



How trees influence the spatiotemporal dynamics of soil moisture in different forest ecosystems

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Abstract. Soil moisture (SM) is a key variable in terrestrial ecosystems, regulating water and energy exchange at the soil-atmosphere interface. In forest ecosystems, SM exhibits pronounced spatiotemporal variability at the tree-scale in the topsoil of the active root zone due to complex interactions among multiple factors such as soil properties, topography, climate, and vegetation. Existing research on spatiotemporal SM characteristics in forests is limited, impeding our understanding of SM-vegetation interactions. A detailed understanding of when and to what extent vegetation influence topsoil moisture spatiotemporal variability in forests is required to quantify its consequences for (eco-)hydrological processes and to test hypotheses about the dominating influences on spatiotemporal patterns across different ecosystems.

This study characterizes spatiotemporal dynamics of topsoil SM. Our objectives are to quantify plot-scale spatial variability and its temporal evolution from event- to seasonal scale, thereby improving our understanding of SM dynamics across wet and dry states in pure- and mixed-species forest stands. We recorded SM with a dense monitoring network of 400 sensors (SMT100, Truebner GmbH, Germany) installed in the topsoil in a tree-centered design across four plots of mixed and pure Douglas fir, Beech and Silver fir trees in the ECOSENSE forest, southwestern Germany. Statistical and Empirical Orthogonal Function (EOF) analysis together with temporal stability (TS) analysis were combined to quantify spatial SM dynamics from a 2.5-year dataset (2023–2025). Spatial SM follows a consistent annual cycle across all plots transitioning between wet- and dry-preferential states. SM shows high variability for all plots and most plots display a characteristic convex upward curve for the spatial mean soil moisture to coefficient of variation ($\bar{SM}$ –CV) relationship. The CV peaks at intermediate wetness and declines toward the driest and wettest states. Only the Mixed plot shows a linear, negative $\bar{SM}$ –CV relationship. Daily SM skewness follows the same convex relation with negative skew for wet conditions ($\bar{SM} > 20\%$) and positive skew for dry conditions. The EOF analysis identified two to three statistically significant modes per plot, together explaining $> 80\%$ of spatial variance. The first EOF explains $> 60\%$ of the variance at each plot and represents the dominant, stable, time-invariant spatial pattern. Seasonal wetting and drying cycles show that spatial variability differs between wet and dry phases, suggesting distinct local and non-local controls dominate the SM patterns according to the wetness state and seasonal phase of the system, increasing or decreasing spatial SM heterogeneity. The temporal stability analysis identified persistently wetter and drier locations. Mean relative difference (MRD) within each plot ranges from -75% (dry) to $+50\%$ (wet), with the widest range in the Silver fir plot and the narrowest range in the Beech plot. Within each plot, a subset of representative locations could be identified, but the exact location in the plot is random. Spearman rank correlations of spatial SM between the Douglas fir and Beech plot show



high spatial stability ($\rho \geq 0.8$) for wet phases (winter) whereas lower correlation ($\rho \approx 0.45\text{--}0.60$) during dry phases. The findings of this study can help to inform sampling strategies and modelling approaches. The dataset presented here is appropriate for detailed analyses of event-based wetting-drying dynamics, and when combined with additional data, it can disentangle the relative contributions of local and non-local controls to the observed spatial patterns and pattern stability.

Summary.

Using a dense 400 sensor network over 2.5 years, we studied how tree types influence forest soil moisture. We found soil moisture varies largely in space and time. In pure tree plots, the moisture variability peaks during intermediate wetness – when vegetation influence is strongest - but remains low during dry and wet phases. Consistently wet and dry zones indicate that spatial pattern are temporally stable. This work highlights small-scale spatiotemporal variability of forest water fluxes.



1. Introduction

Soil moisture (SM) is a key state variable in terrestrial ecosystems, regulating water and energy exchange at the soil-atmosphere interface. In forest ecosystems, SM influences the partitioning of precipitation into evapotranspiration, surface runoff, infiltration and percolation for groundwater recharge (Heathman et al., 2009; Hövel et al., 2025). SM provides the plant-available water pool for transpiration and controls tree growth; it influences nitrogen availability and controls soil organic carbon stocks and decomposition processes.

Soil moisture in forest soils varies in space and time as a result of complex nonlinear process interactions of multiple static and dynamic influencing factors (Vereecken et al., 2014) like soil properties (Pan and Peters-Lidard, 2008; Vereecken et al., 2007b), topography (Famiglietti et al., 1998; Penna et al., 2013), climate (Grayson et al., 1997; Lawrence and Hornberger, 2007; Teuling et al., 2007; Western et al., 2004) and vegetation (Fatichi et al., 2015; Molina et al., 2019; Schume et al., 2003; Teuling and Troch, 2005). Quantifying this spatiotemporal variability, also known as spatiotemporal patterns of soil moisture states, is crucial not only to gain a better understanding of controlling factors and their interactions, but also to elucidate feedback mechanisms of spatiotemporal SM variability on dependent ecohydrological processes. Previous studies made substantial progress in characterizing the spatial variability and temporal stability of SM (Cosh, 2004; Lannoy et al., 2006; Grayson and Western, 1998; Famiglietti et al., 1998; Mälicke et al., 2020; Schume et al., 2003), related control factors (Baroni et al., 2013; Gwak and Kim, 2017; Tromp-van Meerveld and McDonnell, 2006; Western et al., 2004) and feedbacks to depending processes across scales and systems (Seneviratne et al., 2010) based on both experimental observations and modelling approaches. Grayson et al. (1997) concluded that in temperate regions, spatial patterns shift between wet and dry preferred states of soil moisture as a response to two main forcing regimes, the rainfall-driven wetting and the radiation-driven drying. They were able to attribute groups of local controls (vertical fluxes) dominating spatial patterns under dry soil conditions (evapotranspiration > precipitation) and non-local controls (lateral fluxes) dominating SM patterns during wet SM states (evapotranspiration < precipitation). During wet states, non-local controls e.g. soil hydraulic properties and lateral redistribution processes of surface and subsurface lateral flow govern spatial variability as reported by Famiglietti et al. (1998) or Korres et al. (2015). Western and Blöschl (1999) showed how terrain attributes of topography and aspect play a dominant role shaping SM during wet states. During dry states, local controls of vegetation and soil texture determine how precipitation infiltrate considering low soil hydraulic conductivity and fast evaporation (Western and Blöschl, 1999). In these periods, lateral connections are inactive, and local controls such as vegetation-induced processes regulate SM. At intermediate wetness states, a combination of soil properties and vegetation (local and non-local) controls shape spatiotemporal variability: drying soils increase the spatial differences in hydraulic conductivity and initially enhance variability, whereas continued evapotranspiration reduces variability above a certain threshold of mean soil moisture (Korres et al., 2015; Rosenbaum et al., 2012). As soils dry out, vegetation effects, particularly root water uptake and throughfall heterogeneity, become more important and can either increase variability under unstressed conditions or homogenize SM under water limitation (Ivanov et al., 2010). Additionally, seasonality and wetting–drying (hysteresis) dynamics influences the soil moisture pattern (Gómez-Plaza et al., 2001; Fatichi et al., 2015). The relative importance of control factors for SM patterns, as well as their effect on



increasing or decreasing spatial variability, is related to the system's wetness state (Famiglietti et al., 1998; Robinson et al., 2008). Previous research identified three main state-dependent relationships between spatial variability and mean soil moisture ($\bar{SM}$).

- I. Negative relation showing increasing variability with decreasing $\bar{SM}$ (Bogena et al., 2010; Brocca et al., 2007; Choi et al., 2007; Grayson et al., 1997; Hupet and Vanclooster, 2002; Mittelbach and Seneviratne, 2012)
 - II. Positive relation showing increasing variability with increasing $\bar{SM}$ (Grayson and Western, 1998; Famiglietti et al., 1998)
 - III. A convex relation with a maximum variability at intermediate $\bar{SM}$ (Rosenbaum et al., 2012; Ryu and Famiglietti, 2005; Vereecken et al., 2007a; Pan and Peters-Lidard, 2008)
- These findings highlight how spatial patterns differ across states as a result of the dynamic interaction of factors such as soil properties, vegetation processes, and topographic redistribution (Brocca et al., 2010; Heathman et al., 2012; Penna et al., 2009; Penna et al., 2013). In forest ecosystems trees contribute to spatiotemporal variability of SM by throughfall, stemflow, forest floor interception, root water uptake or canopy shading affecting evaporation (Jost et al., 2012; Fischer et al., 2023; Mittelbach and Seneviratne, 2012). Topsoil layers were reported to show pronounced small-scale (tree-level) spatial patterns and temporal fluctuation (Bárdossy and Lehmann, 1998; Martini et al., 2015). The influence may be tree-species specific and vary with stand density and season (Jost et al., 2004; Rolston et al., 1991). Still, the characterization of spatiotemporal patterns in forest soils remains a major challenge in ecohydrological research (Rodríguez-Iturbe, 2000), evidence on forest soil moisture variability remains limited and sometimes contradictory. Whereas analyses of large-scale SM variability driven by precipitation-pattern within a watershed or catchment are feasible with indirectly retrieved SM data from remote sensing (Joshi and Mohanty, 2010; Wigneron et al., 2017) or modelling approaches (Fatichi et al., 2015; Martínez García et al., 2014), the research of spatiotemporal SM dynamics under complex vegetation structure like forests requires observations at the tree to plot scale, at high frequency (<1 d) and for longer, continuous observation periods (>1 yr.). Root water uptake by trees or throughfall inputs can modify spatial soil moisture patterns within hours to days. In particular, for determining critical thresholds, e.g. the switch of an energy-limited into a water-limited system or the partitioning of precipitation into surface runoff or infiltration demands continuous observations at high temporal resolution (Zehe and Sivapalan, 2009). Recent advances in in-situ sensor technology provide new opportunities to map spatiotemporal SM patterns at this required high spatiotemporal resolution (Bogena et al., 2010). However, few of such high-resolution SM sensor networks exist, and even fewer cover forest ecosystems of different tree species, match the required spatiotemporal scales (Martini et al., 2015) and enable monitoring of isolated (and species-specific) vegetation influence on SM. As a consequence, we lack high spatiotemporal, multi-year, continuous datasets generated by these networks (Graf et al., 2014; Vereecken et al., 2008) combined with detailed on-site characterization that allow detailed analyses of soil moisture spatiotemporal variability under the seasonally changing vegetation influence. Detailed insights into spatial SM patterns and their temporal dynamics can contribute to a more comprehensive understanding of their controls and feedbacks on hydrological (Mittelbach and Seneviratne, 2012) and ecological or biogeochemical processes (Kemppinen et al., 2023) in forest ecosystems. Findings may



110 not only inform about the current state of these process interactions (Garcia-Estringana et al., 2013; Zignol et al., 2025), but
also indicate how future changes in spatiotemporal dynamics under increasingly dry periods or more intense precipitation
events modify physical processes such as runoff, infiltration, or evapotranspiration and consequently impact trees (Koehn et
al., 2021; Liu et al., 2025) and entire forest ecosystems including biodiversity, ecosystem services, resilience to disturbances
and climate change.

115 Findings of SM spatiotemporal variability from small-scale observations can also improve the performance of hydrological
and atmospheric models (Brocca et al., 2010; Martínez García et al., 2014) and find application in e.g. whether forecasting
(flooding) water resource and forest management or agriculture (irrigation) (Dari et al., 2019). They may further provide
indications for representative sampling e.g. design of targeted measurements at selected locations or densely-distributed
networks (Cassel et al., 2000; Bárdossy and Lehmann, 1998).

120 The purpose of this study is to conduct a thorough investigation of the spatiotemporal dynamics of topsoil SM across four
distinct pure and mixed deciduous and coniferous tree stands (pure Beech, Douglas fir, Silver fir, mixed Beech & Douglas fir)
in a temperate forest using a high-resolution experimentally derived SM dataset. The objectives are to (1) develop and
implement a monitoring strategy in the form of a dense sensor network that adequately captures forest topsoil SM dynamics
at the tree to plot scale, enables data-driven investigation of SM patterns and allows for the isolated observation of vegetation
125 and even tree species-specific influence on those patterns. Statistically analyzing the collected 2.5 years of high-resolution
spatiotemporal dataset, the further objectives are to (2) quantify the spatial SM variability at the plot scale by identifying the
dominant spatial patterns, (3) characterize their temporal dynamics over the growing and dormant vegetation phases of two
years, and (4) infer potential differences and/or similarities of the spatiotemporal patterns across different pure- and mixed
species forest stands. The findings will then contribute to a better understanding of SM dynamics in forests between wet and
130 dry states, across seasons and among different forest stands and species. Furthermore, the results can inform monitoring
strategies and serve as input for model optimization and improve model conceptualizations.

