



Urban Tree Soil Moisture Dynamics Across Central European Cities: A Multi-Site Approach Showing Links Between Hydrology, Tree and Site Characteristics

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Abstract. Urban trees face intensifying drought stress, and soil water storage and its dynamics are important for the drought resilience of urban trees. Existing evidence is based on process-based growth and ecosystem-service models, on water-balance studies of urban green spaces and irrigation, and on single-city monitoring campaigns, while multi-city in-situ observations under a consistent methodology are missing. We present a continuously growing database of 555 urban tree sites in 41 Central European locations, each instrumented with soil moisture sensors and paired with meteorological data, topographic, sun



exposure and groundwater descriptors, manually digitised land use around the tree and tree characteristics. An event-based workflow detects rain and irrigation events and extracts two response metrics, the normalised soil moisture increase and the drying time. Random Forest models are built for all combinations of target (soil moisture increase, drying time), event type (rain, irrigation) and measurement depth (30, 60, 90 cm). The models explain up to 69 % of the variance of the moisture increase after irrigation and 40 to 55 % for the other combinations in cross-validation. Grouped cross-validation shows that the rain models transfer to unseen sites within 0.03 in R^2 while the irrigation models lose 0.21 to 0.37, therefore encoding a site signature of the few heavily irrigating cities. Rain and irrigation responses differ markedly. The mean air temperature during the event and the pre-event rainfall dominate the rain responses, whereas the pre-event soil moisture and the storage capacity of the substrate control the irrigation responses and how long their effect persists. The unsealed, vegetated area around the tree is the only consistently relevant site characteristic, whereas depth to groundwater shows no effect. The database and workflow are openly available and turn the assessment of planting sites and the verification of irrigation into measurable quantities.

1 Introduction

Urban trees provide multiple ecosystem services that contribute to cities' climate adaptation. They intercept and retain precipitation, reduce surface runoff and ease the load on stormwater infrastructure (Tirpak et al., 2019; Berland et al., 2017; Rahman et al., 2023). The magnitude of this effect depends on physical tree characteristics, site conditions and management (Dowtin et al., 2023; Marrazzo and Raimondi, 2025). It differs considerably between species (Alivio et al., 2025) and with the size of individual trees (Rötzer et al., 2019, 2021). Through transpiration and shading, trees also lower air and surface temperatures and improve human thermal comfort (Gobatti et al., 2025; Cavadini et al., 2026). Globally, they store around 7.4 billion tonnes of carbon and sequester about 217 million tonnes annually across all biomes (Lwasa et al., 2022).

Delivering these services requires vital trees, and vitality in the urban context is limited primarily by water availability. As cities densify, planting sites of urban trees are increasingly sealed, with restricted root space, compacted substrate and interrupted infiltration pathways (Scalenghe and Ajmone Marsan, 2009; Burghardt et al., 2022). Urban soils, modified by anthropogenic material, compaction and sealing, differ fundamentally from agricultural or forest soils in their infiltration and water retention behaviour (Vuono et al., 2026; Burghardt et al., 2022). Field experiments and geoelectrical monitoring of soil water beneath urban tree sites confirm that surface sealing over the root zone alters soil water and gas exchange, which in turn influences tree growth and physiology (Fini et al., 2017; Hoppenbrock et al., 2026). This becomes even more important in the context of intensifying droughts. Western and Central Europe already show increases in drought, projected to worsen even if global warming is limited to 2 °C (Seneviratne et al., 2021). The 2018 and 2019 Central European drought, unprecedented in the last 250 years, is projected to recur about seven times more often in the second half of the century under a high-emission scenario (Hari et al., 2020).

Soil moisture is the link between precipitation input and tree water availability, and its temporal dynamics determine whether a given planting site can sustain a dry spell (Robinson et al., 2008; Volo et al., 2015). Two site-level outcomes are of immediate practical relevance. The first is how much of an incoming water pulse, from rainfall or irrigation, reaches and is retained in



the root zone. The second is how long that moisture surplus persists before the soil returns to its pre-event state. The first determines whether an irrigation event is effective at all, the second how frequently a greenkeeper must return. Both depend on the soil hydraulic properties, surface sealing, surrounding land cover, topographic position and sun exposure (Endreny, 2018; Livesley et al., 2016) and are economically important factors for greenery departments and workers. Land cover over the root zone controls soil aeration and rooting at fine spatial scales (Weltecke and Gaertig, 2012), and infiltration into the root zone differs measurably between individual urban trees (Rahman et al., 2019).

The severe consequences of water stress are well documented. Gilbertson and Bradshaw (1990) observed a mortality of nearly a quarter of newly planted trees in inner-city Liverpool within three years, attributed largely to drought stress in combination with management and design deficits. In New York City, roughly a quarter of a sample of 45 000 young street trees were dead or missing within a few years after planting, with mortality influenced by biological, social and tree-pit-design factors (Lu et al., 2011). Understanding when and why root-zone water becomes limiting is therefore a prerequisite for effective establishment care.

