for the understorey. Nevertheless, ULS point clouds have been successfully used to derive canopy height, stem diameters and plant area volume density (PAVD) (Brede et al., 2017), while their rapid acquisitions compared to other laser scanning methods also make them attractive for higher frequency structural monitoring of forest plots.

Led by GFZ, a flight campaign is ongoing to collect ULS point clouds at distributed super-sites across Europe, primarily at ICOS sites. At each site, a representative area of the landscape is collected, typically in the range between 50 and 250 ha. Although this pan-European campaign does not allow for repeat acquisitions and monitoring, the aim is to produce consistent canopy height models at fine spatial resolution (≤ 0.5 m) which serve purposes such as model parameterisation (e.g. (Cao et al., 2019)) and structural reference data for interpretation of ICOS measurements. These data are hosted at the publicly accessible S3 storage of GFZ with [STAC](#)-capabilities, where it can be explored and is

machine readable. An overview of already available datasets is provided by the EOForestSTAC browser (<https://simonbesnard1.github.io/eoforeststac/>).



FIGURE 4: ULS FLIGHT CAMPAIGN STATUS (GREEN = ACQUIRED, ORANGE = PLANNED)

2.2.2 Monitoring laser scanning

Monitoring laser scanning is a recent technology that captures forest canopy 3D development at high temporal frequency (Calders et al., 2023). Field protocols, processing assumptions and routines, and need for intercalibration were discussed at the StrucNet workshop organised by GFZ on 30 May – 1 June 2023. For intercomparison with other observations modes, one Laser Enabled Assessment of Forest (LEAF) Mk III has been installed at the Hainich site (https://meta.icos-cp.eu/resources/stations/ES_DE-Hai) (Figure 2, Figure 3). The derived plant area index (PAI) is the vertically integrated PAVD and can be compared to PAI from passive optical systems, e.g., Digital Hemispherical Photography as widely used ground-based alternative or satellite observed PAI.

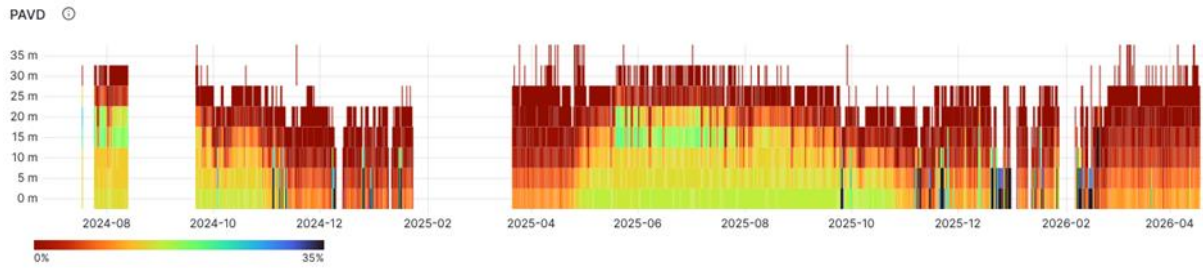


FIGURE 5: PLANT AREA VOLUME DENSITY (PAVD) TIME SERIES DERIVED FROM LEAF POINT CLOUDS AT THE HAINICH SITE. PAVD IS THE PLANT AREA DISTRIBUTED OVER A VOLUME, HENCE ALLOWS TO OBSERVE THE VERTICAL DISTRIBUTION OF FOLIAGE IN THE CANOPY.

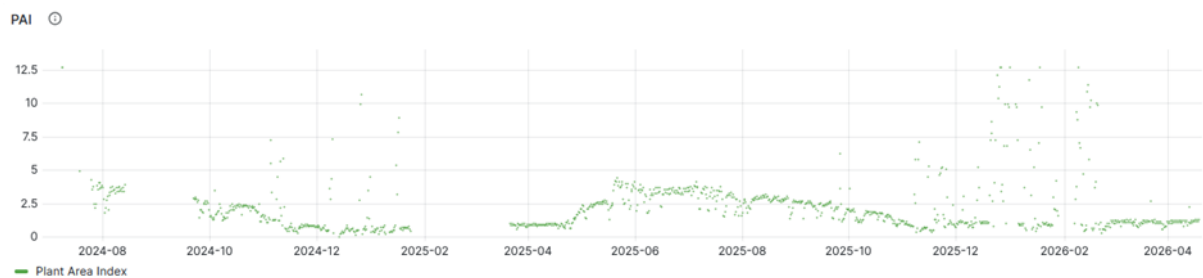


Figure 6: Plant Area Index (PAI) time series derived from LEAF point clouds.

3. Optical indicators for remote monitoring of short- to long-term drought stress

Optical vegetation indices (VIs) combine the information of reflected light at different wavelengths and capture different components of plant physiological and structural responses to drought, operating across short, medium, and long temporal scales. Their interpretation depends on the spectral region targeted and the underlying physiological processes influencing reflectance.

3.1 Short-term indicators: Photoprotection and leaf water content

Photoprotection

Early drought stress typically triggers stomatal closure, which reduces CO_2 assimilation and increases excess absorbed radiation (Brodribb et al., 2017; Sperry, 2000). To avoid photodamage, plants activate photoprotective mechanisms, including non-photochemical quenching (NPQ) mediated by the xanthophyll cycle (Demmig-Adams et al., 1999; Demmig-Adams & Adams, 1996). This rapid pigment conversion alters reflectance near 531 nm, forming the basis of the Photochemical Reflectance Index (PRI) (Gamon et al., 1992).

PRI has been shown to track changes in light-use efficiency and photoprotective activity and is closely linked to physiological stress responses (Gamon et al., 1997; Garbulsky et al., 2011). Because these adjustments occur on short-term timescales (minutes to hours), PRI is considered an early indicator of drought stress.

D’Odorico et al., (2025) demonstrated that PRI correlates with leaf water potential across multiple tree species, capturing both drought-induced declines and post-rainfall recovery dynamics (Figure 7). Importantly, PRI reflected diurnal photoprotective dynamics (the de-epoxidation state of Xanthophylls, DEPS, Figure 8), with higher activation rates and wider daily ranges observed in more drought-stressed species. A combined model using PRI and NDVI explained approximately 65–70% of the variance in leaf water potential, highlighting PRI’s ability to capture rapid physiological regulation linked to hydraulic functioning.