2. Study site and data collection

2.1. Site description

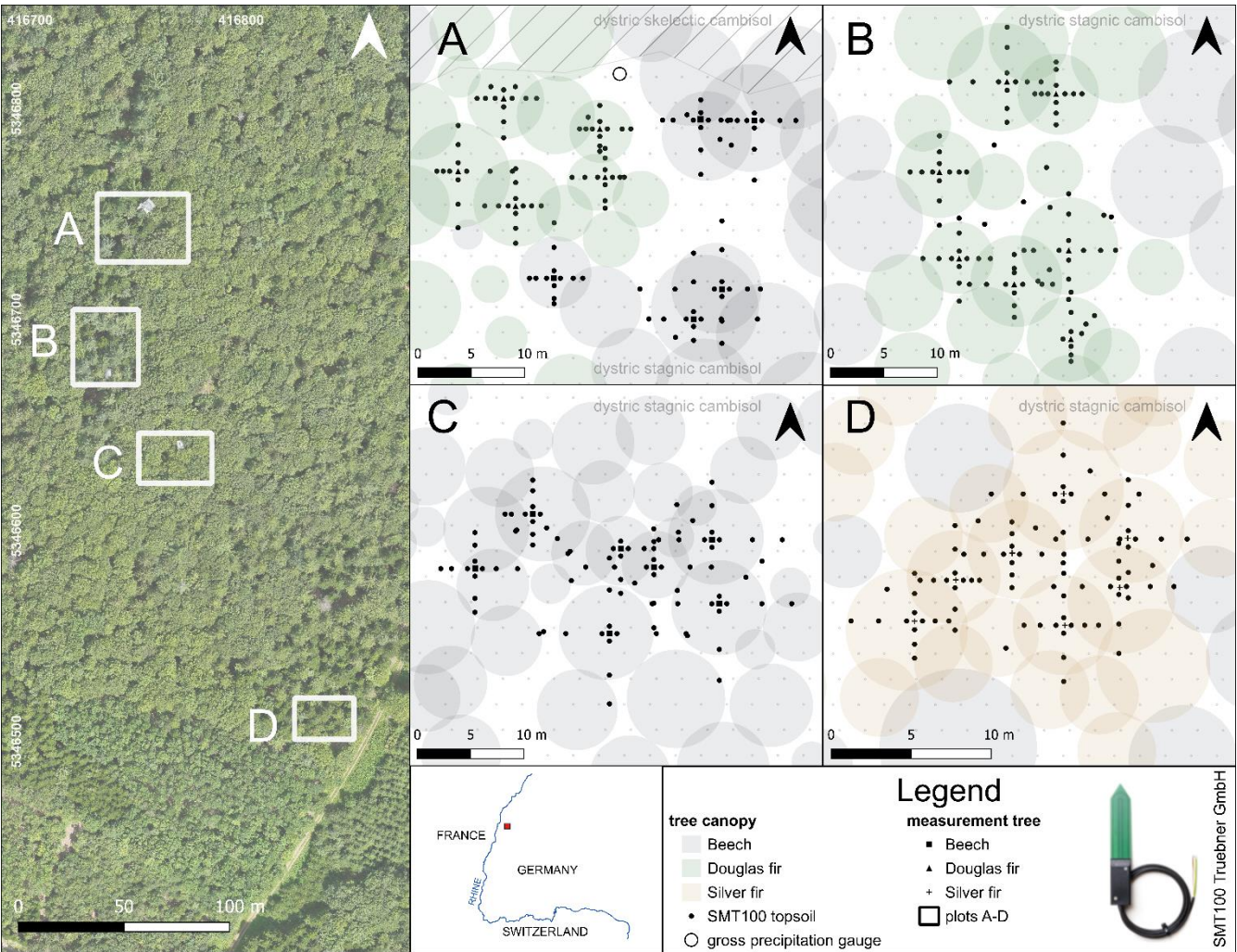
Soil moisture data were collected at the ECOSENSE forest research site (Tesch et al., 2025) located near Ettenheim (48.2685°
135 N, 7.8782° E), between the Upper Rhine Valley and the Black Forest in southwest Germany (Figure 1). The ECOSENSE
forest research site monitors various forest ecosystem processes such as carbon and water flux dynamics in space and time
with a wide range of established measurement technologies and newly developed field sensors (Tesch et al., 2025). The altitude
of the research site ranges from 480–500 m a.s.l. The climate is temperate-humid (Köppen *Cfb*) with mean annual precipitation
of 911 mm and a mean annual temperature of 10.2° C (DWD station Lahr 2812; distance 11 km) for the reference period
140 1991–2020. The climate at the site varies seasonally, with summer (June, July, August) having a mean temperature of 18.9° C
and winter (December, January, February) having a mean temperature of 2.6° C (Landesanstalt für Umwelt Baden-



Württemberg, 2024). Summer precipitation is highest, with an average of 299 mm at the DWD station 14135 at 2.5 km distance to the site. Occasional summer drought can occur (e.g. in 2003 & 2018). Figure 1 shows an overview of the research site where the northern part of the research site is located on a Dystric Skeletic Cambisol (siltic, humic) derived from quaternary loess over Triassic Buntsandstein according to IUSS Working Group WRB (2022). The southern part features a Dystric Stagnic Cambisol (loamic) (IUSS Working Group WRB, 2022) also derived from quaternary loess over Triassic Muschelkalk (Werner et al., 2024). The forest floor – defined as the uppermost layer of fragmented and unfragmented organic material above the mineral soil layer – averages 10 cm in thickness and is classified as moder (Landesamt für Geologie, Rohstoffe und Bergbau Baden-Württemberg, 2024). The litter layer (OI) of < 2 cm thickness consists of loose, uppermost, unfragmented fresh litter including leaves and needles. European Beech-dominated mixed forest covers the research site, formerly managed for timber production. In addition to beech trees (*Fagus sylvatica*), the stand is composed of patches of Silver fir (*Abies alba*) and Douglas fir (*Pseudotsuga menziesii*), aged approximately 80, 60 and 50 years, respectively. Individual spruce and larch trees complement the average tree density of 500 trees ha⁻¹ (Kreuzwieser et al., 2025). Except for a few younger 10–20 m tall Beech and Silver fir trees, there is no understorey vegetation, and the overstorey reaches heights of 25–35 m. The study site was divided into four subplots according to the dominating tree species composition (Figure 1): (A) a mixed Beech & Douglas fir plot, (B) a pure Douglas fir, (C) a pure Beech plot all on the flat plateau and (D) a Silver fir plot located 200 m southeast on a southeast-exposed hillslope with a mean slope of 16% (Figure 1 left panel). Each subplot is approx. 400 m² large and includes 7–10 selected “measurement trees” of comparable age and height. All plots are located on Dystric Stagnic Cambisols, the Mixed plot is close to the border to the Dystric Skeletic Cambisols (Figure 1).

2.2. Soil moisture monitoring network

Soil moisture sensors (SMT100, Truebner GmbH, Neustadt, Germany) (Figure 1 lower right panel) are permanently installed and measure dielectric permittivity, soil temperature and volumetric soil water content using the time domain transmission (TDT) principle. TDT relates SM estimation to the dielectric properties of water. The sensor uses a ring oscillator in which a steep pulse travels along a closed transmission line consisting of two copper strips buried in the soil. Instead of directly measuring the pulse, the pulse is inverted and then fed back to the input of the line driver. The result is an “oscillation” frequency that mainly depends on the pulse travel time and thus the soil properties (Bogena et al., 2017). Here, we used the sensor-calculated SM values based on Topp et al. (1980) for the analysis, which we hereafter refer to as the volumetric soil moisture [%] content. Figure 1 shows the location of the 400 SMT100 sensors for topsoil SM measurements distributed in a radial, tree-centered pattern across the four plots (Figure 1 A–D). Sensors were carefully inserted into the topsoil at a 45° angle from the surface, with all blade tips facing north. This installation resulted in a mean measurement depth of 12 cm below the soil surface.



175 **Figure 1: Study site at the ECOSENSE forest show plots A–D (left); distribution of sensor network in tree-centered design of 400 SMT100 sensors within plots A–D (right); photograph: M. Gassilloud**

180 The sensor network orients towards the dominant features of tree (canopy) architecture; individual “measurement trees” relate each to 12 sensors (7–10 neighboring measurement trees per plot). Sensors are spaced along the four N-W-S-E axes from the corresponding tree stems, with one sensor at 50 cm stem distance, one at the approximate canopy edge, and a third in the middle between the stem and the edge. An additional 28 randomly distributed sensors complete the network across the four plots. The network with a mean sensor density of $0.23 \text{ sensors m}^{-2}$ is capable to capture the (partly) vegetation-induced small-scale spatial variability of topsoil SM at the stand level (within one to several trees’ distance). Furthermore, the differences in tree stem distances and crown extent create a stratified-random grid of sensor distances ranging from 0.25 to more than 10 meters. All sensors connect to connector boxes (TruCon & TruHub, Truebner GmbH, Neustadt, Germany) which link to data loggers (CR350, Campbell Scientific, Logan, USA). All cables are housed and protected in cable channels at a distance of >50



185 cm to the sensors to avoid interference with the measurements. Continuous measurements of SM at 15-minute intervals started in September 2023 and are ongoing. Figure 1 (panel A) depicts gross precipitation measurement conducted with a tipping bucket rain gauge (YOUNG Tipping bucket rain gauge 52202, resolution 0.1 mm) installed above the canopy on a measurement tower at 47 m height located at the center of the Mixed plot. The precipitation data were wind-corrected according to Kochendorfer et al. (2017).

190 2.3. Data

This study is based on a 2.5-year subset of data from October 2023 to January 2026 (Figure 2). Power outages and hardware failure caused by harsh weather conditions and field site infrastructure maintenances led to unrealistic or missing records during the months of January, February and March and May, June and July in both 2024 and 2025. The resulting data gaps are visible in the time series shown in Figure 2. All raw soil moisture data were subjected to a comprehensive data quality control
195 procedure adapted from Dorigo et al. (2013), which included checks against site-specific physical thresholds as well as evaluation of the temporal dynamics. 93.3% of the data were flagged with “good” and selected for further analysis. About 6.5% of the data proved to be erroneous, either physically impossible (SM = 96.8%) or measurements during days of soil temperature < 1° C (flagged “poor”) were excluded from analysis, as well as data flagged “fair”. Even though “fair” data (0.4% of total) did not exceed physical thresholds, measurement values proved to be highly suspicious within the context: e.g. periods
200 > 48 h of invariant soil moisture values up to the second decimal place for phases of changing soil moisture conditions. The overall data loss was acceptable as the dataset still produces a coherent picture of SM dynamics throughout most of the observation period.

The quality-checked data was further examined for outliers. As most SM distributions are not normal distributed and skewed, we applied the outlier test of 3*IQR (inter quartile range) and resulting outlier were excluded from the analysis. Data were
205 aggregated to daily mean SM values per sensor for days with more than 50% (> 48 measurements within 24 h) valid measurements to match the temporal scale of the research objectives, reduce noise while maintaining a sufficiently fine temporal resolution for SM dynamics and avoid a loss of relevant variability. For further analysis, the time series data were subset to days >50% of valid measurements per plot; individual sensors exhibiting strongly fragmented time series (< 50% days of observation period) were excluded. A quality-controlled version of daily soil moisture measurements for the
210 observation period is online available (<https://doi.org/10.60493/pryn4-g4049>, Dedden (2026)).

3. Methods

Three established spatiotemporal SM analysis methods (Molina et al., 2019; Vereecken et al., 2016) were employed to investigate spatial and temporal variability of the topsoil SM across the four plots from annual to daily time scale and from tree- to plot level. First, the relation between the spatial mean ($\bar{S}M$) and the coefficient of variance (CV) (Molina et al., 2014;
215 Brocca et al., 2007) was characterized to gain a general understanding of SM spatiotemporal variability at the four plots for



the whole observation period. Second, the concept of empirical orthogonal functions (EOF) (Joshi and Mohanty, 2010; Korres et al., 2010; Perry and Niemann, 2007) was then applied to synthesize main time-invariant spatial patterns for each plot. Third, temporal stability analysis and Spearman rank correlation complement the analysis by detailed characterization of inside-plot spatial pattern stability (Vachaud et al., 1985; Vanderlinden et al., 2012). All analyses were performed in RStudio (Posit team, 2025) using the package *gstat* (Gräler et al., 2016; Pebesma, 2004).

3.1. Relation of spatial mean topsoil moisture to its coefficient of variation and to skewness

Defining the functional relation of spatial mean ($\bar{SM}$) and its coefficient of variation (CV) is a common approach to gain insights into the evolution of spatial variability of SM across an area (e.g. (Brocca et al., 2010; Korres et al., 2015)). For the soil moisture SM_{ij} at point i and day j , the spatial mean SM of each day ($\bar{SM}_j$) was derived by:

$$\bar{SM}_j = \frac{1}{N} \sum_{i=1}^N SM_{ij} \quad (1)$$

where N is the number of measurement locations. The coefficient of variation for each day, CV_j was calculated as following:

$$CV_j = \frac{\sigma_j}{\bar{SM}_j} = \frac{\sqrt{\frac{1}{N-1} \sum_{i=1}^N (SM_{ij} - \bar{SM}_j)^2}}{\bar{SM}_j} \quad (2)$$

where σ_j is standard deviation. It describes spatial variability of soil moisture for day j for a given spatial SM_j . As a normalized standard deviation, the CV is a robust measure (independent of the mean in difference to the standard deviation) and comparable between different data distributions.

Analogous to the CV, skewness of the SM probability density functions (pdf) were derived for all days j_i to j_j based on sample histograms following the approach of Ryu and Famiglietti (2005). In relation to the corresponding spatial SM_j , the skewness measures the symmetry of the population at a given moisture state providing further insights into the spatial patterns. As SM pdfs are naturally bounded (e.g. lower boundary of 0% volumetric water content), skewness increases as $\bar{SM}$ approaches a boundary (Ryu and Famiglietti, 2005; Western et al., 2002). The daily distributions were also tested for normality using the Shapiro-Wilk test with a p value of 0.05.

3.1.1. Analysis of seasonal wetting-drying cycles

Wetting-drying cycles of two years were analyzed for seasonal and species-specific differences in spatial SM using a joint analysis of $\bar{SM}$ –CV and skewness relations. Visual inspection of the plot-specific time series was used to divide 2.5 years of observations into two complete wetting-drying cycles. Assuming a hydrological year encompasses a complete wetting-drying cycle transitioning between of wettest and driest soil moisture states, then these extremes mark the beginning and end of a cycle. Two entire cycles could be extracted from the data starting with the start of the wetting phase in late autumn at the driest day ($\bar{SM} = \min$). The drying phase begins at the end of winter when the SM state is at its wettest ($\bar{SM} = \max$). The phases



describe the overall development of spatial SM distribution towards an extreme state (highest/lowest spatial mean) based on the time series of spatial $\bar{SM}$ per plot. Within each phase, there were several sub-cycles of event wetting- and drying. Local minima and maxima describe the turning points; for similarly high or low $\bar{SM}$, dates of lowest coefficients of variation were selected, assuming these moments mark the most homogenously wet or dry states of SM. Furthermore, cumulative frequency distributions of $\bar{SM}$ were used to confirm the threshold dates including high or low soil moisture measurements within a plot.

3.2. Empirical Orthogonal Function (EOF) analysis of topsoil moisture patterns

The empirical orthogonal function (EOF) concept was used to identify the main time-independent, non-random reoccurring spatial patterns of topsoil SM variability within the plots following the approach of Korres et al. (2010) and Graf et al. (2014) based on Preisendorfer and Mobley (1988). In an eigenanalysis (S-mode to focus on spatial patterns) of the covariance matrix, observed data are decomposed into a set of time-invariant orthogonal spatial patterns (EOFs) and a set of time series called expansion coefficients (ECs). A detail description of the EOF concepts' theory and their applications in SM research can be found in Preisendorfer and Mobley (1988), Perry and Niemann (2007) or Korres et al. (2010). In the following, we briefly introduce the main ideas and definition of the approach.