Quantitative, transferable evidence linking site characteristics to soil moisture dynamics at the scale of the individual urban tree nevertheless remains sparse. Existing monitoring efforts are typically confined to single cities, small experimental plots or short observation periods (Volo et al., 2015; Livesley et al., 2016), which limits the range of site conditions sampled and prevents generalisation across urban morphologies and climate zones. Networked in-situ monitoring in individual cities (Wiesner et al., 2016; Schaffitel et al., 2020) and single-site physiological or hydrological studies (Rahman et al., 2017; Sun and Li, 2025; Gillner et al., 2017; Schütt et al., 2022b) consistently report strongly site-specific regimes. Field studies that route stormwater to street trees further show that delivering water to a tree does not by itself relieve drought stress (Szota et al., 2019; Gebert et al., 2019). One early study is particularly relevant here. Across 100 Copenhagen street-tree pits, the rate of soil water loss was highest immediately after rainfall or irrigation and declined exponentially over the following ten days, a pattern attributed to rapid drainage from the coarse pit substrate (Nielsen et al., 2007). This is the same post-event decay that the drying-time metric of the present study formalises.

The closest work to the methods presented here is the four-year soil water potential monitoring of Schütt et al. (2022a) at 17 young street-tree sites in Hamburg. They classified soil water availability of each day against a critical level, modelled the resulting occurrence of critical conditions with a Random Forest over meteorological, tree and site variables and found critical soil water availability for three to five months per year in 2018 and 2019. The ten-day precipitation sum and tree age turned out to be the two most important predictors and the long-term precipitation conditions outranked the daily means. The severity of the drought stress of urban trees and the suitability of ensemble-learning attribution for its understanding became clear, but only for a single city and a closed observation campaign. Random Forests with model-agnostic attribution have become a standard tool for such questions, from root-zone soil moisture estimation in agricultural catchments (Carranza et al., 2021) to interpretable analyses of in-situ soil moisture dynamics (Yin et al., 2026), and Taheri et al. (2025) give a broader overview of machine-learning approaches to soil moisture estimation. In forestry, comparable results exist only as a static database release for the plots of the German National Forest Inventory (Schmidt-Walter et al., 2019).



Large-scale, multi-city in-situ datasets that combine continuous, multi-depth soil moisture with co-located topographic, land-use and tree metadata have, to our knowledge, not been reported, and all of the monitoring efforts above are either restricted to a single city or concluded with the end of their project term. This paper introduces and analyses such a dataset, with one property that none of the efforts above share. It is ongoing. The underlying database is a living monitoring infrastructure rather than a completed campaign. The soil moisture time series are updated daily and are available in an online repository (Maier, 2026). They are accompanied by a variety of meteorological data, tree and site characteristics, including topographic and hydrologic indices. Additionally, the monitored tree population grows continuously as further cities and greening programmes join the network with soil moisture sensors. At the time of writing, it comprises 555 urban tree sites across 41 Central European locations in Germany, Austria and Switzerland, each instrumented with capacitive soil moisture sensors at three depths and paired with gridded meteorological data at the sensor coordinates.

Three research questions (RQ) guide the analysis of the dataset:

RQ1 Which tree and site characteristics determine the magnitude of soil moisture increase during a precipitation or irrigation event?

RQ2 Which tree and site characteristics determine the drying time after a precipitation or irrigation event?

RQ3 What can we learn from soil moisture monitoring for the design and maintenance of urban tree sites?

By addressing these questions across a diverse range of urban morphologies and climate exposures, this study aims to provide evidence-based guidance for municipalities seeking to sustain urban tree populations under increasing drought pressure.

2 Materials and methods

2.1 Study area

The dataset comprises 555 urban tree sites distributed across 41 locations in Germany, Austria and Switzerland (Fig. 1). Trees were selected to represent a wide range of urban site conditions, including varying degrees of surface sealing, soil types, topographic settings, tree ages and species. Most species belong to genera typical of Central European street trees, such as *Tilia* (lime), *Acer* (maple) and *Quercus* (oak). However, more climate-resilient tree species were also selected according to the street tree list of the German Horticultural Directors' Conference (GALK, 2026), since species and cultivars from drier native habitats are expected to cope better with the increasing drought risk of Central European cities (Stratópoulos et al., 2018), while common street-tree species differ markedly in their growth response to and recovery from drought (Moser et al., 2016). Each tree was equipped with a climavi soil moisture monitoring station (Agvolution GmbH, Göttingen, Germany) with three measurement depths.