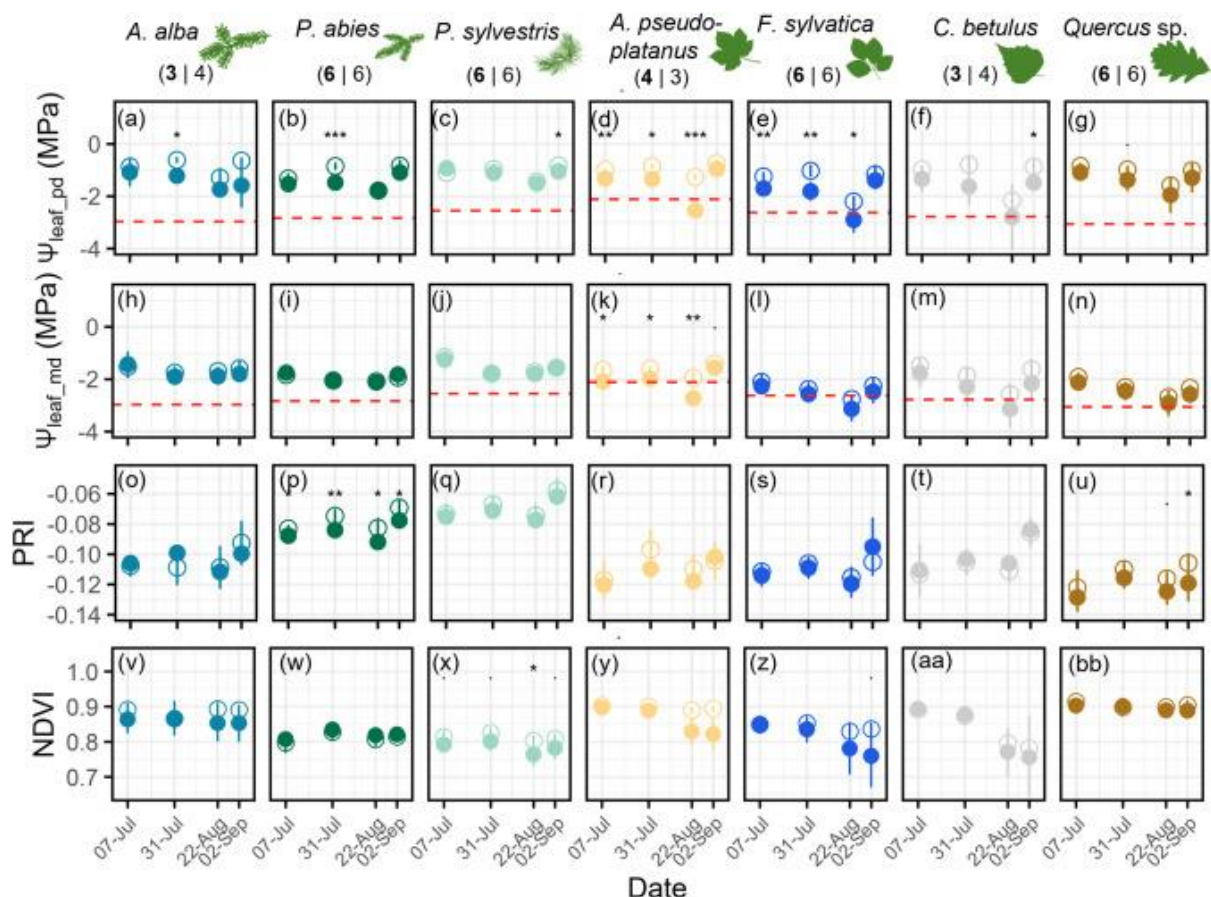


FIGURE 7: DYNAMICS OF LEAF WATER POTENTIALS AND DRONE-BASED CROWN-LEVEL SPECTRAL INDICATORS FOR TREATMENT (FILLED MARKERS) AND CONTROL (EMPTY MARKERS) TREES AT THE SCCII SITE OVER SUMMER 2023. WATER POTENTIALS WERE MEASURED AT PREDAWN ($\Psi_{\text{LEAF_PD}}$; A-G) AND AT MIDDAY ($\Psi_{\text{LEAF_MD}}$; H-N), WITH RED DASHED LINES REPRESENTING SPECIES-SPECIFIC TURGOR LOSS POINTS. SPECTRAL INDICATORS INCLUDE MIDDAY PHOTOCHEMICAL REFLECTANCE INDEX (PRI; O-U) AND NORMALIZED DIFFERENCE VEGETATION INDEX (NDVI; V-BB). TOP: SPECIES AND NUMBER OF TREES ARE REPORTED AS (TREATMENT | CONTROL). SIGNIFICANT DIFFERENCES BETWEEN CONTROL AND TREATMENT TREES FOR EACH DATE ARE INDICATED BY ASTERISKS (. $p < .1$, * $p < .05$, ** $p < .01$, * $p < .001$). FOR ALL PARAMETERS, LOWER VALUES INDICATE HIGHER STRESS LEVELS.**

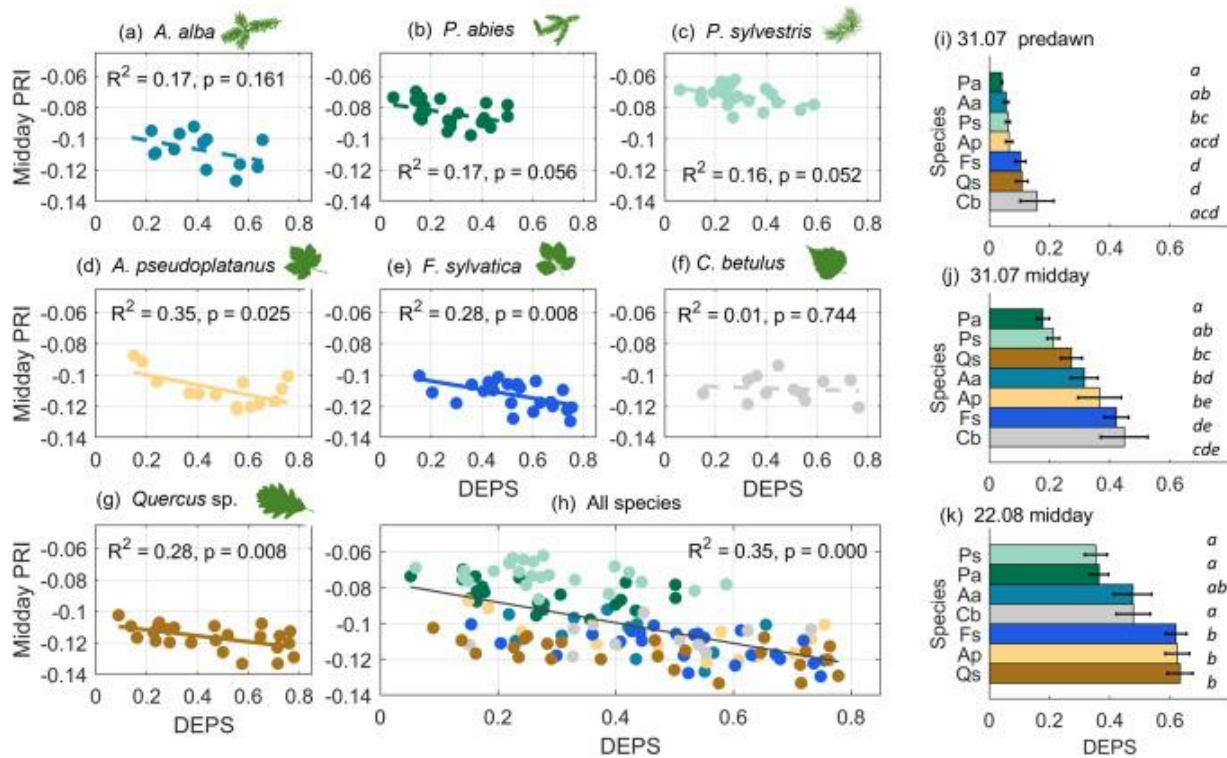


FIGURE 8: SPECIES-SPECIFIC RELATIONSHIPS BETWEEN DRONE-BASED CROWN-LEVEL MIDDAY PHOTOCHEMICAL REFLECTANCE INDEX (PRI) AND LEAF-LEVEL DE-EPOXIDATION STATE OF THE XANTHOPHYLL CYCLE (DEPS), BASED ON LEAF/NEEDLE SAMPLES TAKEN IN PROXIMITY OF DRONE OVERFLIGHTS ON 31 JULY AND 22 AUGUST 2023 AT THE SCCII SITE (A-H). DASHED LINES INDICATE NON-SIGNIFICANT TRENDS, WHILE SOLID LINES INDICATE SIGNIFICANT LINEAR RELATIONSHIPS ($p < 0.05$). LEAF-LEVEL DEPS OF SPECIES SAMPLED ON (I) 31 JULY PREDAWN, (J) 31 JULY MIDDAY, AND (K) 22 AUGUST MIDDAY, ARE RANKED WITH SIGNIFICANT DIFFERENCES BETWEEN SPECIES ($p < 0.05$) INDICATED BY DIFFERENT LETTERS.