For every plot, a data matrix $\mathbf{D}$ of $(p \times n)$ entries was retrieved from the SM dataset, with p = sampling times (days) and n = number of sampling locations (sensors). Based on each data matrix $\mathbf{D}$, individual spatial anomalies matrices $\mathbf{F}$ were computed by:

$$a_{ij} = SM_{ij} - \frac{1}{n} \sum_{j=1}^n \bar{SM}_{ij} \quad (3)$$

a_{ij} describes the difference of the SM at a measurement location i to the spatial $\bar{SM}$ of every timestep j so the matrices contain the spatial anomalies of all individual measurement locations for every sampling time (day). Missing data were substituted with zeros. Next, for every spatial anomaly matrix $\mathbf{F}$, the covariance matrix $\mathbf{R}$ was retrieved by:

$$\mathbf{R} = \frac{1}{N-1} \mathbf{F}^t \mathbf{F} \quad (4)$$

where $\mathbf{F}^t$ indicates transposed matrix and N is the number of observations (days). The co-variance matrix $\mathbf{R}$ from $\mathbf{F}$ was then diagonalized to find eigenvectors (matrix $\mathbf{E}$) and eigenvalues (matrix $\mathbf{L}$) according to:

$$\mathbf{R}\mathbf{E} = \mathbf{E}\mathbf{L} \quad (5)$$

with $\mathbf{L}$ indicating a diagonal matrix of eigenvalues (EV) of $\mathbf{R}$. The eigenvector matrix $\mathbf{E}$ contains in its columns all EOFs for the plot; the first column describes as much as possible of the variance of $\mathbf{F}$. With a projection of matrix $\mathbf{F}$ onto the eigenvectors of $\mathbf{E}$, matrix $\mathbf{A}$ was produced containing the expansion coefficients (EC) that describe how the associated patterns (EOFs) evolve in time:

$$\mathbf{A} = \mathbf{F}\mathbf{E} \quad (6)$$

The fraction of variance explained (EV) by each EOF was calculated dividing the EV by the sum of all eigenvalues. The EOF-EC pairs were ranked according to the amount of explained variance and tested for statistical significance (mode separation) by North's rule of thumb (North et al., 1982) with a 95% confidence interval for the k -th eigenvalue calculated as:



$$\delta\lambda_k \approx \lambda_k \times \sqrt{\frac{2}{n_{eff}}} \quad (7)$$

where $\delta\lambda_k$ is the sampling error for the k -th eigenvalue and n_{eff} is the number of independent sampling locations. In case of overlapping confidence limits (e.g. 95%) of eigenvalues, the respective eigenvalues may be statistically indistinguishable because their sampling errors are comparable to the “nearby” EOF (“effective degeneracy”) and EOFs may mix under sampling variability and spatial patterns are not uniquely defined. The independent realizations n_{eff} were calculated using Moran’s I criteria. When reduced to the statistically significant pairs of EOFs and ECs, the spatial structures account for the majority of total spatial variance (Joshi and Mohanty, 2010; Perry and Niemann, 2007; Perry and Niemann, 2008; Hannachi et al., 2007) In a following Monte Carlo simulation eigenvalue uncertainties (N rule, Preisendorfer and Mobley (1988)) were estimated to prove EOFs’ ECs are significantly different to randomly generated patterns (“signal-to-noise”) (Korres et al., 2010; Wang et al., 2017).

3.3. Temporal stability analysis and Spearman rank correlation of soil moisture

To investigate temporal dynamics of the spatial topsoil SM patterns, temporal stability (TS) analysis and Spearman rank correlation were used. The time stability concept following Vachaud et al. (1985) characterizes the location-specific temporal stability in SM as the relative difference of individual locations in relation to the time-averaged plot $\bar{SM}$. Eq. 7 describes the relative difference in time-averaged soil moisture δ_{ij} for a location i and a day j to the plot average by:

$$\delta_{ij} = \frac{(SM_{ij} - \bar{SM}_j)}{\bar{SM}_j} \quad (8)$$

Based on all relative differences of time-averaged soil moisture δ_{ij} , the mean relative difference $\bar{\delta}_i$ and its standard deviation $\sigma(\delta_i)$ were calculated for each location i for the whole observation period by Eq. (8) and (9), $\bar{\delta}_i$ describes how much the SM at a location i deviates from the spatial $\bar{SM}$ during the observed period.

$$\bar{\delta}_i = \frac{1}{M} \sum_{j=1}^M \delta_{ij} \quad (9)$$

$$\sigma(\delta_i) = \sqrt{\frac{1}{M-1} \sum_{j=1}^M (\delta_{ij} - \bar{\delta}_i)^2} \quad (10)$$

$\sigma(\delta_i)$ is an index of temporal variability of the mean relative differences (MRD). Locations of small standard deviation of relative difference (SDRD) follow closely the temporal pattern of field-average soil moisture (Grayson and Western, 1998). To quantify representative measurement locations – referring to locations that accurately follow the spatial $\bar{SM}$ characteristics over time – the Index of Temporal Stability (ITS) (Zhao et al., 2010) was calculated for all individual locations by:

$$ITS_i = \sqrt{MRD_i^2 + SDRD_i^2} \quad (11)$$



and locations of $ITS_i \leq 0.15$ qualified as representative in this study. Non-parametric Spearman's rank correlation coefficients of daily spatial soil moisture distributions were calculated. The coefficients indicate the degree of correlation of the daily location rankings, a specific "configuration" over time (Vachaud et al., 1985; Dari et al., 2019). Strong rank correlation of daily distributions from one day to another suggests high spatial stability of patterns. The coefficient for a given day j were calculated by:

$$r_s = 1 - \frac{6 \sum_{i=1}^n (R_{ij} - R'_{ij})^2}{n(n^2 - 1)} \quad (12)$$

where R_{ij} = rank of variable S_{ij} , the SM observed at location i on a selected day j . R'_{ij} is the rank of variable S_{ij} at the same location for day j' and n = number of observations. The resulting coefficients r_s describe the correlation of ranks from day j to day j' : The closer r_s is to 1 for a given timestep (day j to day j'), the less locations change their rank and the spatial pattern remains stable during this period (1 = perfect time stability). In those cases, wetter areas would remain (persistently) wetter whereas drier areas would remain (persistently) drier. r_s values close to zero indicate low stability of spatial patterns: location rankings are inconsistent and largely reconfigured between days due to spatially variable in- and outputs to SM (Cosh, 2004). Comparing several consecutive time steps using a sequence of coefficients r_s allows to assess potential "pattern memory": a sequence of invariant high r_s for several time steps can be interpreted as a strong "memory of pattern" indicating a well-preserved spatial configuration of location rankings over time. In such a case, the spatial SM pattern based on location rankings would not change or SM changes would homogeneously affect all locations e.g. by gradual wetting affecting only the emphasis of the pattern.

4. Results

4.1. Statistical analysis of topsoil moisture

The spatial $\bar{SM}$ time series for all four plots are depicted in Figure 2. They follow a similar seasonal dynamic over the observation period at all four plots, being highest in at the end of winter and during early spring (e.g. 13th February 2025 for Beech plot $\bar{SM}$ = 35.1%, Douglas fir plot $\bar{SM}$ = 34.7%, Silver fir plot $\bar{SM}$ = 28.6%, Mixed plot $\bar{SM}$ = 30.9%) and lowest during summer between July and October (e.g. 13th October 2023 for Beech plot $\bar{SM}$ = 7.3%, Douglas fir plot $\bar{SM}$ = 7.7%, Silver fir plot $\bar{SM}$ = 5.7%, Mixed plot $\bar{SM}$ = 8.0%) of both observed years.

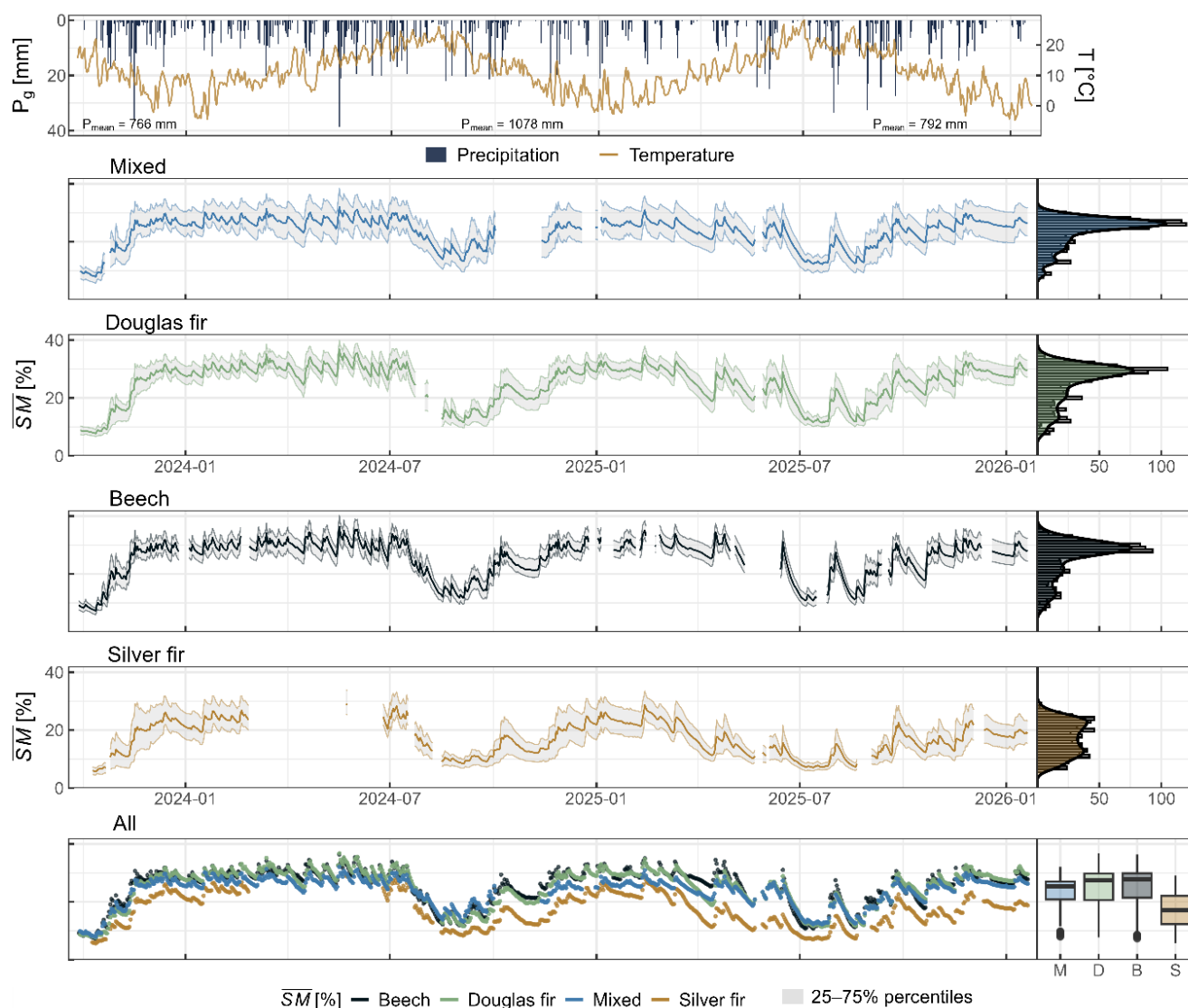


Figure 2: 2.5 years of topsoil moisture across four plots of (from top): 1. mixed Beech and Douglas fir, 2. Douglas fir, 3. Beech and 4. Silver fir trees. Histograms and fitted probability density functions indicate the distribution of all valid daily mean spatial soil moisture measurements.

Throughout the relatively wet years 2024 ($P_g = 1078$ mm with 18% above the long-term mean) and 2025 ($P_g = 792$ mm) (Figure 2 upper panel), the time series of $\overline{SM}$ at the Silver fir plot is significantly lower, whereas the $\overline{SM}$ levels at Douglas fir, Beech and Mixed plots are quite similar. Boxplots highlight the similar $\overline{SM}$ conditions by proximate SM medians (Figure 2, lower right panel): The Beech plot is the wettest plot (global median SM = 27.8%) followed by Douglas fir (global median SM = 27.5%), Mixed (global median SM = 25.6%) and Silver fir (global median SM = 17.2%) plot. The largest SM IQR of 9.7% has the Silver fir plot, the smallest the Mixed plot of 6.3%. The $\overline{SM}$ for the Beech, Douglas fir and Mixed plots ranges between



20–40% for most of the observation period. During the vegetation periods from April to October the $\bar{S}M$ progressively decreases to a minimum of $< 10\%$ (Figure 2 left panels). For the Silver fir plot, the probability density functions of daily $\bar{S}M$ is bimodal with two local maxima at approx. 10% and 25%. For all other plots the distributions are unimodal with left-skewed probability density functions spread their tails towards low $\bar{S}M$ values.

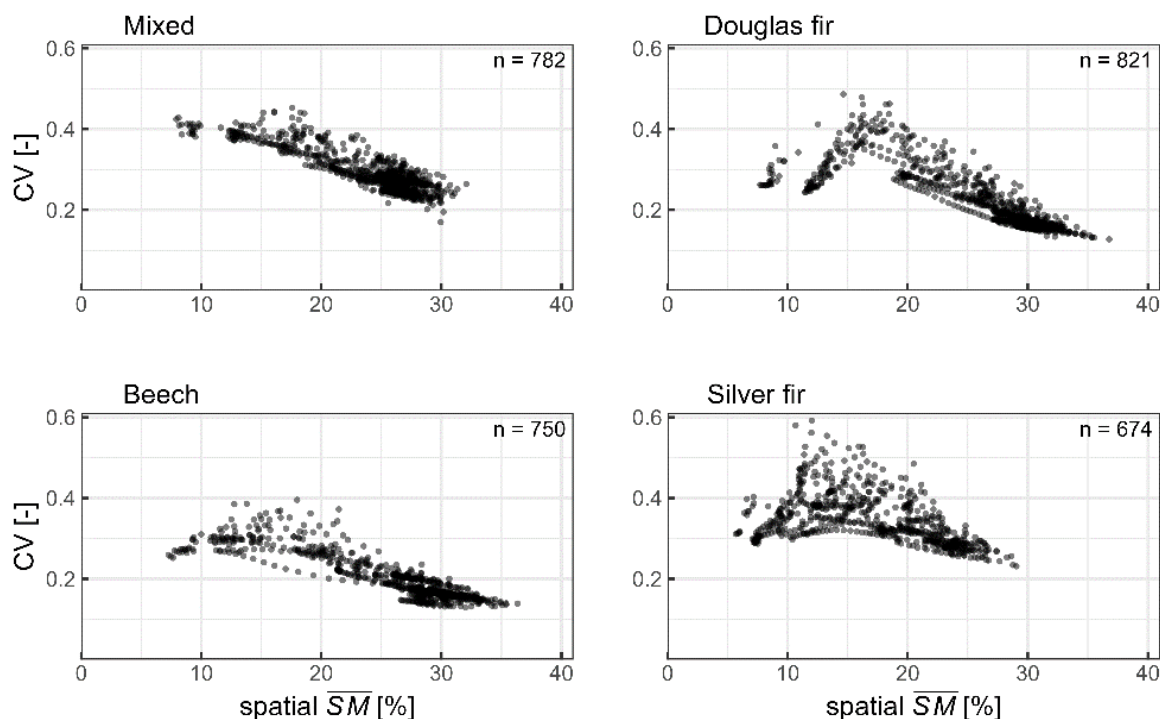


Figure 3: Relation of the daily mean spatial soil moisture to its daily coefficient of variation (CV) per plot for the 2.5-yr. observation period

Figure 3 give an overview of the $\bar{S}M$ –CV relationship for the four plots. The Silver fir, Douglas fir, and Beech plots show the highest CV at the intermediate spatial $\bar{S}M$ (peak CV at 10–20%). The Mixed plot shows the highest variability for drier states around 10% $\bar{S}M$. The lowest CV for Beech, Douglas- and Silver fir plots exhibit wet $\bar{S}M$ states between approx. 30–40%. The $\bar{S}M$ –CV relationship characterizes a convexly-shaped upward-facing curve for the Beech, Douglas, and Silver fir plots, with a peak at intermediate wetness states between 10 and 25% and lower limits towards dry and wet SM conditions. This relationship is most pronounced for the conifer species. At the Mixed plots, a linear negative relation for $\bar{S}M$ –CV is visible. The $\bar{S}M$ –skewness relationship in Figure 4 shows an upward convex shape for the Douglas and Silver fir plot, whereas Beech and Mixed plot show a linear relation. Daily SM skewness values range from -1.8 to 1.4. The daily spatial distributions show strongest negative skew at the Mixed plot and strongest positive skewness at the Douglas fir plot. At all plots, wet $\bar{S}M$ states exhibit strongest negative skewness. For the Mixed plot, low skew and normal distributed (black dots) are related to a $\bar{S}M$ between 15% and 25%; whereas dry $\bar{S}M$ states are related to positive skewness (Figure 4). Beech, Silver and Douglas fir plots



show strongest positive skewness for intermediate wetness state distributions (10–20%); normal distributed daily spatial SM
 355 states occur across all SM ranges for these plots (<10 to >30%).