The tree locations span a geographic range from northern Germany (Hannover, Bremen) across the Central European lowlands and uplands to the Alps (Salzburg, Leogang, Riedingtal, Laax), covering different climate zones, urban morphologies and municipal management practices. Figure 2 illustrates two contrasting sites of the network. A few sites in the Salzburg

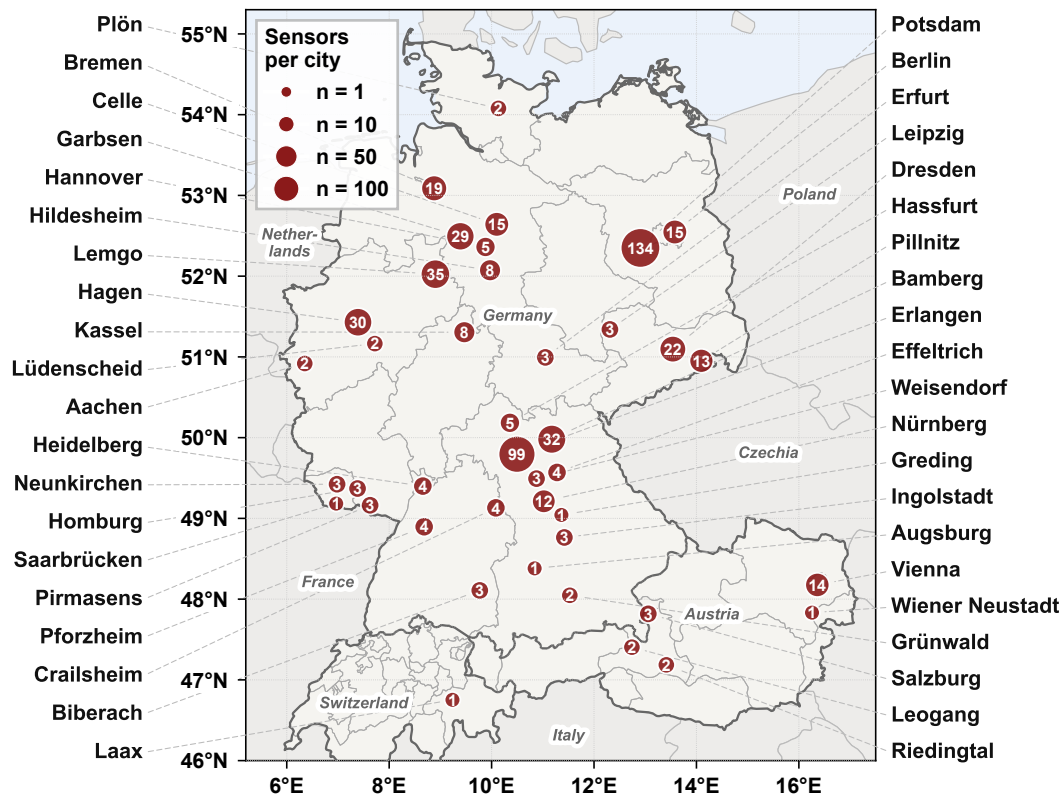


Figure 1. Spatial distribution of the 555 monitored urban tree sites across 41 locations in Germany, Austria and Switzerland. Numbers indicate the number of trees monitored in each location as of August 2026. Locations are only approximate to increase readability.

region lie in wooded, near-natural surroundings and serve as the near-natural end of the sealing gradient. Site selection was coordinated with local green space authorities who provided access to their urban tree cadastre data. The monitoring network was established progressively, with the earliest installations dating from April 2023 and ongoing expansion.

Table 1 gives an overview of the climatic conditions at the tree locations, characterised by the closest available weather stations of the German Weather Service, GeoSphere Austria and MeteoSwiss (DWD, 2026; GeoSphere Austria, 2026; MeteoSwiss, 2026), based on the climate reference period 1991–2020 and comprising mean annual precipitation, summer precipitation from April to September, mean annual temperature and the means of the coldest and the warmest month. Station elevations range from 4 m AMSL in Bremen to 1772 m AMSL at Obertauern. Mean annual precipitation (MAP) ranges from 535 mm to 1494 mm, thereof 45–73 % occurring during the summer half-year, which is the more relevant period for tree drought stress. The mean annual temperature is between 2.9 °C and 12.6 °C, the mean temperature of the coldest month spans



Figure 2. Two contrasting monitoring sites. **(a)** Buschey, street tree surrounded by sealed surface in a dense residential street. **(b)** Kapellensteg, tree in a large unsealed and vegetated area.

from -4.8 to 3.3 °C and that of the warmest month from 11.6 to 23.0 °C. The three Alpine sites Laax, Leogang and Riedingtal
 115 are outliers within the lowland-dominated network, above 900 m AMSL with mean annual temperatures below 7.5 °C, while
 all other stations lie below 605 m AMSL with mean annual temperatures between 8.5 °C and 12.6 °C. These climate variables
 describe the network at site level and were not offered to the models as predictors, as they vary between cities but not between
 the trees within a city and would act as a city identifier rather than as a physical covariate.

Soil properties of the tree sites are mostly unknown, since soil analyses could be conducted only in Potsdam and Erlangen
 120 (Sect. 2.2). Some trees were planted in the original soil, others in specialised planting substrates, which also vary in their
 specific properties. Among the instrumented trees, some (mostly the younger trees) are irrigated during dry periods. Irrigation
 is usually applied manually by a greenkeeper, with 100 to 200 litres of water on a fixed schedule. In a few cases in the city
 of Bremen, automatic irrigation is implemented, linked to the measured soil moisture content to provide water exactly when



Table 1. Climate characteristics in the study area according to the nearest station of the German, Austrian or Swiss weather service, 1991–2020, with mean annual precipitation (MAP), precipitation during the summer months (April–September, SP), mean annual temperature (MAT), temperature of the coldest (TCM) and warmest (TWM) month.