Moving from highly resolved PRI measurements of individual tree crowns to coarser data from airborne and satellite instruments, **Fawcett et al. (2025)** showed that PRI remained sensitive to spatial variations in water availability (e.g., available water capacity, Figure 9), indicating that early physiological stress signals linked to photoprotection can be detected even at coarser spatial resolutions. However, PRI values were also strongly influenced by canopy structure and species composition, emphasizing the need to account for these factors when interpreting signals at landscape scale.

Water content

Drought directly affects leaf and canopy water content, influencing absorption features in the shortwave infrared (SWIR) region (Gao, 1996). Water-sensitive indices such as NDWI and MSI are commonly used proxies for vegetation moisture status. From (simulated) satellite measurements, water-content-related indices showed sensitivity to spatial gradients in environmental water availability, including available water capacity (**Fawcett et al., 2025**). This suggests their applicability for landscape-scale drought monitoring. However, there are studies providing contrasting results (Dotzler et al., 2015) and, similar to other indices, their signals were

modulated by canopy structure and particularly functional type, which can confound direct interpretation of water status. Normalisation attempts to remove some of this sensitivity to confounding effects gave mixed results (Fawcett et al., 2025).

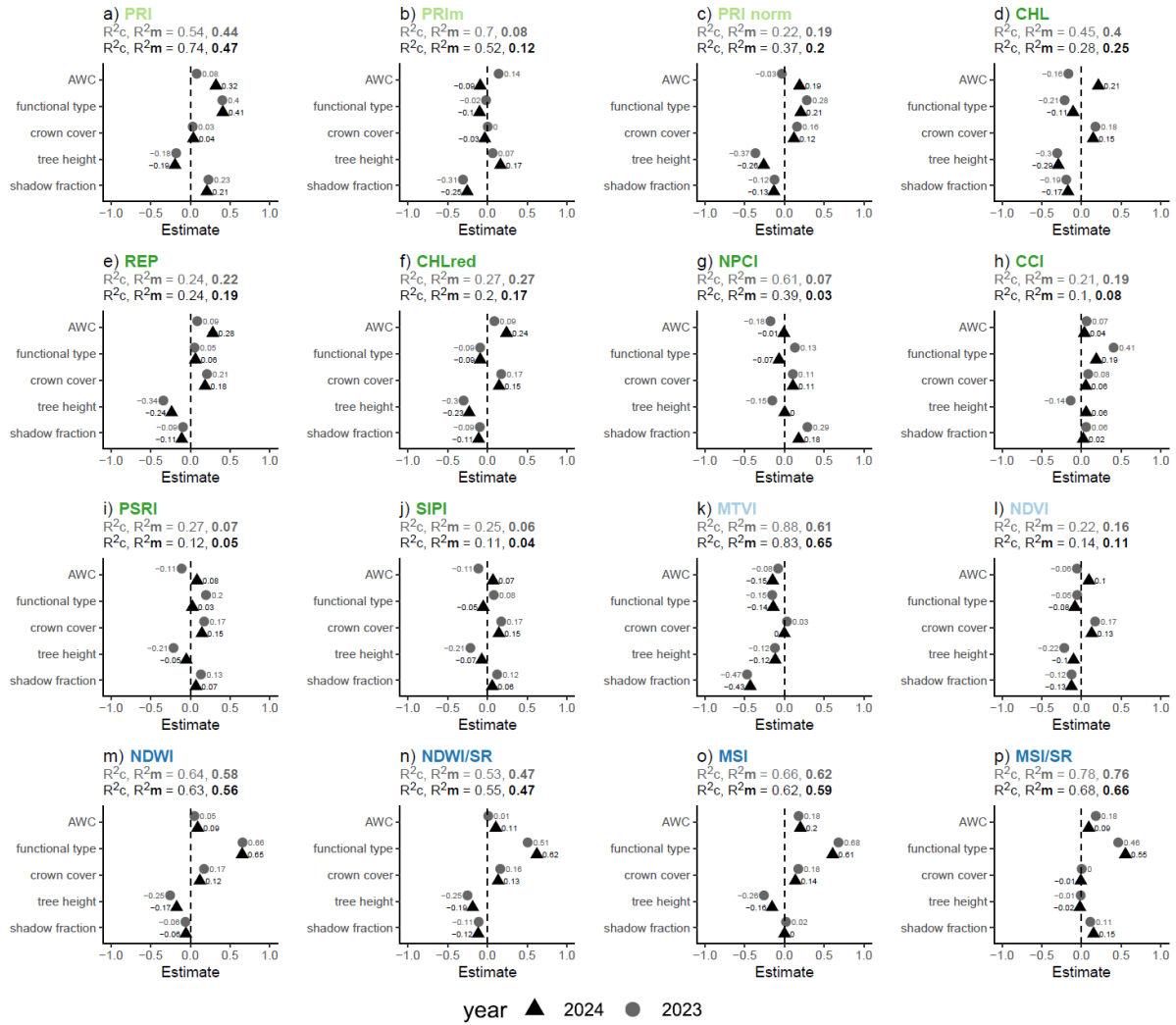


FIGURE 9: ESTIMATES OF FIXED PREDICTOR EFFECTS ON 2023 AND 2024 MODERATE (30 M) RESOLUTION PIXEL VI VALUES (SCALED CHANGE IN VI PER ONE UNIT INCREASE IN THE PREDICTOR VARIABLE). EFFECTS OF AVAILABLE WATER CAPACITY (AWC) AND THE STRUCTURE-RELATED VARIABLES FUNCTIONAL TYPE, CROWN COVER, TREE HEIGHT AND SHADOW FRACTION ARE DISPLAYED. POINTS AND R^2 STATISTICS ARE COLOURED BY YEAR. FOR FUNCTIONAL TYPE, POSITIVE VALUES INDICATE HIGHER VI VALUES FOR HIGHER CONIFER FRACTION AND VICE VERSA. THE CONDITIONAL R^2_c (VARIANCE EXPLAINED BY RANDOM AND FIXED EFFECTS) AS WELL AS MARGINAL R^2_m (VARIANCE EXPLAINED BY ONLY FIXED EFFECTS, BOLD) ARE REPORTED. NON-ZERO EFFECTS WERE SIGNIFICANT AT $P < 0.001$

3.2 Medium-term indicators: Pigment pool dynamics

With sustained drought, plants undergo biochemical adjustments, including reductions in chlorophyll content and shifts in carotenoid pools (Biswal, 1995). These changes influence reflectance in the green, red, and red-edge regions prior to visible senescence.

Indices sensitive to pigment composition, such as chlorophyll indices, the Chlorophyll-Carotenoid Index (CCI), the Structure Insensitive Pigment Index (SIPI), and the Plant Senescence Reflectance Index (PSRI), capture these medium-term responses (Gitelson et al., 2003; Sims & Gamon, 2002). These indices reflect acclimation processes including pigment degradation and altered photosynthetic capacity.