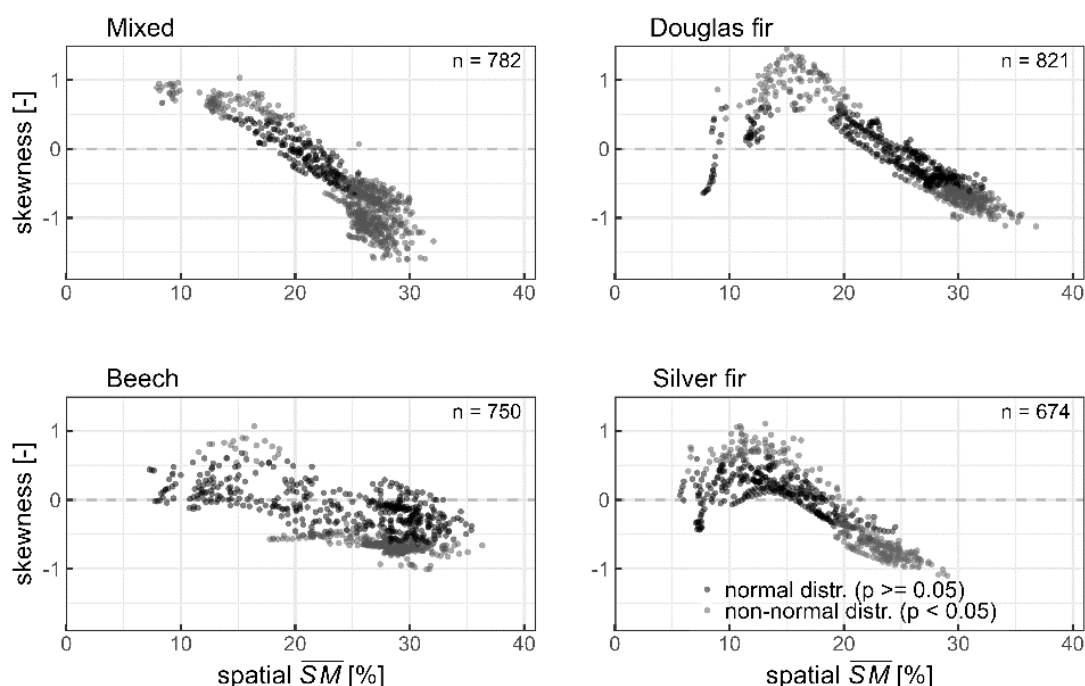


Figure 4: Relation of the daily spatial mean soil moisture to its daily skewness per plot for the 2.5-yrs. observation period. Daily soil moisture following a normal distribution is displayed in black, non-normal distributions are displayed in grey.

4.2. EOF analysis of time-invariant spatial structures of soil moisture variability

360 The EOF analysis yielded a series of EOF-EC pairs for each of the four plots. At a 95% probability level, 7–9 EOFs were identified as significant. To truncate this group of statistically significant EOF-EC pairs with separated modes, the first two to three pairs that cumulatively explain at least 80% of total explained spatial variability (e.g. Korres et al. (2010)) were extracted and are presented in Figure 5 and Figure 6. Higher order modes contribute minimally to the overall variance and are less likely to represent meaningful patterns. For the Beech, Douglas fir and Mixed plot, the three leading EOF-EC pairs explain more
 365 than 80% of the total spatial variance; for the Silver fir the two leading EOF-EC pairs. The first EOF (EOF1) is the most dominant mode across all plots, accounting for > 60% of spatial variability (see Table 1 and Figure 5 & Figure 6). This finding suggests that the spatial variability of SM within the four plots is largely determined by a small number of underlying spatial structures that remain relevant over time. The first EOF captures the most prominent spatial structure within each of the four plots. The Silver fir plot exhibits the highest degree of dominance (EV) in EOF1, exceeding the other plots by more than 10%.
 370 Consequently, EOF2 plays a more important role at the Beech, Douglas fir and Mixed plots with EVs of approx. 15% (Silver



fir plot = 6.6%). EOF3 accounts for 7.2%, 7.0% and 5.9% of spatial variance at the Beech, at the Douglas fir and the Mixed plot respectively; although negligible for the Silver fir plot, it is included in Figure 5 for completeness.

The relative importance of EOF1–3 varies throughout our observation period. The weighted EC time series of EOF1–3 in Figure 5 show the relative contribution of the individual EOFs to the daily SM patterns of spatial variability at the individual plots. All EC1 values are strictly positive over the entire observation period at all plots; EOF1 reflects the most prominent spatial structure. While the general temporal evolution of weighted EC1 of EOF1 is similar across plots; the magnitude of the weights and the amplitude of their oscillations varies by seasons; the Silver fir has the highest overall EC levels and most pronounced dynamics, while the Beech plot generally displays the lowest. The EC1 time series characterize two contrasting phases: during wet winter months (approx. November to April), EC1 values remain relatively stable, indicating a consistent influence of the EOF1 spatial patterns. In contrast, drier SM states during the vegetation period have widely varying EC1 values, with peaks coinciding with high-precipitation events mostly in October 2023, 2024 and 2025, and minima occurring during strong drying phases in October 2023, August 2024 and July 2025, when the relevance of EOF1 fades. This seasonal contrast is most pronounced for the Douglas fir and Beech plot, followed by the Mixed and least pronounced in the Silver fir plot, where fluctuation persists throughout the year. A reoccurring annual cycle is observed, beginning in fall 2023 with a sharp increase in EC values for all plots following a preceded SM dryness of late summer. As the SM increased during autumn rainfall, the importance of EOF1 intensifies across all plots. In consecutive months of wet winter SM conditions, the weighted EC diverges across plots: EOF1 is generally most relevant at the Silver fir plot, but shows also strongest temporal variation in EC in response to individual precipitation inputs/pulses. The Douglas fir and Beech plots maintain a relatively constant, high level of EOF1 dominance. For increasingly dry SM conditions in spring and summer, EOF1 loses importance, while EC1 values drop across all plots and spike during periods of high SM input from precipitation. This annual cycle is repeated from autumn 2024 to early 2026. For the Beech and Mixed plots, the temporal dynamic of EC values during winter and summer 2025 is more uncertain due to limited data availability.

Table 1: Explained spatial variance by EOF 1–5 for the four plots

Plots	EOF1	EOF2	EOF3	EOF4	EOF5
Mixed	66.1*	14.4*	5.9*	3.8	2.3
Douglas fir	63.7*	14.5*	7.0*	3.2	2.3
Beech	62.7*	16.0*	7.2*	4.7	2.7
Silver fir	79.9*	6.6*	3.6	2.3	1.3

* the first two to three selected EOFs cumulatively explain > 80% (defined threshold) of total spatial variability

The spatial distribution of EOF1 displayed in Figure 6 varies across the four plots, reflecting plot-specific SM regimes with small-scale spatial heterogeneity, which only partially reflects regional clustering. At the Beech plot, EOF1 is characterized by a distinct center-to-margin contrast; positive values concentrate in the plot center, while most negative values locate towards



the west, the plot margins – particularly at the eastern canopy edges – and in the immediate vicinity of several tree stems (Figure 6). In the Douglas fir plot, EOF1 also exhibits a widely distributed pattern of contrast with the majority of sampling locations contributing significantly to the mode through high positive or negative amplitudes. Positive values, which may indicate increased SM levels, are concentrated in the southeast, in the plot center, and generally on the southern side of the tree stems. Conversely, the negative values concentrate on the northern side of the trees and at the canopy edges, with the three northern trees exhibiting the most pronounced contrast. The Silver fir plot exhibits the highest explained variance and displays a relatively clear spatial structure for EOF1: positive values range throughout the south and west of the plot, with isolated higher values at the canopy edges of the northern and western trees. Negative values are primarily located in the upper and western portions of the plot with lowest values occurring near the stems. Finally, the Mixed plot exhibits for EOF1 a strong spatial contrast: Negative values concentrate within densely sampled areas, specifically in the upper-central and south-western regions, coinciding with the locations with narrow canopies. In contrast, several highly positive values group in the north-west; among the trees in this area, several positive amplitudes are located below canopy edges and near the stems, suggesting a localized increase in moisture variability in this sector of the plot (Figure 6). The intensity of EOF1 is modulated by the mean state of the system; the relationship between weighted EC1 and $\bar{S}M$ is illustrated in Figure 7. Generally, the convex upward relation is visible across all plots, with the Douglas fir plot having the most pronounced shape. Transitioning into a wetter state of the system, the EOF1 gains importance, reaching maximum weighted EC1 values at intermediate wetness states – at approx. 20% $\bar{S}M$ at the Silver fir and 25-30% at the Beech, Douglas fir, Mixed. Beyond these SM levels, the influence of EOF1 decreases, implying that the wettest SM states are less explained by the first EOF.

For all periods, secondary and tertiary modes (EOF2 & EOF3) cumulatively explain less than 10% of the total explained spatial variance across all plots, indicating a minor contribution compared to the dominant EOF1. The temporal dynamics of EC2 and EC3 appear similar in temporal dynamic during the observation period characterized by periodic reversals of EOF influences shown in Figure 5. Weighted EC values for EOF2 range between -7.5% and 5%, while EC3 for EOF3 range between approx. -3% and 2%. These dynamics are most pronounced in the Mixed and Douglas fir plots, while the temporal dynamic is less pronounced for Silver fir and Beech plot. Both time series of EC2 and EC3 oscillate between phases of negative and positive EC values, indicating the influence of EOFs is reversed for specific phases within the observation period. EC2 exhibit a shift in polarity of negative values from the beginning of time series in autumn 2023 and gradually approach zero until approx. August 2024. After late summer 2024, the influence is reversed; EC2 values vary but are almost strictly positive despite a brief decline during a precipitation-rich phase in September 2024. Following a period of minor contribution beginning October 2024, EC2 values increase with the start of the vegetation phase in April 2025, reaching up to 5%. Until November 2025, EC2 exhibits a temporal evolution mirrored to EC3; variable increases of convex phase during dry periods and sudden drops proceeding precipitation events which are most pronounced for conifer and mixed plots. This suggests EOF2 captures elements of a summery drying pattern (Figure 5). The EC3 time series closely follow a consistent temporal dynamic characterized by two recurring phases. From beginning of time series in autumn 2023 until late winter 2024, and again during late vegetation



period 2024 and entire vegetation period 2025, EC3 values are negative and strongly fluctuating between zero and negative peaks of -3 to -1%. EC3 values transition into an invariant, strictly positive influence phase from February to August 2024, as well as during winter 2024/25. The influence of EOF1 varies according to the strictly positive magnitude of the EC1 value, whereas the influences of EOF2 and EOF3 are seasonally reversed in an annual cycle indicated by the polarity shift in EC2 values.

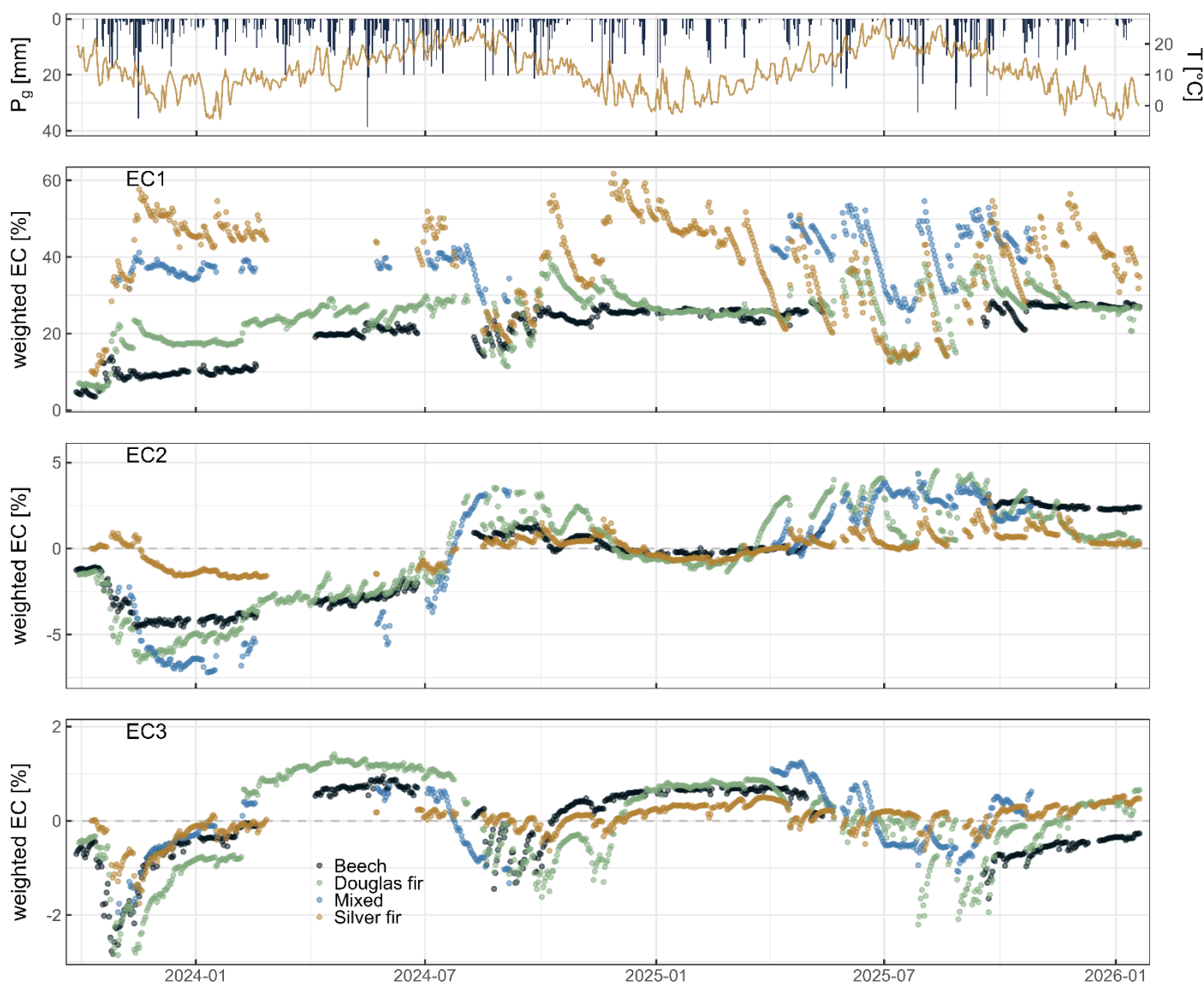


Figure 5: Weighted expansion coefficients (EC) for EOF 1–3 derived from each of the four plots over 2.5-yr observation period. Note the different scales of the weighted EC among the three EC.