Location	Country	Station	Elevation	MAP	SP	MAT	TCM	TWM
Augsburg	Germany	Augsburg	461.5	749.4	470.6	8.9	-0.1	18.3
Bamberg	Germany	Bamberg	240.0	722.2	385.6	9.2	0.4	18.6
Berlin	Germany	Berlin-Alexanderplatz	35.8	580.1	320.8	10.7	1.5	20.4
Biberach	Germany	Warthausen-Birkenhard	599.0	857.8	548.7	8.5	-0.3	17.9
Bremen	Germany	Bremen	4.0	670.3	354.5	9.8	2.2	18.3
Celle	Germany	Celle (Stadt)	38.0	674.8	340.4	10.0	1.9	19.1
Crailsheim	Germany	Crailsheim-Alexandersreut	423.0	783.0	395.0	9.2	0.4	18.6
Dresden, Pillnitz	Germany	Dresden-Strehlen	119.0	554.0	316.0	10.3	1.1	19.8
Elsdorf	Germany	Elsdorf/Erftkreis	85.0	672.6	357.5	10.9	3.3	19.2
Erfurt	Germany	Erfurt-Weimar	316.0	534.7	339.1	9.0	0.3	18.4
Erlangen, Weisendorf, Effeltrich	Germany	Möhrendorf-Kleinseebach	267.5	659.3	349.9	9.8	0.8	19.6
Hagen	Germany	Hagen-Fley	100.0	856.8	415.9	10.5	3.1	18.8
Garbsen, Hannover	Germany	Hannover	55.2	626.7	325.8	10.0	2.1	18.7
Heidelberg	Germany	Heidelberg	110.0	696.9	371.1	11.6	2.8	20.8
Homburg	Germany	Homburg/Saar	235.0	797.1	372.0	10.0	1.9	19.0
Kassel	Germany	Kassel	231.0	683.8	358.6	9.5	1.1	18.4
Leipzig	Germany	Leipzig-Holzhausen	138.0	611.0	356.1	10.1	1.3	19.7
Lüdenscheid	Germany	Lüdenscheid	386.7	1091.2	486.1	8.9	1.1	17.1
Neunkirchen	Germany	Neunkirchen-Wellesweiler	236.0	858.0	383.0	10.1	2.0	18.9
Nürnberg	Germany	Nürnberg	313.8	600.5	343.3	9.8	0.7	19.5
Pforzheim	Germany	Pforzheim-Ispringen	332.0	831.0	424.0	9.9	1.5	19.1
Pirmasens	Germany	Pirmasens	385.0	912.0	422.0	9.5	1.3	18.2
Plön	Germany	Plön (See)	24.0	709.3	371.4	9.3	1.8	17.7
Potsdam	Germany	Potsdam	80.9	577.6	325.8	9.7	0.7	19.4
Saarbrücken	Germany	Saarbrücken-Sankt Johann	193.0	815.2	376.6	10.9	2.6	19.9
Lemgo	Germany	Salzuflen, Bad	134.6	799.1	402.4	9.9	2.1	18.3
Hassfurt	Germany	Schonungen-Mainberg	305.0	680.0	362.0	9.6	0.6	18.9
Neumünster	Germany	Padenstedt (Pony-Park)	16.5	832.0	411.0	9.4	1.8	17.9
Grünwald	Germany	Oberhaching-Laufzorn	603.5	1101.0	690.0	8.6	-0.5	18.0
Hildesheim	Germany	Hildesheim-Drispensiedt	85.0	651.5	341.8	10.0	2.0	18.6
Aachen	Germany	Aachen-Orsbach	231.0	867.0	432.0	10.3	2.9	18.3
Greding, Ingolstadt	Germany	Ingolstadt	367.0	696.5	408.0	9.3	-0.2	19.1
Laax	Switzerland	Disentis	1197.0	1125.4	659.1	7.1	-1.1	15.8
Salzburg	Austria	Salzburg_Freisaal	419.0	1493.5	972.9	10.4	0.4	20.0
Vienna	Austria	Wien_Innere_Stadt	177.0	669.2	421.3	12.6	2.1	23.0
Wiener Neustadt	Austria	Wr.Neustadt_Flugh.	275.0	607.8	417.3	10.5	0.0	20.9
Leogang	Austria	Saalbach	975.0	1227.1	779.8	6.1	-3.7	15.8
Riedingtal	Austria	Obertauern	1772.0	1071.4	781.5	2.9	-4.8	11.6



needed. Slow-release watering bags, which spread the input over several hours and would fall below the per-step detection threshold of Sect. 2.7.2, were not used at any of the monitored sites. As irrigation volumes and timings are only partially documented, irrigation events are detected directly from the soil moisture signal (Sect. 2.7.2) rather than taken from municipal records.