In **Fawcett et al. (2025)**, we showed that pigment-sensitive indices were able to distinguish likely stress-related differences between tree crowns and species at high spatial resolution and the information was retained when derived from airborne data with 1 m resolution. However, pigment indices varied greatly in their sensitivity to within-crown shading, depending on their formulation (Figure 10). This influences their suitability for scaling to larger scales.

all (n=1378)	0.86	0.75	0.53	0.83	0.69	0.52	0.76	0.86	0.85	0.77	0.46	0.79
beech (n=369)	0.74	0.74	0.6	0.76	0.7	0.33	0.77	0.81	0.77	0.8	0.27	0.79
silver fir (n=692)	0.6	0.54	0.3	0.65	0.5	0.35	0.64	0.72	0.57	0.62	0.34	0.47
spruce (n=317)	0.59	0.53	0.2	0.51	0.45	0.07	0.37	0.56	0.62	0.38	0.33	0.41
	PRI	PRInorm	PRIm	CHL	CHLred	NPCI	SIPI	REP	CCI	PSRI	MTVI	NDVI

FIGURE 10: R² VALUES OF OLS REGRESSION FITS BETWEEN SUNLIT CROWN-AVERAGED DRONE AND AIRCRAFT DATA VALUES FOR ALL VIS, ACROSS ALL PLOTS IN 2023 AND 2024. VALUES ARE REPORTED BY SPECIES AND OVER ALL CROWNS, THE TOTAL SAMPLE SIZE (N) IS DENOTED, EQUAL TO APPROX. TWICE THE NUMBER OF INDIVIDUALS PER SPECIES (ONE VALUE FOR EACH YEAR, EXCLUDING DEAD TREES).

VIs retained moderate explanatory power when aggregated to coarser (30 m) resolutions. This confirms that pigment pool shifts remain detectable beyond the leaf scale. However, their sensitivity decreased with spatial aggregation, and structural and functional-type differences increasingly influenced index variability (Figure 9).

3.3 Longer-term and severe stress indicators: Vegetation structure and greenness

Greenness-based indices such as NDVI primarily capture structural changes such as leaf area loss, discoloration, and defoliation (Buras et al., 2021). These changes typically occur later in the drought response trajectory and often reflect legacy effects rather than immediate stress signals.

At the crown-scale, **D’Odorico et al. (2025)** showed that NDVI was effective in detecting greenness declines in certain species but failed to capture short-term recovery following rainfall events,

highlighting its limitation as an early-warning indicator (Figure 7). Compared to PRI, NDVI primarily reflected structural canopy changes rather than real-time physiological dynamics. Its low requirement regarding spectral bands and relative robustness to confounding effects arising from the atmosphere and view angle still often make NDVI and its modifications (enhanced vegetation index (EVI), kernel NDVI (kNDVI)) the indices of choice for longer-term monitoring of structural and greenness changes related to disturbance, phenology and severe drought (Dalponte et al., 2025; Fitts et al., 2025; Forzieri et al., 2022).

4. Scaling ground-based measurements for large-scale monitoring and modelling of forest health

Building on the complementary strengths of proximal measurements and optical remote sensing outlined above, their integration enables the translation of tree-level physiological signals into spatially explicit assessments of forest condition. Combining these data streams is therefore key to overcoming scale mismatches and improving the representation of drought impacts in monitoring and modelling frameworks. Recent developments in machine learning offer new opportunities to link in situ measurements with environmental and spectral data for spatial upscaling (Reichstein et al., 2019), while satellite-based time-series analysis reveals areas in different stages of resilience loss and drivers can be investigated by linking satellite-based VIs to plot-level measurements of growth conditions. Together, these approaches support more consistent and scalable assessments of forest health and drought response.

4.1 Machine learning for generating country-scale tree water deficit maps from point-dendrometer measurements and modelling

We designed and trained a long short-term memory (LSTM) model to forecast future values of tree water deficit (TWD) using environmental predictors such as meteorological variables, elevation, and day of the year. The reference data for model training were obtained from dendrometer measurements collected within the TreeNet network. Our analysis indicates that longwave radiation together with precipitation exerts the strongest influence on predictive performance. To date, the model has been applied exclusively to *Picea abies*, with both seasonal dynamics and longer-term patterns successfully reproduced.

Current efforts focus on extending the input feature set to include soil water potential and vapor pressure deficit (VPD). Beyond temporal forecasting, we have also implemented a Gaussian process framework to estimate the spatial distribution of TWD, with the objective of generating continuous maps across Switzerland. Key predictors in this spatial model include VPD, evapotranspiration, and total soil water storage integrated over all soil layers, with the latter two variables derived from the LWF-Brook90 model.

This data-driven approach is intended to complement existing process-based models for near-real-time assessment of tree water stress, particularly in cases where LWF-Brook90 may not fully capture

stress dynamics, such as during late-season conditions. Ultimately, the aim is to integrate the machine learning and mechanistic modeling approaches with remote sensing data to enable more accurate nowcasting and to support projections of drought stress under varying climate and forest management scenarios.

4.2 Towards operational satellite-based drought impact detection

4.2.1. Staging of resilience loss – a theoretical concept of impact detection

With a new concept of staging resilience loss from time-series analyses, we introduce four phases of **critical slowing down (CSD)**: As a system approaches a tipping point (state transition), it recovers increasingly slowly from small disturbances. Autocorrelation, variance, and anomaly frequency are all indirect metrics of this process, each becoming more informative at different stages of decline (Table 1, Figure 11). This concept can be applied to both, proximal and remote sensing data, given the measurement frequency is appropriate for the process timescales and noisiness of the data. The use of rising autocorrelation as indicator of resilience loss has been demonstrated by previous work using NDVI or VOD data (Boulton et al., 2022; Verbesselt et al., 2016) . This new concept provides the basis for a more comprehensive assessment of time series, covering all phases of CSD.

TABLE 1: PHASE-BY-PHASE BREAKDOWN OF THE DIFFERENT PHASES OF CRITICAL SLOWING DOWN (CSD) AND EARLY WARNING SIGNAL (EWS) INDICATORS

Phase	Stress / Biomass	CSD Signal	Key EWS Indicator
Normal	Stress well below lethal thresholds; biomass stable	No CSD; fast recovery from disturbances	Baseline — no meaningful rise in autocorrelation, variance, or anomalies
Latent	Stress below lethal values but eroding resilience	CSD begins — recovery times start increasing	Rising autocorrelation & variance in biomass-related indicators; changes are subtle and invisible to direct observation
Lingering	Stress intermittently exceeds lethal values; system near stability boundary	Strong CSD — recovery preceded by long trajectories toward degraded state	High-amplitude anomalies become the defining feature; system oscillates near the tipping point