4.3. Analysis of the temporal dynamics of soil moisture patterns

4.3.1. Temporal stability analysis

Figure 8 shows the results of the temporal stability analysis: for each of the plots, measurement locations were ranked according to MRD with locations of negative MRD the left site and locations of positive MRD the right side of the plot (Vanderlinden et al., 2012; Heathman et al., 2012). The whiskers (standard deviations of relative differences, SDRD) indicate how strongly the relative differences in SM at individual locations vary in relation to the spatial mean over time. Measurement locations at the Silver fir plot span over the largest range of relative differences to spatial mean: wettest locations are 64.4% wetter than the overall mean, driest locations of the plot are 75.1% drier. For the Beech plot, measurement locations span over the smallest range of relative differences: driest locations are 39.3% drier than average, and the wettest locations exceeds the spatial mean by 28.0%. At the Douglas fir plot the range similarly runs from -47.8% for the drier locations to 39.3% for the wetter locations relative to the time-averaged mean. The driest locations in the Mixed plot are up to 46.5% drier, while the wettest are up to 56.3% wetter than the spatial $\bar{SM}$. All plots exhibit a pronounced spatial variability in topsoil moisture at the observed spatial scale; within a few meters' distance, topsoil moisture content can change by more than 25% at all plots. At this scale, topsoil moisture is most heterogeneous at the Silver fir and most homogenous at the Beech fir plot (Figure 8). Regarding the temporal stability of the rankings in Figure 8, whisker lengths (SDRD) range from 6.4% (SDRD = 0.064) to 51.9% (SDRD = 0.519) across the measurement locations. Mean whisker lengths of 13% at the Beech plot, 15% at the Douglas fir, and 16% at the Silver fir and Mixed plot. The Mixed plot has the largest IQR_{SDRD} of 8% indicating locations vary most in their relation to the spatial mean over time.; Douglas fir plot has the smallest IQR_{SDRD} of 6% reflecting the most stable spatial ranking of locations (most stable spatial pattern). Some locations exhibit unstable conditions, e.g. the wettest and driest locations at the Mixed plot have large whiskers of > 0.5 . For the conifer plots, the wettest locations (MRD > 0.25) show larger temporal variability than the driest locations (MRD > -0.25). Locations of MRD near zero usually have short whiskers.

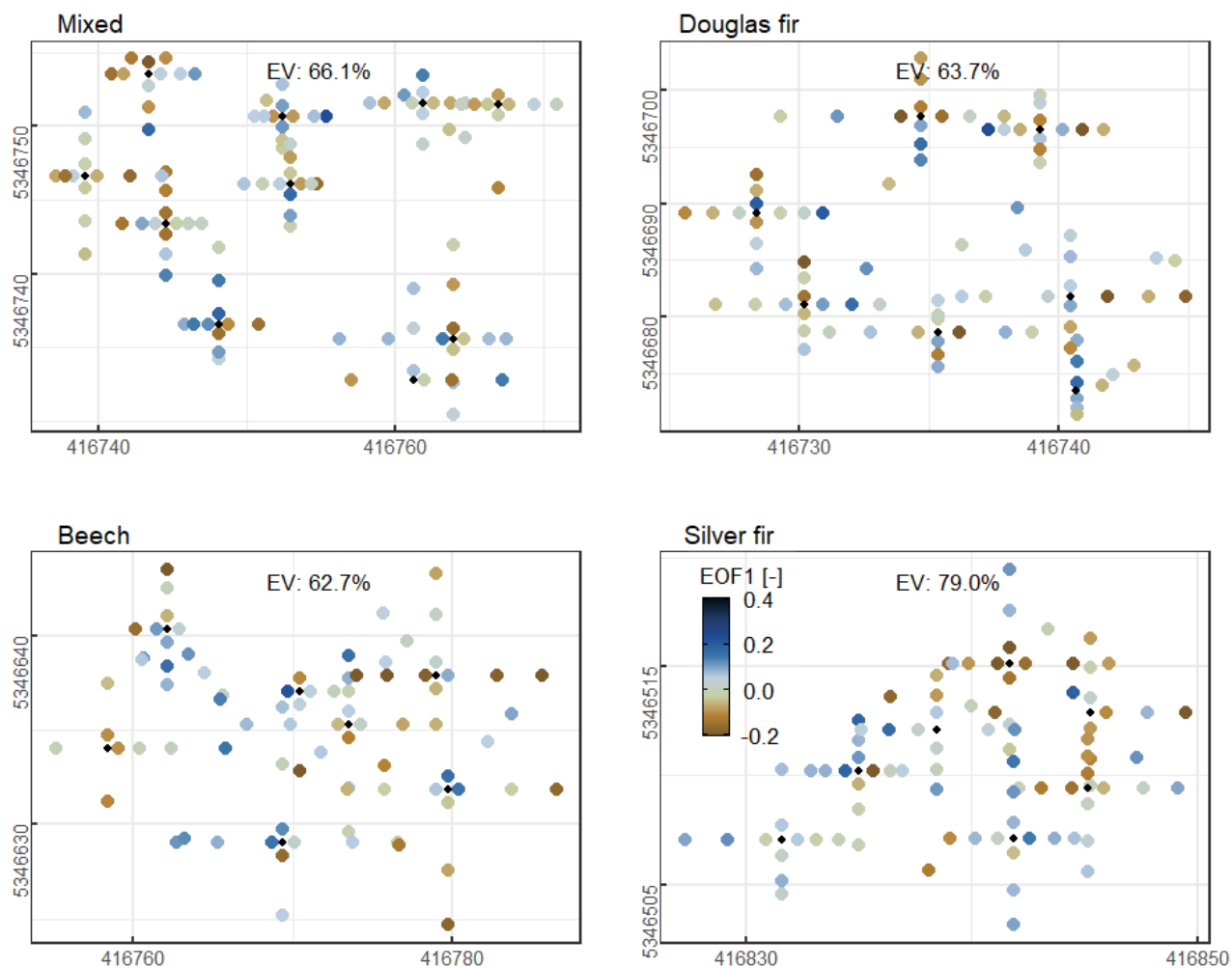


Figure 6: EOF 1 gradient projected in space at respective measurement locations for all four plots

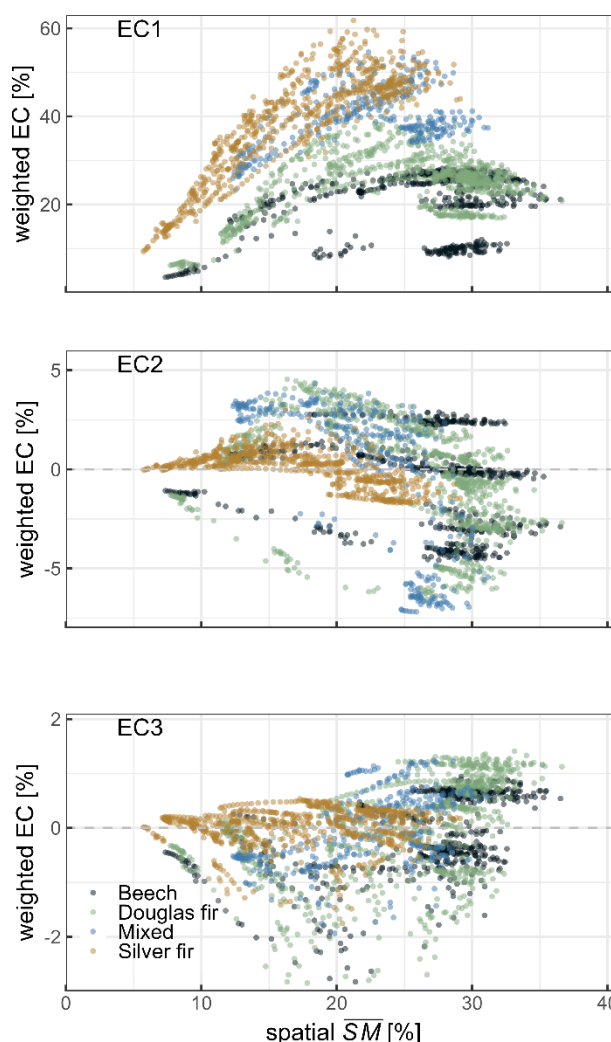


Figure 7: Relation of daily mean soil moisture to the respective weighted expansion coefficients EC1–3 for EOF 1–3 for the four plots

Figure 8 highlights several locations in blue: measurement locations of mean relative differences near zero and short whiskers indicate “representative locations” defined by the ITS criteria (see Sect. 3.3). According to the herein defined ITS threshold ≤ 0.15 , these locations are representative for the plot spatial $\overline{SM}$ dynamics as they (1) match the SM characteristics of the spatial plot mean (MRD close to zero) and (2) follow closely the spatial mean of the plot over the observation time (low SDRD). These locations would be the most useful for representative measurements in spatially sparse samplings. The Beech plot is the most spatially homogeneous, with 30 representative locations; Douglas fir has 24, Silver fir has 11, and Mixed plot has 17.



Figure 9 depicts the relative differences in SM to the temporally average plot mean across the plots (Figure 8). Blue dots indicate wetter-than-average measurement locations; brown dots describe a drier-than-average location. The more pronounced color gradient at the Silver fir and the Mixed plot reflects the stronger spatially heterogeneous SM conditions, whereas the pale color gradient at the Beech and the Douglas fir plot reflects the more homogenous conditions. The distribution of wetter and drier locations appears to be random, with no clear clustering based on factors such as topography or tree location. At the Silver fir plot, several locations of negative MRD cluster in the north-east of the plot area near stems, whereas wetter locations are mostly in the center, to the south and east but also at the northernmost area of the plot. Near-average SM locations are primarily clustered in the plot center. At the Beech plot, several drier locations are located at canopy edges and for the Douglas fir plot, a group of largely wetter than average locations is found to the south-eastern plot region. Some of the wettest and driest locations are in direct vicinity to the tree stem, however drier and wetter locations can be found across the entire plots. Overall, Figure 9 shows not clear relationship between the distance to the stem distance and the MRD; both negative and positive MRD values occur at all stem distance and plot regions (direction N/E/S/W). As a result, the representative locations are distributed across the plots at varying distances from the stem. As a result, a representative sampling location is difficult to be determined a-priori and can be found across the entire plot region rather than just one area.

4.3.2. Spearman rank correlation of soil moisture distribution over time

In correspondence to the results presented in Sect. 4.3.1, the temporal evolution of daily spatial patterns of SM within every plot were evaluated. Spearman's rank correlation coefficients – displayed by a gradient of grey shades in triangular correlation matrices of Figure 10 – describe whether spatial patterns in form of a daily measurement location rankings are either preserved or reconfigured. The upper matrix shows correlation coefficients (ρ) for significant ($\alpha = 0.05$) autocorrelations between ranks at monthly timesteps for the Douglas fir plot, the lower matrix shows autocorrelations for the Beech plot. Analysis at monthly timestamps enables a comprehensive overview of the entire observation period while maintaining sufficiently high temporal resolution.

Both plots in Figure 10 exhibit a large range of ρ from strong ranking correlation ($\rho \geq 0.8$) between subsequent dates to weak ($\rho < 0.65$) or no sign. correlation ($\rho = 0$) for consecutive dates. The overall pattern of strong to weak autocorrelations among the ranked locations in the two matrices appears similar for the two plots. Observing the daily rankings at subsequent monthly timesteps, strongest correlations ($\rho > 0.95$) for both the Beech and Douglas fir plot mainly occur during the months of November to May 2023/24 and 2024/25 and November to January 2025/26 at comparably high $\bar{SM}$. Overall, correlation coefficients during these winter periods (Figure 10 blue dashed lines) are significant and high ($\rho \geq 0.8$) representing temporally stable spatial patterns of SM within the plots. In 2024, the timesteps of strong correlations extend till July. Interestingly, during these periods changes in SM states (Figure 10) cause little to no loss of correlation. The variation in $\bar{SM}$ during wet winter periods does not lead to a reconfiguration of the spatial SM pattern (change in ranking) wetter areas would remain (persistently) wetter whereas drier areas would remain (persistently) drier. Hence, the SM gain or loss across the locations is spatially homogenous or follows the magnitude of spatial SM variability patterns gradually pronouncing or attenuating it without



changing the ranking. In the summer (June to October) the drier SM conditions, and individual timesteps show strong correlations similarly to winter periods, e.g. September to October 2024 with $\rho = 0.87$ for Beech and $\rho = 0.82$ for Douglas fir plot (Figure 10). However, strong correlations ($\rho \geq 0.8$) between dates during these periods are markedly fewer and moderate ($0.65 < \rho < 0.8$) to weak correlations ($\rho < 0.6$) are frequent e.g. July to September 2024 with $\rho = 0.46$ for the Douglas fir and $\rho = 0.57$ for the Beech plot. The periods illustrate how moderate and weak correlation coefficients reflect unstable rankings and major reconfigurations of spatial SM.