2.2 Volumetric water content and plant available water

A measured volumetric water content (VWC) is not by itself interpretable in terms of plant water supply, since it relates the volume of water to the unit volume of soil and therefore depends on bulk density and texture rather than on the water demand of a plant (Gardner et al., 1998; Topp et al., 1980; Cassel and Nielsen, 1986). Soils are commonly grouped by their content of clay, silt and sand into twelve or more classification groups (Whitney, 1911; Soil Science Division Staff, 2017), which differ in capillary size and gas permeability (Armstrong et al., 2009; Vogel et al., 2019). Each texture class has a characteristic field capacity (FC), the water remaining after saturation and free drainage (Datta et al., 2017), and a permanent wilting point (PWP), below which root absorbency cannot overcome the capillary forces of the soil matrix (Kramer and Boyer, 1995). The difference between them is the available water capacity (AWC) (Cassel and Nielsen, 1986; Vogel et al., 2019), which forms the basis of plant available water (PAW), also called normalised field capacity, where 100 % corresponds to soil at FC and 0 % to soil at PWP (Cassel and Klute, 1986; Datta et al., 2017; Topp et al., 1980). It is crucial for this study that the width of that range is itself a property of the soil. It spans roughly 3 % to 6 % VWC in sand but 26 % to 40 % VWC in clay (Kramer and Boyer, 1995), so the same absolute VWC change represents a very different fraction of the storage available to a plant.

In the urban context, this ambiguity is more consequential than in agriculture. Urban trees are frequently planted in whatever disturbed material is available at the site, which may contain construction rubble, demolition fragments or imported planting substrates of unknown composition (Burghardt et al., 2022; Scalenghe and Ajmone Marsan, 2009). Since soil analyses were available only for the tree sites in Potsdam and Erlangen, FC, PWP and therefore AWC are unknown for the large majority of the monitored trees. They differ not only between trees but also between the three measurement depths of a single sensor, since the substrate is frequently layered. An absolute VWC increase of, for example, 3 % may represent a substantial recharge at a sandy site and a marginal one at a clay-rich site.

A laboratory-derived AWC per site is therefore not obtainable at network scale and this constraint shapes the entire analysis pipeline. In place of it, the storage capacity of each sensor and depth is approximated empirically from the observed range of its own time series (Sect. 2.6), all soil moisture responses are expressed relative to that range rather than as absolute VWC values, and the resulting normalised increase is additionally log-transformed before modelling (Sect. 2.8). The quantity predicted by the Random Forest models is thus not an absolute soil moisture change in percent VWC, but a transformed, site-normalised response amplitude, which has to be kept in mind when interpreting the model outputs in Sect. 3.



Table 2. Structure of the tree database. Type and temporal resolution are given per category.

Category	Type and resolution	Source
<i>Static attributes, observed</i>		
Tree metadata (species, planting year, height, stem and crown diameter, vitality)	static, one value per survey campaign	municipal tree cadastres, own field surveys
Soil chemistry and particle-size fractions	static, single lab analysis	own sampling (2 cities only)
Land-use composition (attached green, detached green, buildings, sealed surface)	static, single digitisation	own manual digitisation on aerial orthophotos in QGIS
<i>Static attributes, derived from public geodata</i>		
Topographic Wetness/ Position Index (TWI, TPI) and related slope, flow accumulation & elevation	static, single computation	derived from public DEM
Sky view factor	static, single computation	derived from public DSM
Depth to groundwater	static, reference date varies by federal state	derived from public groundwater data and DEM
<i>Time series</i>		
Soil moisture, soil temperature (three depths: 30, 60, 90 cm)	continuous, 15–240 min raw, resampled to 30 min	own measurement (climavi sensor)
Meteorological parameters (air temperature, humidity, precipitation, wind, evapotranspiration)	continuous, hourly	Meteoblue gridded weather service at the sensor coordinates
On-device auxiliary measurements and telemetry (housing temperatures, battery, signal quality)	continuous, 15–60 min	own measurement (IoT device)
Documented irrigation volumes	event-based, incomplete, irregular	municipal partners

2.3 Data

155 2.3.1 The tree database

For each monitored tree site, the tree database integrates three categories of information (Table 2). Static tree and site data were recorded in the field or taken from municipal tree cadastres, further site characteristics were derived from external spatial data and continuous time series comprise the in-situ sensor measurements and the meteorological data. The irrigation records documented by the municipal partners complement these as event-based information. All figures reported in this paper therefore describe a snapshot of a continuously growing collection, and every analysis in Sect. 3 can be re-run on the current state of the database at any time.



All static tree attributes are maintained as georeferenced point layers in QGIS, keyed by the Device Extended Unique Identifier (devEUI) of the sensor at each tree, which links them to the sensor telemetry on the cloud platform. A daily pipeline retrieves only data newer than the most recent local entry and archives the time series as one CSV file per sensor in a unified timestamp–value format. When the event dataset is assembled, events are joined to the tree and site metadata via the devEUI, retaining the most recently assessed record where several exist. The database schema and the retrieval pipeline are documented in the data repository (Maier, 2026). The following subsections describe how the individual data sources are collected and pre-processed.