Transient	Stress and biomass cross critical thresholds; reinforcing feedbacks active	CSD breaks down — system is no longer recovering at all	EWS signals may collapse or become uninformative; the system is on an irreversible trajectory toward death/degradation
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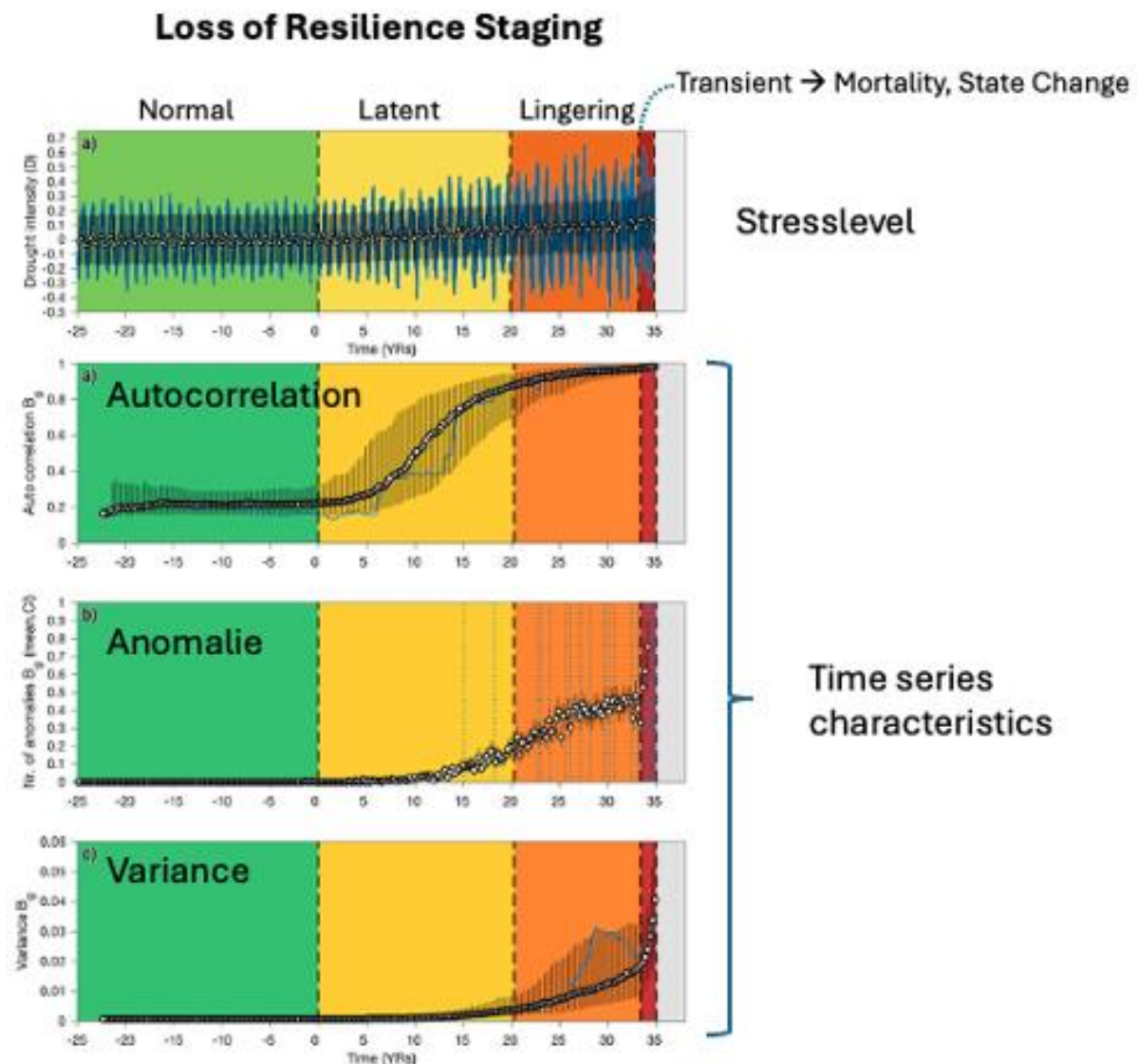


FIGURE 11: CONCEPTUAL SCHEME THAT SHOWS HOW CHANGES IN STRESS INTENSITY AND VARIABILITY AFFECT AUTOCORRELATION, ANOMALIES AND VARIANCE IN TIME SERIES OF REMOTELY OR PROXIMATELY SENSED PARAMETERS.

4.2.2. Assessment of the effects of multiyear droughts on forest ecosystem resilience

Focussing on changes in temporal autocorrelation and thus the latent phase of resilience loss, we combined data on global multiyear droughts with satellite-derived vegetation dynamics to assess how extreme drought events affect forest resilience at the global scale (Wu et al., 2026). We quantified forest resilience by computing the temporal autocorrelation of the kernel-normalized difference vegetation index (kNDVI) before and after the top-10 global multi-year drought (MYD) events, thereby mapping the spatial patterns of resilience loss across all major forest biomes. As illustrated in Figure 12, extreme multi-year droughts consistently reduced forest resilience, with diminished resilience detected in over 70.9% of forests following MYD events compared to pre-drought conditions. The spatial variation in resilience loss can be primarily explained by plant species richness, followed by climatic drivers including vapour pressure deficit, temperature, and soil moisture, though the effect of species richness became consistently negative once human footprint was accounted for.

On a broad global scale, we could demonstrate, as a proof of concept, that disturbances (here, MYD events) have a clear impact on vegetation resilience. On the European scale, resilience and different disturbance types can now be integratively displayed as maps of forest disturbance, vulnerability and risks (FORWARDS deliverable D2.2).