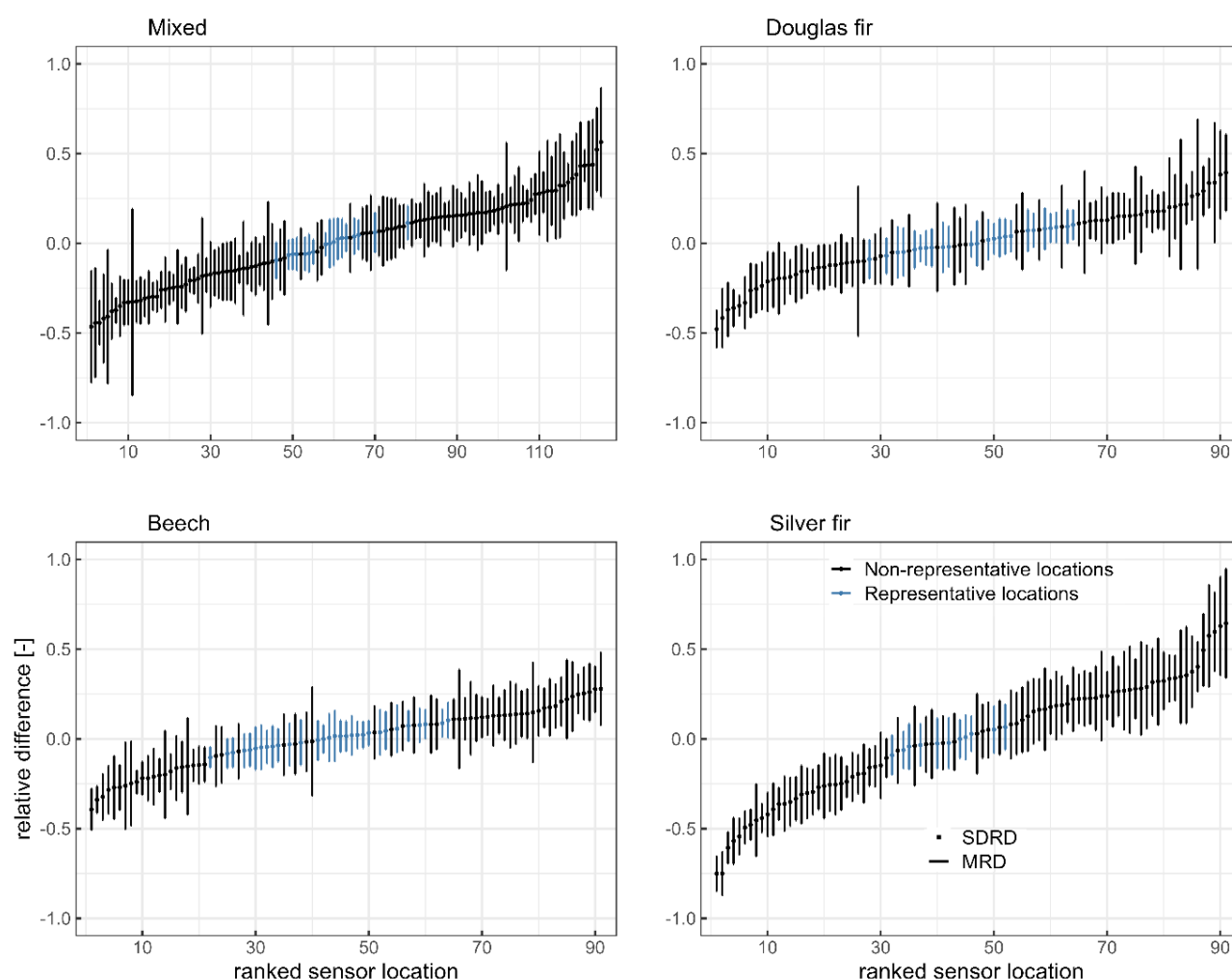


Figure 8: Time-average relative mean difference (MRD) and its standard deviation (SDRD) in soil moisture for Spearman-ranked measurement locations within each plot in relation to the spatial plot mean soil moisture

Comparing several consecutive time steps – a sequence of coefficients r_s – allows to assess potential “pattern memory”. A sequence of invariant high r_s for several time steps can be interpreted as phase of strong “memory of pattern” indicating a



well-preserved spatial configuration of location rankings over time. In both matrices, consecutive dark shading show for both wet winter and dry summer periods phases of strong spatial correlation of location rankings correlate for several months. Sudden drops in correlation signal the onset of wet and dry periods (Figure 10 orange and blue fields). For the Douglas fir plot, the beginning of a first wet phase (wet phase I) begins with very strong correlation of $\rho = 0.95$ for the timestep December 2023 to January 2024. The phase extends with continuously high $\rho > 0.65$ until July 2024, when correlation to the phase beginning in December 2023 still reaches $\rho = 0.76$. At the Beech plot, wet phase I does starts in February 2024, with correlation to March 2024 of $\rho = 0.96$. Correlations to the initial date remain high for several months and pattern stability slowly decreases with time and the spatial pattern fades over several months. Markedly weaker correlations e.g. of February to August 2024 with $\rho = 0.45$ at the Beech plot or December 2023 to October with $\rho = 0.5$ at the Douglas fir plot define the end of the wet phase. These high-instability periods of spatial reconfiguration with indicate transitions from wet to dry (or vice versa SM) states during which spatial SM changes heterogeneously across locations.

At both plots, the following dry phase (phase dry I) spans over late summer 2024: the sequences exhibit only moderate correlations ($0.65 < \rho < 0.8$). During phases dry I and II, high correlation coefficients ($\rho > 0.8$) occur only between two consecutive months, indicating a rapid loss of spatial pattern memory and significant changes of spatial SM pattern. Starting in October 2024, a new sequence of continuously high correlation coefficients marks the onset of wet phase II. S The strongest correlations span over the period of November 2024 to mid-May 2025 (phase wet II); weaker correlations in the subsequent summer months mark the end of the wet phase and the start of a dry phase (phase dry II) and a third sequence of subsequent strong correlation coefficients begins in October 2025.

Furthermore, strong inter-annual correlations are present, e.g. at the Douglas fir plot for January 2025 to January 2026 or at the Beech plot between February 2024 to February 2025 both with $\rho = 0.85$. This “inter-annual pattern memory” shows that under wet SM conditions, spatial configuration remains stable. For example, dates of wet period III correlate strongly with dates from phase wet II ($\rho > 0.8$) and even with wet I ($\rho > 0.65$). Dry phase I & II correlate, e.g. at the Beech plot August 2024 and July 2025 with $\rho = 0.9$. A specific spatial pattern of ranked measurement locations may reoccur annually, depending on the system’s mean wetness state.

In summary, Figure 10 reveals temporally stable spatial configurations: correlations are primarily high during wet periods large, yet during periods of low $\bar{SM}$ ($< 15\%$) strong correlations and hence temporal stability exist. Nevertheless, dry conditions are more prone to instability; changes in SM conditions (precipitation) cause spatial reconfiguration more readily during dry than during wetter to wet conditions ($> 25\% \bar{SM}$). The $\bar{SM}$ state and the change in SM within a timestep may determine temporal stability of pattern. Recurring data gaps in the time series for the Silver fir and Mixed plots precluded a congruent Spearman rank correlation analysis for the selected timesteps. Consequently, we could not derive a similarly reliable picture of the temporal evolution of soil moisture spatial autocorrelation for these plots, and they were excluded from this step.

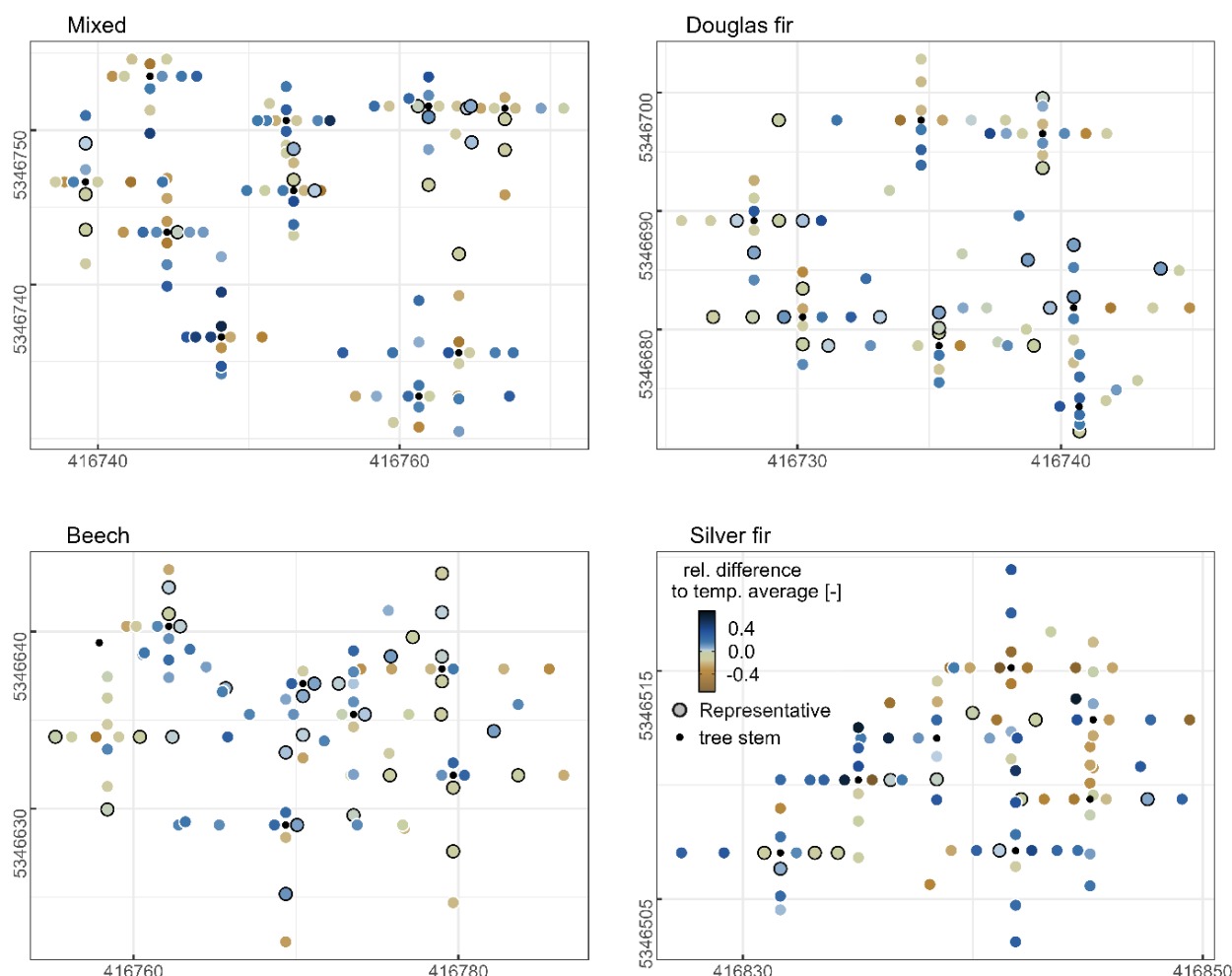


Figure 9: Spatial pattern of time-average relative mean difference in soil moisture of Spearman-ranked measurement locations

4.4. Analysis of seasonal wetting-drying patterns

Figure 11 & Figure 12 show the $\bar{S}\bar{M}$ -CV and $\bar{S}\bar{M}$ -skewness relation – analogous to the results presented in Sect. 4.1– separately for the two years of October 2023 to September 2024 and October 2024 to September 2025. Each of these years covers one large wetting-drying cycle: with its beginning at the driest SM state at the end of summer, gradual wetting of the soil occurs until the wettest SM state at the end of winter is reached. The drying phase then spans over spring and summer until the driest SM state is newly reached (see Section cycle segmentation). The cycle segmentation was equally applied to all four plots. Left side panels in Figure 11 & Figure 12 show the $\bar{S}\bar{M}$ -CV relation, right side panels show the $\bar{S}\bar{M}$ -skewness relation for these cycles.



Overall, the characteristics of $\bar{S}\bar{M}$ -CV and $\bar{S}\bar{M}$ -skewness relation vary across plots, but resemble between the two years for the individual plots. The Mixed plot exhibits a linear negative relation $\bar{S}\bar{M}$ -CV relation for both annual cycles; CV increases with decreasing $\bar{S}\bar{M}$. Wetting gradually increases $\bar{S}\bar{M}$ and decreases the corresponding CV; this relation is reversed during drying. The wetting phase occurs at similar spatial variability in SM than the drying phase; the variability depends solely on the mean wetness state of the soil. The Beech, Douglas and Silver fir plot show relations in shape of a convex upward curve (see Sect. 4.1) for both years.

These curves are most pronounced for the two conifer plots Douglas and Silver fir: CV peaks at the intermediate range whereas low CV values occur towards the extremes of high and low $\bar{S}\bar{M}$. With initial wetting in autumn, distributions from October and November show spiking CV values up to 0.48 (Douglas fir), 0.59 (Silver fir) and 0.40 (Beech) indicating a strong increase in spatial variability and heterogeneous SM conditions during early wetting of dry soils. CV in early autumn peaks higher in 2024 than 2025 due to the antecedent very dry conditions in September 2023 which results in pronounced deviation of drying and wetting curve (Figure 11 & Figure 12). With further wetting during winter, the spatial variability decreases and the CV approaches a minimum of 0.15 – 0.2 for high $\bar{S}\bar{M}$ (25–35%) in late winter. Data for this period are densely clustered (narrow) as the $\bar{S}\bar{M}$ -CV relation remains stable over months. With spring, $\bar{S}\bar{M}$ decreases gradually and CV increases at a generally lower level compared to the wetting phase. For the first cycle, significant drying starts in May 2024: $\bar{S}\bar{M}$ remains high at all plots (min. 25%), the CV values of corresponding daily SM distribution remain homogeneously low (Figure 11). Only with the months of June, July, and August, $\bar{S}\bar{M}$ decreases gradually and the $\bar{S}\bar{M}$ -CV relation diversifies again. Drying in the second cycle in Figure 12 begins in early spring of 2025: April and May show increasing, scattered CVs together with decreasing $\bar{S}\bar{M}$. Driest SM states (< 10%) occur during the months of July, August, September and October and range between CVs of 0.25 and 0.4. The driest moments of the year in later summer/fall are spatially more variable than the wettest moments during late winter at all plots (Figure 11 & Figure 12).

Comparing wetting and drying curves, for the Beech, Douglas fir and Silver fir plot, the spatial variability of spatial SM at intermediate wetness states ($\bar{S}\bar{M}$ = 10–25%) is determined by the occurrence of their respective spatial distributions during autumn/winter wetting or spring/summer drying. Early wetting phases at the end of summer create the most spatial variability (high CV), whereas similar mean wetness conditions during a spring drying period produce spatial patterns of comparably lower variability. Hence, the soil wets at different spatial variability than it dries. Above and below a certain $\bar{S}\bar{M}$, variability remains low and spatial patterns of SM are (almost) equally homogenous during driest and wettest states. Also, data points of the wetting curve form an irregular, spiking pattern, whereas drying curve points are narrowly clustered and follow a monotonous, gradual trend.