2.3.2 Soil moisture time series

Soil moisture was measured with the climavi sensor platform of Agvolution GmbH, which is a spin-off of the Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU) for long-term autonomous monitoring of urban and agricultural soils. Each station carries a capacitive multi-depth probe that records the volumetric water content (VWC, in %) and the soil temperature at 30 cm, 60 cm and 90 cm below the surface. The measurement exploits the dielectric permittivity of the soil–water mixture, each sensing layer returning a raw capacitance (in pF) that is calibrated to VWC. Probe design, equivalent-circuit model, calibration to VWC and plant-available water, and the laboratory and field validation against reference instruments are described in the companion sensor paper (Maier et al., 2026). Readings are transmitted every 15 to 240 minutes over a low-power wide-area network (NB-IoT, LTE-M, mioty or LoRaWAN, depending on site infrastructure) to a cloud platform and retrieved through its REST API as described above. Transmission metadata (RSSI, SINR, RSRP, RSRQ) and battery state are logged as telemetry. Part of the stations run solar-powered and maintenance-free over several growing seasons and up to 28 time-series parameters are recorded per station with the full inventory documented in the data repository (Maier, 2026).

Figure 3 shows the daily count of installed sensors and the subset of actively transmitting VWC data over the study period. At its peak, the network comprised 534 installed sensors, with a maximum of 467 transmitting on any given day. Some sensors were removed again during the study period. The gap between the two series reflects brief connectivity outages, seasonal access restrictions and the lag between physical installation and first successful transmission. Sensors confirmed as offline for an extended period were removed or replaced.

2.3.3 Tree and soil characteristics

For each monitored tree site, the following metadata were collected from municipal tree cadastres, field surveys and supplementary records. Species were identified at genus, species and variety level. Planting year and estimated germination date allow age computation. The age estimate differs in quality between groups of trees. For the oldest individuals, planting plans of the botanical gardens and historical records allow an estimate with an uncertainty of about five years. For young trees within their first five years at the site, an age of ten years at planting was assumed as an approximation that does not hold equally for every species. In Potsdam, ages were taken from expert assessments by a certified tree surveyor. Tree height, stem diameter and crown diameter were recorded in m, and the vitality class was assessed. Where laboratory analysis was performed, soil chem-

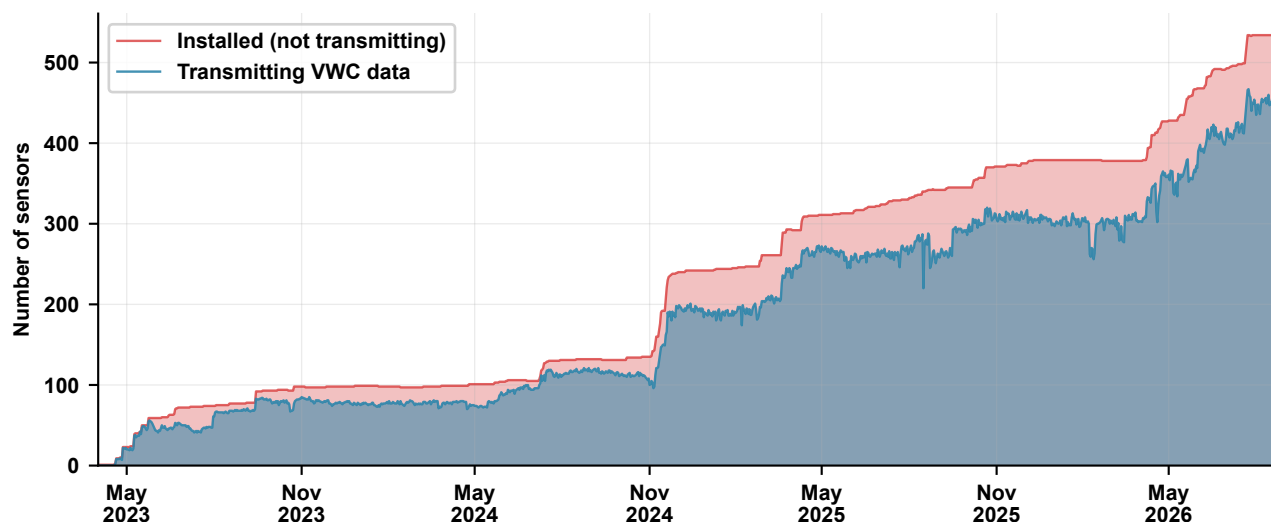


Figure 3. Daily sensor count over the study period (May 2023 – August 2026). The red area shows the number of stations with a recorded installation date that had not yet been decommissioned. The blue area shows the subset that transmitted at least two valid VWC depth channels on that day. The red region visible above the blue represents installed but non-transmitting sensors.

istry included pH, salt content, electrical conductivity, soluble nitrogen (total, ammonium, nitrate), magnesium, phosphorus
 195 and potassium. Soil physics included the seven particle-size fractions from sieving and sedimentation analysis.