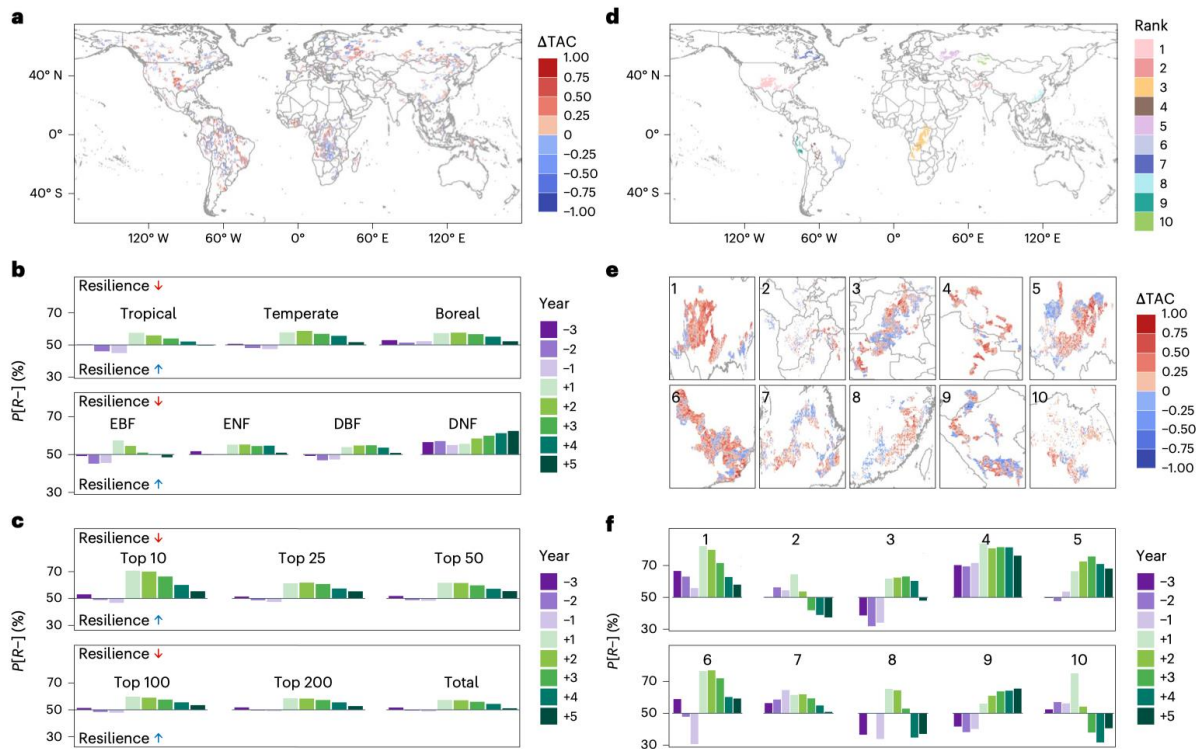


FIGURE 12: EXTREME MULTI-YEAR DROUGHTS REDUCED FOREST RESILIENCE. A, SPATIAL PATTERNS OF RESILIENCE CHANGES (ΔTAC) AFTER ALL MYDs IN COMPARISON TO RESILIENCE BEFORE DROUGHTS BASED ON THE TEMPORAL BASELINES. POSITIVE ΔTAC INDICATES A DECLINE IN RESILIENCE. B, THE PROPORTION OF RESILIENCE LOWER THAN THE BASELINE ($P[R-]$) BETWEEN 1 (–1), 2 (–2), 3 (–3) YEARS BEFORE THE START YEAR OF ALL MYDs AND 1 (+1), 2 (+2), 3 (+3), 4 (+4), 5 (+5) YEARS AFTER THE END YEAR OF ALL MYDs ACROSS CLIMATE ZONES (TROPICAL, TEMPERATE, BOREAL) AND LAND-COVER TYPES (EBF, EVERGREEN BROADLEAVED FOREST; DBF, DECIDUOUS BROADLEAVED FOREST; ENF, EVERGREEN NEEDLELEAVED FOREST; DNF, DECIDUOUS

NEEDLE-LEAVED FOREST). $\Delta TAC > 0$, $P[R-] > 50\%$ INDICATES THAT MORE PIXELS IN THIS GROUP EXPERIENCED REDUCED RESILIENCE. THE COLOURS REPRESENT 1 (–1), 2 (–2), 3 (–3) YEARS BEFORE THE START YEAR OF ALL MYDs AND 1 (+1), 2 (+2), 3 (+3), 4 (+4), 5 (+5) YEARS AFTER THE END YEAR OF ALL MYDs. $P[R-]$ WAS CALCULATED BY COMPARING RESILIENCE IN THE TARGET YEAR TO THE TEMPORAL BASELINE. C, THE PROPORTION OF PIXELS EXPERIENCING RESILIENCE CHANGES AGAINST THE BASELINE ($P[R-]$) BETWEEN 1 (–1), 2 (–2), 3 (–3) YEARS BEFORE THE START YEAR OF ALL MYDs AND 1 (+1), 2 (+2), 3 (+3), 4 (+4), 5 (+5) YEARS AFTER THE END YEAR OF THE TOP-TEN, TOP-25, TOP50, TOP-100, TOP-200 AND ALL MYDs. D, SPATIAL DISTRIBUTION OF THE TOP-TEN MYDs. E, SPATIAL PATTERNS OF RESILIENCE CHANGES (ΔTAC) AFTER THE TOP-TEN MYDs. F, THE PROPORTION OF RESILIENCE LOWER THAN THE BASELINE ($P[R-]$) BETWEEN 3 YEARS BEFORE AND 5 YEARS AFTER THE TOP-TEN MYDs. (WU ET AL., 2026)

4.2.3. Species-specific drought sensitivity and satellite-based indicators of canopy dynamics

Medium resolution satellite data (10 – 30 m) is becoming available at increasing temporal frequencies, but understanding the predictive power and limitations of derived drought indicators requires case studies covering a variety of forest types and tree species across Europe, that are experiencing drought stress.

In southern Finland, water limitation has intensified over the past decade, driving clear species- and site-specific responses (Szejner et al., in review). Norway spruce (*Picea abies*) showed a pronounced decline in basal area increment (BAI) after 2015, whereas Scots pine (*Pinus sylvestris*) exhibited only minor and earlier reductions (Figure 13). In parallel, intrinsic water use efficiency (iWUE) increased more strongly in Scots pine, consistent with tighter stomatal regulation, while Norway spruce displayed weaker physiological adjustment and higher drought vulnerability. These responses were additionally modulated by soil moisture conditions: Scots pine was more sensitive on upland mineral soils, while Norway spruce showed stronger declines on poorly drained organic soils. Overall, the results highlight the combined role of species traits and soil-moisture regimes in shaping drought sensitivity, with direct implications for boreal forest management under warming and increasing atmospheric demand.

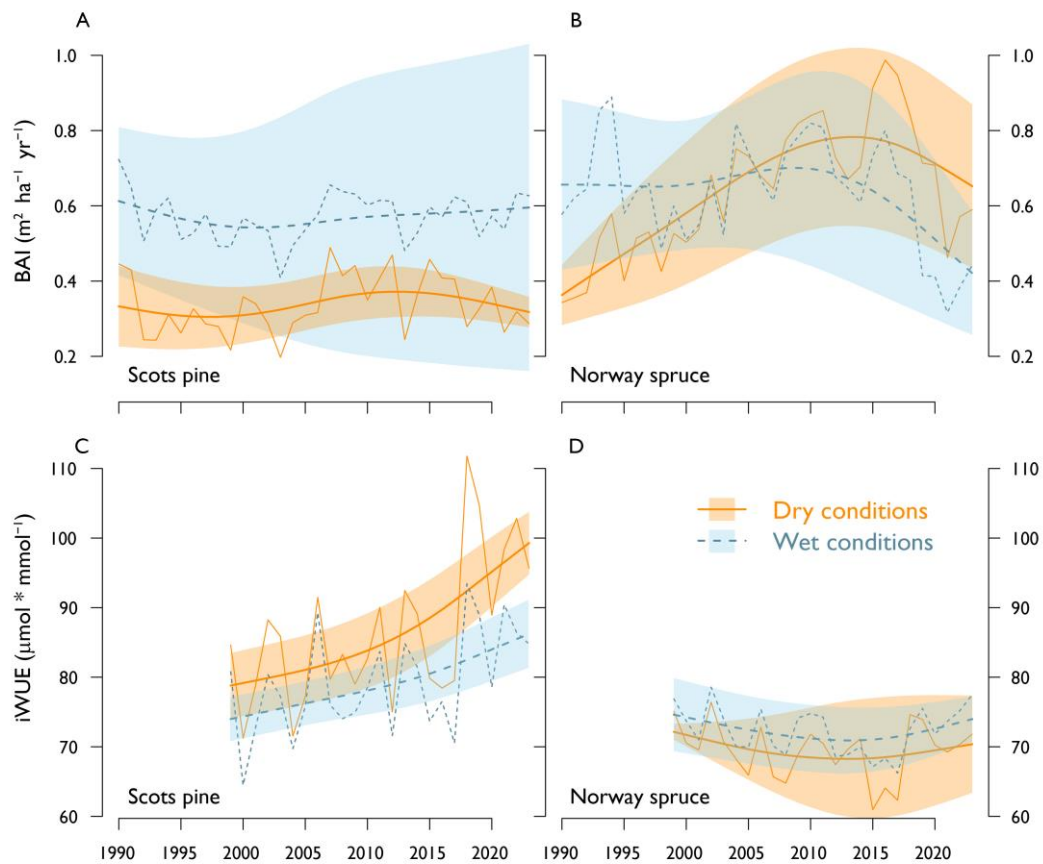


FIGURE 13: TRENDS IN BASAL AREA INCREMENT (BAI) AND INTRINSIC WATER USE EFFICIENCY (iWUE) FOR SCOTS PINE AND NORWAY SPRUCE UNDER ‘DRY’ AND ‘WET’ CONDITIONS DURING 1990-2022. FOR SCOTS PINE, ‘DRY’ AND ‘WET’ CONDITIONS CORRESPOND TO UPLAND AND LOWLAND MINERAL SOILS, RESPECTIVELY. FOR NORWAY SPRUCE, ‘DRY’ AND ‘WET’ CONDITIONS REFLECT NARROW AND WIDE DITCH SPACING IN DRAINED ORGANIC SOILS, RESPECTIVELY. PANELS A–B SHOW BAI, AND PANELS C–D SHOW iWUE. SOLID AND ORANGE LINES DISPLAY DRY CONDITIONS, WHILE DASHED AND BLUE LINES REPRESENT WET CONDITIONS. SHADED AREAS INDICATE THE 90% CONFIDENCE INTERVALS AROUND THE SMOOTHED LINES USING A 30-YEAR SMOOTHING SPLINE.