Corresponding to the results above, right panels of Figure 11 & Figure 12 display the $\bar{S}\bar{M}$ -skewness relation for the two wetting-drying cycles. Skewness ranges from -1.6 to 1.4 across the plots according to the wetness state of the soil. Similarity to $\bar{S}\bar{M}$ -CV (see Sect. 4.4; Figure 11 & Figure 12), the $\bar{S}\bar{M}$ -skewness relation follows the shape of a convex upward curve for the Beech, Douglas, and Silver fir plot for both cycles: wettest states ($\bar{S}\bar{M}$ = 25–35%) generally exhibit negative skewness whereas driest states ($\bar{S}\bar{M}$ = 10–25%) are either non-skewed, slightly positively skewed or slightly negatively skewed. For all

four plots, wetness states of $> 20\%$ $\bar{SM}$ produce negatively skewed distributions, whereas states of $< 20\%$ $\bar{SM}$ result in strictly positive skewness. However, for the Douglas fir, Silver fir and Beech driest states in individual cases slightly left skewed. The Mixed plot characterizes a negative linear relation with negative to positive skewness for increasing $\bar{SM}$. These findings confirm that similar $\bar{SM}$ states exhibit different spatial configurations of SM depending on their occurrence in a drying or wetting phase. The seasonal differences underline the changes in spatial SM patterns and their limited temporal persistence throughout annual cycles.

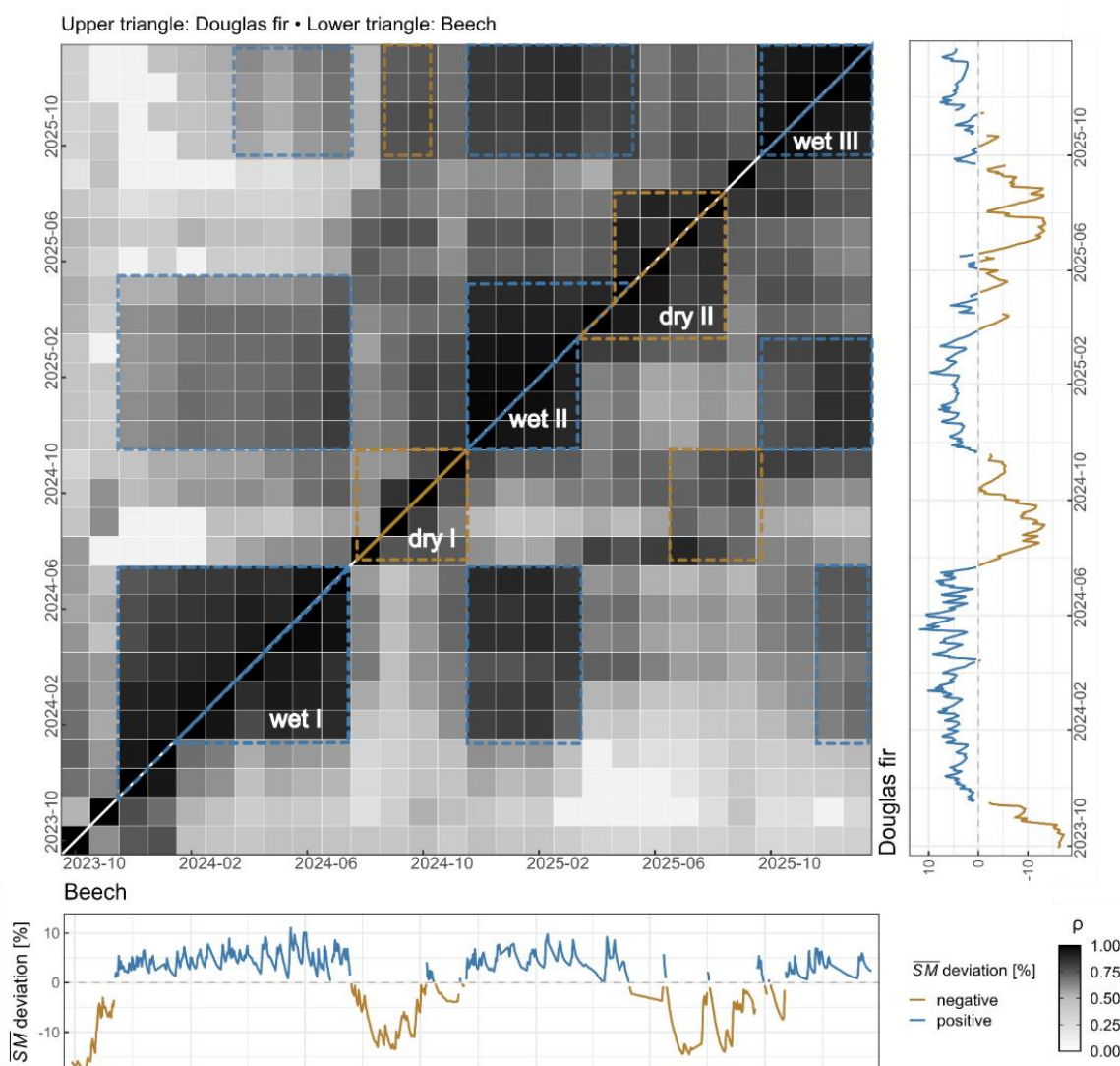


Figure 10: Spearman rank correlation coefficients of spatial soil moisture distribution over time for the Beech (lower triangle matrix) and the Douglas fir plots (upper triangle matrix).



5. Discussion

5.1. Spatial soil moisture distribution as functions of the mean wetness state

The daily mean topsoil moisture shows a convex-upward relation with its coefficient of variation across the Beech, Douglas
605 and Silver fir plots with a variability peak at intermediate wetness state and a decline toward both drier and wetter conditions.
As expected for constrained soil moisture distributions, the skewness shifts from negatively skewed wetness states of >20%
to positively skewed states of <20% $\bar{S}\bar{M}$ (see Figure 3 & Figure 4) (Western et al., 2002). These relations underline the large
spatial and temporal variability of the SM patterns in the forest topsoil controlled by the overall soil wetness state. Measured
variability (CV) for daily $\bar{S}\bar{M}$ distributions match the results reported e.g. by Ivanov et al. (2010) with CVs = 0.05–0.35 for
610 $\bar{S}\bar{M}$ = 8–25 % for fully vegetated catchments. A similar convex shape has been reported for other temperate ecosystems
(Rosenbaum et al., 2012; Korres et al., 2015; Vereecken et al., 2007a; Hills and Reynolds, 1969). However, the majority of
earlier studies described a linear-to-exponential relation of $\bar{S}\bar{M}$ –CV (Choi et al., 2007; Brocca et al., 2010; Famiglietti et al.,
2008), which is present at the Mixed plot. The contrasting findings underline how system conditions like vegetation as well as
the temporal and spatial observation scale, shape this system-specific functional relation.

615 The observed convex shape (see Figure 3) can be explained by a number of modifying factors, including vegetation and
variation in hydraulic conductivity and porosity (Pan and Peters-Lidard, 2008; Famiglietti et al., 1998). Wet soils with a higher
hydraulic conductivity are non-locally controlled and redistribution of water is facilitated resulting in comparatively
homogeneous soil moisture distribution. A few consistently drier-than-average measurements in an overall wet system
approaching saturated conditions during winter months with limited spatial variability due to an upper boundary are the source
620 of the strong negative skewness for the wettest moisture regimes (Ryu and Famiglietti, 2005). In this condition, vegetation
may not have a significant impact on the spatial patterns at any of the plots due to low transpiration demands or heterogeneous
throughfall (Famiglietti et al., 2008). High CV at intermediate wetness states possibly emerges from the heterogeneous
character of combined influences of local and non-local controls. Here, the species-specific rooting strategies, and hence root
water uptake together with interception processes may explain the differences between Mixed and pure plots regarding the
625 $\bar{S}\bar{M}$ –CV and $\bar{S}\bar{M}$ –skewness relations. Low hydraulic conductivity of dry soils produce more homogenous spatial patterns
governed by dominantly local controls (Grayson et al., 1997). The observed positive skewness emerges from isolated
permanently wet patches as lateral redistribution is minimized in our plots.

The hysteretic relation between $\bar{S}\bar{M}$ and spatial variability for the wetting-drying cycle (see Figure 11 & Figure 12) had been
reported by Ivanov et al. (2010), Rosenbaum et al. (2012) and Mascaro and Vivoni (2016). Differences in spatial variability
630 of SM between wetting phases starting in autumn and drying phases starting in spring may reflect the varying impact of
controlling factors throughout these periods. Mälicke et al. (2020) demonstrated that spatial soil moisture heterogeneity differs
between wetting and drying phases. At the beginning of the wetting phase in early autumn, precipitation events together with
species-specific root water uptake strategies may result in the species-specific heterogeneous water in- and output to dry soils.
Local controls such as spatial heterogeneous throughfall and stemflow, or evapotranspiration limit infiltration and



635 redistribution and vertical fluxes prevail. Ma et al. (2014) found throughfall to produce distinct wetting signatures in the soil only at the later growing season for dry soils, whereas in the early parts throughfall did not interrupt the drying phase of the soil. With progressive wetting of the soil, the effects of local controls decline. Similar to this, the increased spatial variability that results from the drying of wet (saturated) soil may be caused by both local and non-local factors, such as heterogeneous transpiration (Teuling and Troch, 2005) and spatial variations in soil properties (Penna et al., 2009). Also, drainage-driven
640 drying – potentially more dominant during the still wet conditions reduces the spatial variability compared to the evapotranspiration-driven drying which is more relevant for drier soils (Graf et al., 2014).

Generally, the magnitude of variability during the drying-up of the soil does not reach the variability during the initial wetting phase. Below a critical $\bar{SM}$, variability decreases with further drying from evapotranspiration and transpiration becomes supply-limited and more soil-controlled (Albertson and Montaldo, 2003; Baroni et al., 2013; Teuling and Troch, 2005). This
645 “homogenization” of SM may emerge from root water uptake as the system approaches mean soil moisture states near the permanent wilting point in the topsoil layer. Conifer plots have roots concentrated in the uppermost soil layer, may preferably take up water from shallow layers and quickly compete for moisture as the soil dries. The Beech plot may experience similar effects, to a smaller degree because its roots accesses also deeper soil layers. For the Mixed plot this “homogenization” of spatial soil moisture with drying may be absent; the combination of shallow-rooted deciduous trees and deeper-rooted conifers
650 may moderate these signatures. Hence, we hypothesize that local controls of heterogeneous throughfall, stemflow and interception are dominant during the beginning of a wetting phase, while evapotranspiration supports the decline in spatial variability during the late drying phase. In this context, it should be noted that the 2.5 years observation period (see Figure 2 top panel) depict relatively moist soil moisture conditions. Additional observations covering prolonged dry spells ($\bar{SM} < 10\%$) may enhance the picture of species-specific differences and similarities in $\bar{SM}$ –CV relation.

655 5.2. Empirical Orthogonal Functions (EOFs) analysis of topsoil moisture patterns

The analysis identifies several statistically significant EOFs across all plots (see Figure 5). This is a large number compared with previous studies (Korres et al., 2010; Wang et al., 2017). The large number of significant modes likely reflects the dataset’s high spatiotemporal resolution. Graf et al. (2014) attribute the higher number of modes in their study to enhanced significance testing from continuous and frequent measurements over three years that favored significance tests, as opposed to datasets
660 derived from manual, less frequent sampling campaigns also at sparser spatial resolution. Hence, the continuous data from our dense sensor network over a 2.5-year provide an appropriate foundation for the EOF analysis. Despite the larger number of significant EOFs, the first three EOFs cumulatively explain more than 80% of the spatial variability for each of the plots. This indicates that the spatial soil moisture patterns are governed by a small number of underlying spatial structures. Across all plots, the first EOF (EOF1) accounts for more than 60% of the total spatial variability. Perry and Niemann (2007) discovered
665 that EOF1 explains 55% of the spatial variability of soil moisture at a grassland site, while Yoo and Kim (2004) describe a first EOF that explains more than >60% of variance. Korres et al. (2010) reported 55% explained variance for EOF1 for a grassland site and Hui et al. (2025) reported 64.6% for EOF1 in a large forested catchment. The Silver fir plot has high EV of



79.9% for EOF1, consistent with Wang et al. (2017) reporting >75% for a grassland site and Graf et al. (2014) with 85.8% for a forested site. These findings demonstrate that the spatial soil moisture variability at the four forest plots is primarily
670 determined by a single dominant spatial pattern that remains constant over time. Although the observation period covers a wide range of different soil moisture states, the first EOFs remain remarkably relevant, particularly at the Silver fir plot. While EV2 for EOF2 is low, it corresponds to other studies such as Perry and Niemann (2007) reporting a second EOF explaining 9% of spatial variance. EVs for EOF2 and EOF3 at the Beech, Mixed and Douglas fir plot are comparably higher, suggesting a more important role of secondary spatial patterns. Higher-order EOFs explain marginal fractions of the overall spatial
675 variability (minor spatial patterns) and are neglected. The absence of polarity changes and but constantly high weighted EC1 values indicate that EOF1 describe the dominant pattern, which is never replaced or inversed. However, the influence of EOF1s is affected (weight of influence) by seasonally changing spatial $\bar{S}\bar{M}$ as shown in Figure 7, which has also been found by Jawson and Niemann (2007). The convex relation with peak EC values at intermediate wetness states qualitatively resembles the relation of $\bar{S}\bar{M}$ –CV. These findings are consistent with Rosenbaum et al. (2012) and Graf et al. (2014) who report similar
680 patterns when relating the standard deviation to $\bar{S}\bar{M}$. Unlike EOF1, EOF2 occurs with positive or negative loadings over time, indicating a reversal of its spatial influence as shown in Figure 5. EC2 values are approximately linearly related to soil water content over a wide range. High EV for the first EOF1s suggest very stable patterns largely controlled by quasi-constant spatial properties such as porosity, slope location or vegetation. Because this study focusses solely on spatiotemporal pattern analysis, potential controlling factors can only be hypothesized. The increasing weight of EC1 with progressive wetness of the system
685 may indicate a strong contribution of non-local controls such as topographic features (e.g. Grayson et al. (1997); Korres et al. (2010)). However, the peak in EC1 for EOF1 at intermediate wetness states as well as low variability of topographic properties for our plots point to a mixture of local and non-local controls mutually shaping soil moisture to varying magnitudes. Within this context, higher EV of EOF1 at the Silver fir plot may be attributed to a stronger “topographic imprint” on EOF1 partly visible in Figure 6, as the Silver plot lies on a gentle slope. The overall random appearance of EOF1 and its partly clustering
690 with vegetation features (e.g. stem distance) suggest that EOF1 is also shaped by a combination of local controls such as throughfall, stemflow, root water uptake, evapotranspiration heterogeneity and soil properties. This is consistent with Mascaro and Vivoni (2016), who found that EOFs in semi-arid shrub lands are primarily correlated with vegetation cover and soil properties rather than slope alone. The increasing EC1 for EOF1 after precipitation events during dry to intermediate soil moisture states underlines this relation to heterogeneous water inputs from throughfall and aligns with Yoo and Kim (2004)
695 who state land-use factors become more relevant after rainfall compared to topographic landscape features. The comparably smaller increases in EC1 for precipitation events during wet winter months go in line with the results in Sect. 4.1 & 4.3.2, and mark the relatively stable and heterogeneous soil moisture conditions for high spatial $\bar{S}\bar{M}$. For the Beech and Douglas fir plot, the EOF1s become increasing dominant over the 2.5 years of observation. This may hint that stand growth enhances canopy structural contrasts, or the dominantly wet observation period amplifies the influence of EOF1 controls. The periodic reversal
700 of influence in EOF2 may indicate a “summer drying pattern”, that flips at points that potentially mark critical site conditions and $\bar{S}\bar{M}$; e.g. the change from a moisture-limited regime in summer to an energy-limited regime (winter). Areas, which are



important during positive influence of EOF2 – e.g. pronounced drying – would in a reversed period of EOF2 contribute least to a wetting. EOF1 primarily describes the time-averaged pattern of relative soil moisture differences in the plot as indicated by comparing spatial EOF1 gradients and results of Sect. 4.3.1 and Figure 6 & Figure 7, also found by Graf et al. (2014),
705 Korres et al. (2010) and Mascaro and Vivoni (2016). While the EOF analysis quantifies the magnitude of temporal variance, the stability analysis identifies the physical predisposition of the system to deviate from its mean state.