In total, 60 attribute fields were maintained per tree site at the initial data collection, and the current schema comprises 78
 fields, 75 of them content fields and three administrative, since 18 fields were added later through extended laboratory analyses
 and GIS derivations. Unlike the sensor and meteorological time series, these attributes are not monitored automatically. They
 are recorded by staff in the field, typically during sensor installation or maintenance visits, and updated when a municipality
 200 provides a city-wide refresh of its tree cadastre. Not all fields are populated for every tree site. Completeness varies by city,
 and the resulting data availability is reported in Sect. 3.1. Species identification and the soil chemistry and physics fields were
 not used as model predictors, since translating a species name into a water demand would require botanical assessment beyond
 the scope of this study and the soil laboratory data cover only two of the 41 sensor locations. The vitality class was offered to
 the rain strata and rejected by the feature selection in all six models. The predictors actually entering the models are listed in
 205 Sect. 2.9.

2.3.4 Meteorological data

Meteorological data for each sensor location are provided by the Meteoblue weather service (meteoblue AG, 2026). Meteoblue
 operates proprietary numerical weather models of the NMM/NEMS family that simulate the atmosphere on nested grids of
 3–30 km resolution, incorporating detailed topography and land cover, and archives every simulation so that a gap-free hourly
 210 record is available for any point on Earth from 1984 onwards. Temperature variables are additionally downscaled to the altitude



of the queried location using a high-resolution terrain model (meteoblue AG, 2026). The climavi platform ingests these data server-side. For each registered sensor, hourly air temperature, relative humidity, dewpoint, air pressure, precipitation, wind speed and direction, evapotranspiration, and modelled soil temperature and moisture are stored as time series at the sensor coordinates, alongside the in-situ soil measurements.

215 A gridded model source was deliberately preferred over ground-based weather stations. Several partner cities do operate stations, but these are often kilometres away from the monitored trees, their records frequently contain gaps, and a rain gauge is representative only of its immediate surroundings. Mixing station records where available with model data elsewhere would moreover introduce two different measurement methodologies into one event dataset and make the detected events incomparable across cities. The Meteoblue integration instead pairs every one of the 555 sensor locations with a consistent, gap-free
 220 record produced by a single methodology at hourly resolution. Of the listed parameters, precipitation and air temperature enter the event detection and feature extraction described in Sect. 2.7.

Additionally, irrigation events documented by municipal partners are recorded in the dataset as point annotations with the irrigated volume in litres (Sect. 2.7.2).

2.4 External spatial input data

225 2.4.1 Aerial and satellite imagery

The land-use composition around each tree was digitised manually in QGIS on publicly accessible satellite and aerial imagery basemaps from Bing and Esri World Imagery (Microsoft Corporation, 2026; Esri, 2025), complemented for the Erlangen sites by the digital true orthophoto of the City of Erlangen (Stadt Erlangen, 2025). No single provider offers the clearest imagery everywhere, since acquisition dates differ between providers and regions, and leaf-on summer scenes hide the ground
 230 surface beneath large crowns. For each city, the provider with the most recent and most useful imagery was therefore selected, preferring leaf-off (autumn or winter) acquisitions in which sealed surfaces below tree canopies are visible. The chosen provider was not recorded per tree. The digitised polygons themselves are part of the published dataset (Maier, 2026).

2.4.2 Digital elevation model and digital surface model

The digital elevation model (DEM) describes the bare-earth ground elevations, while the digital surface model (DSM) also
 235 includes vegetation and buildings. Both are publicly available for all study regions as products of airborne LiDAR surveys. No commercial elevation products were used. Access routes and tile schemes, however, differ considerably between Austria and the individual German federal states, ranging from web coverage services with freely selectable extent to fixed tile archives of varying size (LGB, 2026a; HVBG, 2026; LGL, 2026a, b; Bezirksregierung Köln, 2026; BVV, 2026; LVermGeo, 2026; TLBG, 2026; BEV, 2026; LGLN, 2026; LVermGeo SH, 2026; GeoSN, 2026; Landesamt Geoinformation Bremen, 2026; LVGL,
 240 2026). Most products have a native resolution of 1 m. Only the DSM of Bavaria is distributed at 0.2 m and was resampled to 1 m for consistency. Our repository provides a largely automated workflow that downloads, merges, clips, reprojects and resamples both rasters to a circular extent of 200 m radius around each tree at a uniform 1 m resolution (Maier, 2026).