We will now link long-term ground-based measurements of BAI (1990–2023) and iWUE (1999–2023) with VIs derived from multi-decadal Landsat (1990–2023) and Sentinel-2 (2017–2023) observations. This analysis is currently under preparation. The work will 1) assess Dry–Wet differences in VIs and identify those (greenness, moisture, stress/structure) that best capture soil-moisture-related variability in Scots pine and Norway spruce, 2) quantify temporal trends in VIs and test for shifts in canopy dynamics before and after 2015, and 3) evaluate relationships between VIs and ground-based indicators (BAI and iWUE), including cross-sensor consistency between Landsat and Sentinel-2. To improve interpretability of canopy time series and reduce noise, harmonic predictors will be used to separate cyclical variability from interannual departures in reflectance.

Preliminary analysis of moisture-related differences in canopy trends were summarized using the distribution of Δ slope (Wet – Dry) across Landsat-derived indices (Figure 14). Scots pine showed a slightly positive median Δ slope (+0.35), indicating marginally stronger long-term spectral trends under Wet relative to Dry conditions. In contrast, Norway spruce showed a negative median Δ slope (–0.41), indicating generally weaker long-term trends under Wet conditions. These results are consistent with site-level BAI patterns, showing higher growth under wet conditions for Scots pine and under dry conditions for Norway spruce. Although subject to further validation, these contrasting patterns indicate that the effect of site moisture regime on canopy trajectories is likely species-dependent, supporting the need for species-specific interpretation when assessing drought sensitivity and site suitability.

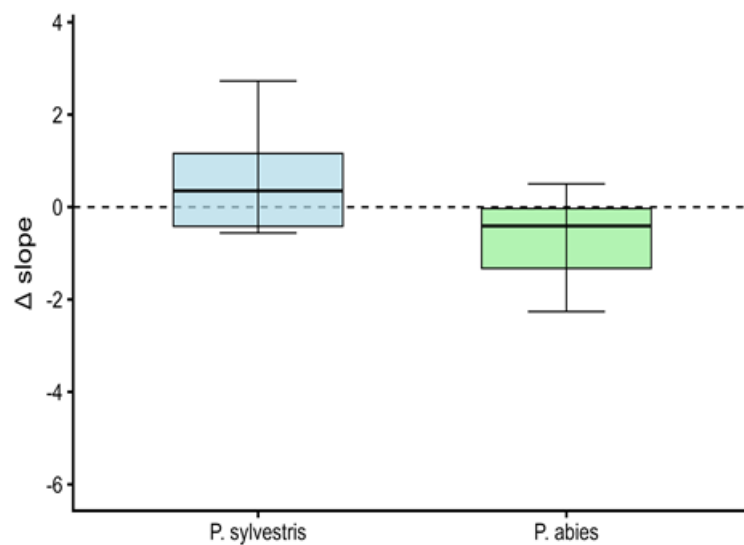


FIGURE 14: DISTRIBUTION OF Δ SLOPE VALUES (WET – DRY) ACROSS LANDSAT-DERIVED SPECTRAL INDICES FOR SCOTS PINE AND NORWAY SPRUCE. POSITIVE VALUES INDICATE STRONGER LONG-TERM INDEX TRENDS UNDER WET THAN DRY CONDITIONS; NEGATIVE VALUES INDICATE WEAKER TRENDS UNDER WET CONDITIONS.

Preliminary association analyses further suggest that the sign and consistency of canopy spectral–growth linkages differ between species and soil-moisture regimes (Figure 15). In Scots pine, BAI–VI relationships are generally weak in Dry plots, while Wet plots show predominantly negative associations across indices. In Norway spruce, associations tend to be more positive under Dry conditions, whereas under Wet conditions they are typically weak, slightly negative, and less consistent. Overall, these early patterns indicate that the direction and strength of canopy–growth coupling may depend on both species traits and soil moisture regime, highlighting the need for species- and condition-specific interpretation of satellite indices when assessing forest productivity dynamics.

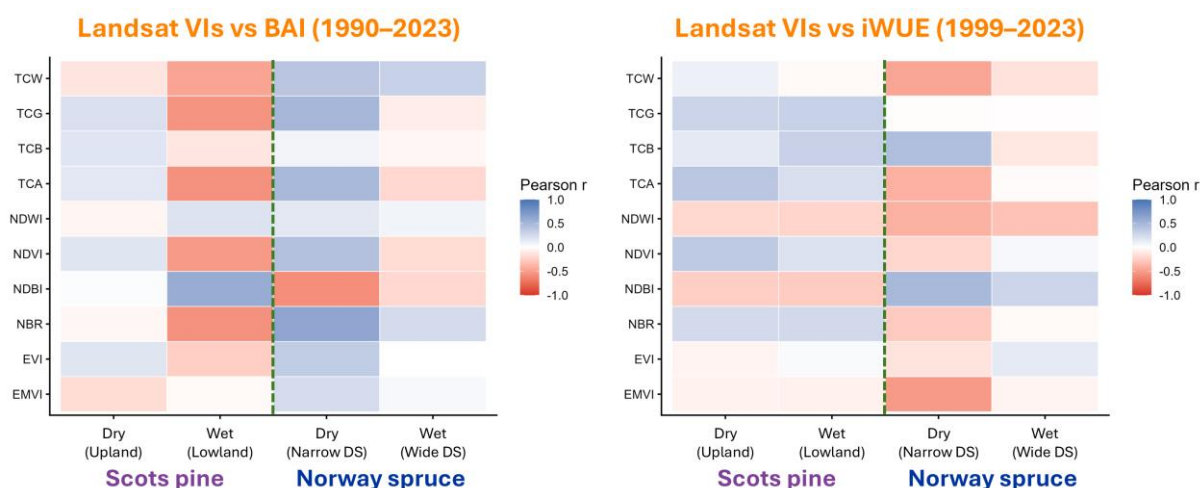


FIGURE 15: DESCRIPTIVE RELATIONSHIPS BETWEEN LANDSAT VEGETATION INDICES (VIS) AND GROUND-BASED INDICATORS OF FOREST FUNCTIONING (BAI AND IWUE), SHOWN AS PEARSON CORRELATION COEFFICIENTS (R) BY SPECIES AND SOIL-MOISTURE REGIME (DRY/WET).

Patterns observed in these preliminary results motivate the application of model-based approaches, specifically mixed-effects models currently under development. These models will enable more robust inference than correlation-based summaries by accounting for repeated measurements, the nested sampling design, and the post-2015 structural change in the time series.