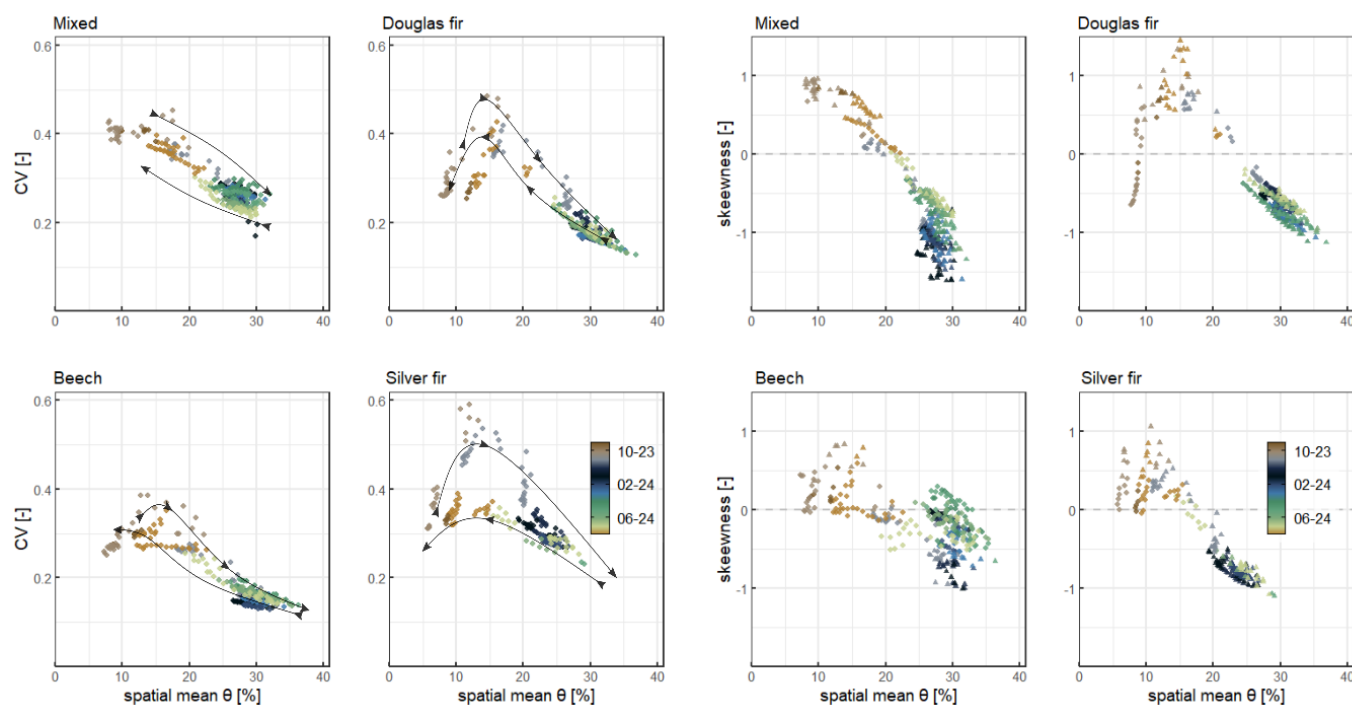
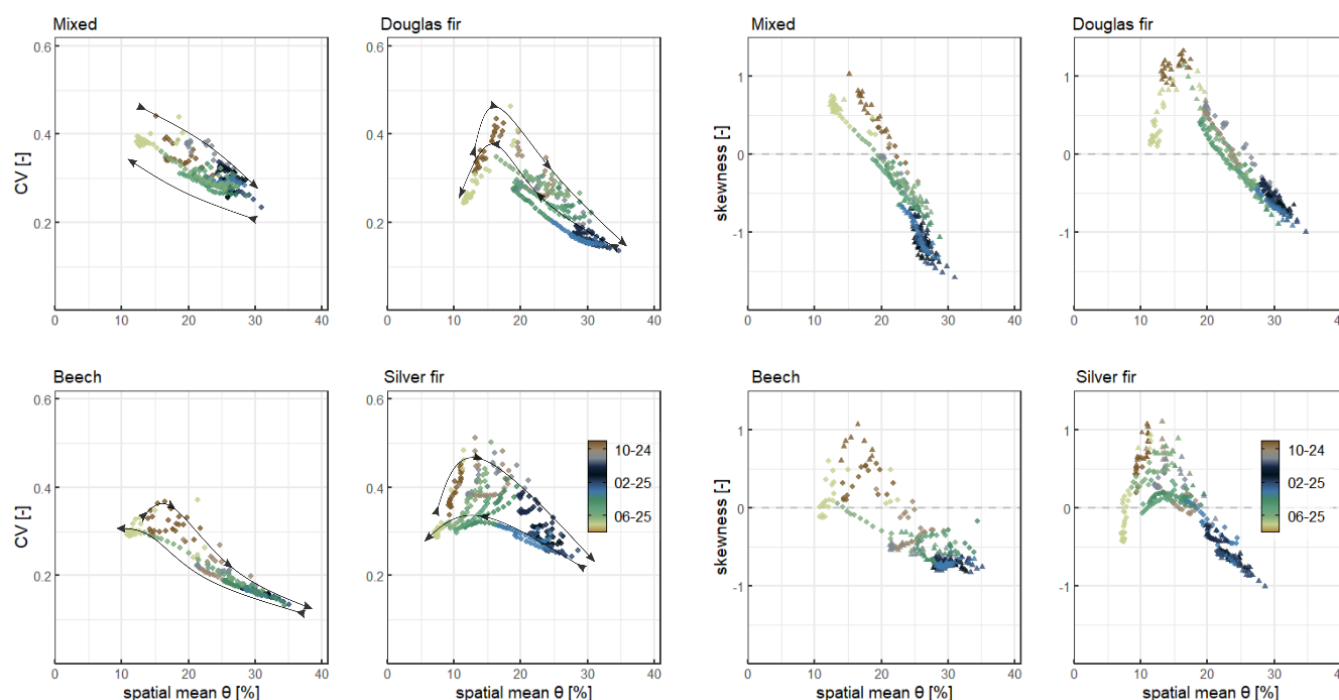


Figure 11: Annual drying-wetting cycle of topsoil moisture across the four plots from October 2023 until August 2024



710 **Figure 12: Annual drying-wetting cycles of topsoil moisture across the four plots from October 2024 until August 2025**

5.3. Temporal stability analysis and Spearman rank correlation of soil moisture

The results reveal pronounced temporal persistent spatial variability with a maximum range of mean relative difference (MRD) from the spatial average of -75% to $+50\%$ (Silver fir plot). This variability exceeds values reported in previous studies such as Brocca et al. (2010) with $MRD = -12\%$ to $+16\%$ or Heathman et al. (2012) with $MRD = -40\%$ to $+25\%$ both for grassland
 715 sites. The spatial pattern of persistently wetter- or drier-than-average locations cannot be identified without further information of soil properties and vegetation structure. Root density and preferential flow paths in a forest topsoil may be possible drivers for the large MRD range. Several persistently drier locations are located near conifer stems. Persistently lower soil moisture in these areas may result from tree branch architecture directing throughfall toward canopy edges (Douglas fir or Silver fir), but it could also be due to increased root water uptake from shallow layers (Jackson et al., 1996; McCormack et al., 2020) or
 720 preferential flow along roots. Further investigation including information on canopy density, understory, stem distance, or topographic parameters such as slope and aspect may shed light on underlying controls. Then, representative measurement locations could be predicted rather than just identified. It should be noted that sensor installation in densely rooted zones is difficult; perfect contact between the sensor and the soil matrix may not always be achieved, resulting in additional measurement artifacts.

725 Multiple factors influence the temporal stability of spatial patterns. Martínez-Fernández and Ceballos (2003) discovered that soil wetness and moisture conditions affect the stability of spatial patterns over time. During stable soil moisture conditions –



particularly during wet states – Spearman correlation coefficients of the spatial patterns are high ($\rho = 0.8\text{--}0.9$), as also reported by Dari et al. (2019) or Penna et al. (2013) ($\rho = 0.7\text{--}0.9$). Under intermediate to dry conditions, growing vegetation may provoke the reconfiguration of spatial patterns resulting in lower Spearman rank correlation (TS) as described by Gómez-Plaza et al. (2000) or Cassel et al. (2000). Schneider et al. (2008) found higher ρ values between consecutive measurement days at a homogeneously vegetated site compared to a site of more heterogeneous vegetation structure. Biswas and Si (2011) found inter-annual cycles in time-stable soil water content with $\rho > 0.97$ for observations from the same seasons and even from different years, which is consistent with our results. The limited temporal persistence of spatial patterns can also be interpreted in terms of temporal scale influence. Previous studies have found strong temporal persistence for short observation periods, such as two months (Heathman et al., 2012). Our relatively long 2.5-year observation period captures a broad spectrum of soil moisture states, making the spatial pattern susceptible to reconfiguration.

As subplots share identical experimental setups, similar topographic, geological, and climatic setting as well as comparable soil properties, species-specific differences and similarities of the presented results are partly relatable to the vegetation influence. However, the mechanistic interpretations remain hypotheses and the comparability of subplots should be interpreted with caution regarding small-scale within-plot differences in micro-climate or soil properties, measurement limitations and spatial and temporal scale dependency. To fully understand the impact of vegetation on soil moisture patterns, it's necessary to analyze species-specific vegetation structure, such as rooting depth, root density, or isotopic water source tracers as well as soil moisture in depth profiles, interception fluxes including throughfall, stemflow and forest floor interception, micro topography and soil properties.

6. Conclusion

Statistical analysis and Empirical Orthogonal Function analysis together with temporal stability analysis were combined to quantify the observed spatiotemporal dynamics of topsoil moisture across four plots of pure Beech, Douglas fir, Silver fir, mixed Beech & Douglas fir. For 2.5 years, a dense monitoring network recorded high forest topsoil moisture variability at the tree scale with high resolution. Except for the Mixed plot, all plots show a characteristic convex upward $\bar{S}\bar{M}$ –CV curve, with variability peaking at intermediate wetness ($\bar{S}\bar{M} \approx 10\text{--}25\%$) and decreasing to the driest and wettest states. The Mixed plot shows a linear, negative $\bar{S}\bar{M}$ –CV relation. The skewness of daily soil moisture follows the same convex trend, with negative skew for wet conditions ($\bar{S}\bar{M} > 20\%$) and positive skew for dry conditions ($\bar{S}\bar{M} < 20\%$). The EOF analysis identified two to three statistically significant modes (potential dominant spatial patterns) per plot, collectively explaining more than 80% of the spatial variance in each plot. The first EOF explains more than 60% of the variance at each plot and represents the dominant, stable, time-invariant spatial pattern. The magnitude of EC1 (influence of EOF1 on spatial soil moisture structure) varies with the spatial average soil moisture, confirming the $\bar{S}\bar{M}$ –CV/skewness relations described above. EC2 and EC3 show polarity reversals that align with wetting-drying transitions, indicating secondary, seasonally-driven structures.



Detailed insights into plot-specific seasonal wetting and drying cycles reveal that spatial variability differs between wet and dry phases, implying distinct dominant controls with non-local controls dominating the wet conditions and local controls controlling soil moisture during dry periods by vertical fluxes. At intermediate wetness states, both local and non-local controls mutually shape patterns and thereby create greatest spatial heterogeneity.

Temporal stability analysis revealed persistently wetter and drier locations. Mean relative differences across plots range from -75% (dry) to +50% (wet), with the widest span at the Silver fir plot and the narrowest at the Beech plot. Within each plot, a subset of representative locations was identified that reliably reproduces the average plot soil moisture throughout the observation period. However, these points cannot be spatially identified a priori from site and forest stand characteristic alone. Spearman rank correlation of spatial soil moisture at the Douglas fir and Beech plot indicate high spatial stability ($\rho \geq 0.8$) for wet phases (autumn winter). Dry phases (spring summer) have temporally-limited spatial stability; particularly during changing site conditions correlations decline and soil moisture structures tend to reconfigure ($\rho \approx 0.45 - 0.6$). Inter-annual memory of spatial structures are evident, mostly for wet phases, with correlations ($\rho \approx 0.85$) between the same calendar month of consecutive years, indicating that site-specific spatial patterns recur across years.

Further research needs to disentangle the relative contributions of local and non-local controlling factors to the derived spatial patterns and to their pattern stability. There is strong potential to combine the results on spatial patterns and temporal stability with observed vegetation metrics from detailed LiDAR analysis of the canopy. For example, time series of remote sensing-derived stand structure parameters but also data on micro topography, ecohydrological fluxes of throughfall or stemflow and soil properties support future analyses. Additional information is required to resolve species-specific water-use strategies and transpiration patterns, such as sap flow, depth profile soil moisture, isotopic tracers, and root sampling or modelling. The study's findings can help to inform sampling strategies and modeling approaches. The dataset is suitable for in-depth analyses of wetting-drying dynamics based on events or seasons, as well as their spatial distribution.

Code availability.

The code is available upon request from LD.

Data availability.

The soil moisture dataset is freely online available at <https://doi.org/10.60493/pryn4-g4049>.



Author contribution.

LD and MW conceptualized this study and designed the experiment. LD performed the investigation, managed data curation
 785 and conducted the analysis. Funding was organized by MW. LD prepared an initial draft and MW contributed to writing,
 visualization and internal revision of the manuscript.

Competing interest.

The authors have no competing interests to declare.

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