Importantly, these results indicate that satellite-based indicators can support large-scale monitoring of forest condition, but only when interpreted in the context of local soil moisture and species composition. Integrating long-term ground observations with Earth Observation products therefore offers a powerful basis for evidence-informed decision-making, helping policymakers and land managers identify vulnerable stands, target adaptive interventions, and improve the resilience of boreal forests under a warming and increasingly water-limited climate.

5. Synthesis

We provided an overview of the approaches used within the FORWARDS project and associated studies to seek to bridge the gap between ground-based monitoring on forest plots and remote sensing. These approaches along with their strengths and limitations are summarised in *Table 2*. Advances in proximal monitoring methods implemented on forest plots of FORWARDS partners have increased the quality, frequency and comparability with remote sensing data. This included the simultaneous gap-filling of point dendrometer and concurrent meteorological measurements and the installation and testing of monitoring laser scanning methods. We demonstrated the physiological links between leaf-level measurements and drone-based optical remote sensing at the tree-level, showing that vegetation indices from drone data reflected drought events and subsequent recovery. As leaf water potential (LWP) and pigment contents are difficult to measure continuously, further work should investigate tree water deficit (TWD) as an equivalent proxy of tree water status and drought stress, facilitating the

link to satellite data-based monitoring. In a scaling study, we showed the challenges involved when seeking to use the same optical indicators across spatial scales and functional types, when moving from the single tree to the 30 m satellite pixel level. There were promising relationships between VIs and available water content (AWC) at the landscape scale across years, though they are considerably influenced by forest functional type mixture. Further evidence from a study targeted at wet and dry conifer stands supported that VIs from satellite data can resolve differences in forest growth conditions, though these indicators remain species specific. A promising top-down approach for deriving general indicators of forest condition and status is to rely only on satellite time series analysis to identify different phases of forest resilience loss. As an example, we included results from a recent study using temporal autocorrelation to show the latent phase of resilience loss. While these methods do not provide a direct link to the underlying stressors, they can flag areas for more detailed investigation of drivers by incorporating ground-based information. Machine learning models taking ground-based measurements such as TWD and concurrent gridded meteorological and remote sensing data as inputs provide an alternative, more bottom-up, method for creating wall-to-wall maps of forest condition and stress, while explainable machine learning may also provide important information on what is driving regional anomalies. Combined, different approaches can be used to identify consistent risk areas in European forests to target and prioritize further research work.

TABLE 2: APPROACHES AND TOOLS THAT ALLOW SCALING OF FOREST STRUCTURES AND PROCESSES.

Approach	Ground Measurement	Link to Remote Sensing	Spatial Scale	Temporal Scale	Key Variables / Indices	Strengths	Limitations
Point Dendrometer Networks + Deep Learning Gap-Filling	Stem radius (dendrometers), air temperature, RH, soil temperature, soil water potential (TreeNet/LWF, 92 sites)	Virtual sensor reconstruction enables spatially consistent, gap-free time series comparable to satellite overpass frequency	Point → network scale	Sub-daily (10-min)	Stem radius, TWD, meteorological variables	High temporal resolution; exploits inter-variable physiological correlations; generalises to unmonitored sites	Limited to network extent; requires co-located meteorological data
Proximal Laser Scanning (TLS / ULS / Monitoring LS)	3D canopy structure at plot level; Plant Area Index (PAI), canopy height, stem diameters	PAI from monitoring LS (LEAF system) directly comparable to satellite-derived PAI; bridges structural detail to coarser sensors	Tree / plot → landscape	Periodic to continuous	PAI, PAVD, canopy height, stem diameter	Captures 3D structure; high detail for upper crown (ULS) and understorey (TLS)	Occlusion effects; high data volume; intercalibration needed across systems
Short-term Optical VIs: Photoprotection & Water Content (PRI, NDWI, MSI)	Leaf water potential, tree water deficit, xanthophyll pigment measurements, spectroradiometry at leaf/crown level	PRI and water indices (NDWI, MSI) detectable from drone, airborne, and satellite sensors; sensitive to spatial gradients in water availability	Leaf → crown → landscape	Diurnal to days	PRI (531 nm), NDWI, MSI (SWIR)	Early stress detection before visible decline; captures rapid physiological regulation	Confounded by canopy structure and species composition; requires careful landscape-scale interpretation
Medium-term Optical VIs: Pigment Pool Dynamics (CCI, SIPI, PSRI, Chl indices)	Leaf pigment sampling (chlorophyll, carotenoid content)	Pigment-sensitive indices from multispectral/hyperspectral sensors capture biochemical acclimation prior to visible senescence	Leaf → crown → landscape	Days to weeks	CCI, SIPI, PSRI, chlorophyll indices (green, red-edge)	Detects acclimation processes before structural decline; applicable to medium-resolution satellites	Requires hyperspectral or red-edge bands; species-specific responses complicate generalisation

Long-term Structural VIs: Greenness & Canopy Decline (NDVI, kNDVI, EVI, NIRv)	Crown condition assessments, basal area increment (BAI) from tree rings	Greenness indices from medium-resolution satellites (10–30 m) track structural changes; linked to plot-level growth data	Crown → landscape → global	Weeks to years	NDVI, kNDVI, EVI, NIRv	Widely available; long time series; captures legacy effects and severe stress	Detects stress late in trajectory; insensitive to early physiological stress; limited early-warning capacity
LSTM + Gaussian Process for Country-Scale TWD Mapping	Dendrometer-derived Tree Water Deficit (TWD) from TreeNet network	LSTM forecasts TWD from meteorological predictors; Gaussian process spatially interpolates to generate continuous country-scale maps; intended for integration with RS data	Point → country scale	Daily to seasonal	TWD, VPD, ET, soil water storage (Brook90), longwave radiation, precipitation	Near-real-time nowcasting; complements process-based models; explainable ML identifies key drivers	Still under development, relies on Brook90 model outputs; RS integration still in progress
Satellite Time-Series Analysis: Critical Slowing Down (CSD) / Resilience Staging	Plot-level time series (dendrometers, VIs) used to validate CSD phases	Temporal autocorrelation, variance, and anomaly frequency of satellite VIs (kNDVI, NDVI, VOD) identify four phases of resilience loss	Landscape → global	Months to decades	kNDVI autocorrelation, variance, anomaly frequency	Top-down, scalable, no field data required for application; flags areas for targeted investigation	No direct link to underlying stressors; requires high-frequency, low-noise satellite data; indirect metric only
Multi-Year Drought + kNDVI Global Resilience Assessment	Global drought event records combined with satellite vegetation dynamics	Temporal autocorrelation of kNDVI before/after drought events maps resilience loss across all major forest biomes	Global	Multi-year	kNDVI, VPD, temperature, soil moisture, species richness	Proof-of-concept at global scale; identifies biome-level vulnerability patterns	Broad spatial resolution; human footprint confounds species richness effects; limited mechanistic insight
Species-Specific VI + Tree-Ring Growth Analysis	Basal area increment (BAI) from tree rings; intrinsic water-use efficiency (iWUE)	Medium-resolution satellite VIs (10–30 m, e.g. Sentinel-2) linked to plot-level growth data to assess species- and site-specific drought sensitivity	Plot → landscape	Annual to decadal	BAI, iWUE, satellite VIs (10–30 m)	Captures species- and soil-specific responses; validates satellite indicators against long-term growth records	Species-specific; limited transferability across forest types; requires long-term plot data



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