2.4.3 Depth to groundwater

Depth to groundwater (DTGW) indicates whether groundwater is within reach of tree roots. No depth threshold was imposed, DTGW enters the models as a continuous descriptor, and whether a given root system actually reaches the water table is not resolved by this variable. Its availability is even more heterogeneous than that of the elevation models. For Baden-Württemberg, Hessen, Lower Saxony, Saarland and Schleswig-Holstein, no usable public groundwater data could be found at all, and the remaining sources differ in format, spatial resolution and reference date. Two source types occur. Austria (BOKU, 2026) and Thuringia (TLUBN, 2026) publish polygons whose attribute directly encodes the depth to the groundwater table, which was assigned to each tree by point-in-polygon join. Bavaria (LfU Bayern, 2026), Berlin and Brandenburg (LGB, 2026b), Bremen (SUKW, 2026), North Rhine-Westphalia (IT.NRW, 2026), Rhineland-Palatinate (LGB-RLP, 2026) and Saxony (LfULG, 2026) publish groundwater isolines, from which DTGW was derived as the difference between the site elevation and the elevation of the nearest groundwater contour line. Where contour lines are sparse, this assignment can be off by the order of the contour interval, and it produced one negative value at a Bamberg floodplain site that was identified after the analysis. Its 105 events are included in the subset counts of Table 4 and do not affect the result of Sect. 3.8. The underlying maps range from single-season surveys (e.g. Berlin and Brandenburg: spring 2015, Bremen: autumn 2011, Saxony: spring 2016) to long-term averages (North Rhine-Westphalia: 2006–2015, Austria: 1961–1997), and for Bavaria, Thuringia and Rhineland-Palatinate the reference period is mixed or undocumented. The attribute carrying the information likewise differs between sources, from groundwater surface elevations in various vertical datums to directly encoded depth classes. The exact layer, attribute and join method per region are documented in the data repository (Maier, 2026).

As a consequence of this heterogeneity, DTGW is available for tree sites in only 15 of the 41 locations, and the reference dates of the underlying maps differ by up to two decades. DTGW is therefore treated separately in the analysis. In addition to the main models, which median-impute the missing values, the coverage subset and the Potsdam and Berlin subset are evaluated (Sect. 2.9).

2.5 Derivation of site characteristics

2.5.1 Terrain metrics: slope, flow accumulation, TWI and TPI

All point-scale terrain metrics were extracted from the per-tree DEM patches using a bespoke Python pipeline that operates on the 200 m local window centred on each sensor. The computation uses `numpy` and the Python standard library only, without dependence on a desktop GIS or on external hydrological libraries. This keeps the terrain derivation reproducible from the repository without a GIS installation, at the cost of implementing the algorithms directly.

Slope, the topographic wetness index (TWI) and the topographic position index (TPI) were derived from the DEM following Zevenbergen and Thorne (1987) and Beven and Kirkby (1979). Their definitions and the parameter choices are given in Appendix A.



2.5.2 Land use classification

Land use around each tree was characterised in three concentric annuli with outer radii of 2.5 m, 5 m and 7.5 m from the trunk centre. The latter is only exceeded by a few of the largest monitored trees, so the outer buffer encloses the crown projection of most trees. The smallest radius of 2.5 m resolves the immediate surroundings of small and recently planted trees, and 5 m provides the intermediate scale. Within each annulus, the surface was classified into four categories. The distinction is motivated by the observation that diverse soil-cover types alternate on a small scale at urban sites and compete with the soil's function as rooting space (Weltecke and Gaertig, 2012):

1. **Sealed surface:** Impervious surfaces such as asphalt, concrete, paving stones or compacted gravel.
2. **Green space (attached):** Permeable vegetated areas directly adjacent to and hydrologically connected with the tree's root zone.
3. **Green space (detached):** Permeable vegetated areas within the radius but hydrologically disconnected from the tree pit (e.g., separated by kerbs, raised beds or infrastructure).
4. **Building footprint:** Areas covered by building structures.

The land use categories were digitised manually in QGIS. Automated approaches, including the zero-shot segmentation and classification of previous work (Shrirama, 2026), introduced substantial errors, because urban morphology, land-cover composition and imaging conditions differ between sites (Benjdira et al., 2019; Tuia et al., 2016; Tasar et al., 2020). Since the land-use areas enter the models directly as site characteristics, an unverified classification error would propagate into the attribution, while the labelling task itself is bounded at four classes within a 7.5 m radius of each tree. Figure 4 illustrates the classification scheme.

In addition to the individual annuli, we quantified the land use categories for two further radii: the actual crown radius of each tree and the maximum buffer radius of 7.5 m.

2.5.3 Sky view factor

In urban environments, shading by surrounding trees and buildings varies substantially and is expected to affect the drying time after a rainfall or irrigation event. We therefore use the sky view factor (SVF) as a measure of sun exposure of the tree sites.

The SVF describes to what extent the sky is visible above an observation point, i. e. in our case not obstructed by trees, buildings or other objects. It can be computed from the vertical elevation angle of the horizon in the specified maximum radius and search directions (Zakšek et al., 2011). In this study, SVF was calculated from the per-tree 1 m DSM patch using the function `sky_view_factor` from the Python package `rvt` (Relief Visualization Toolbox) (Kokalj et al., 2025, 2019; Kokalj and Somrak, 2019), with a search radius of 100 m, 16 equidistant search directions. The 100 m search radius lies well inside the 200 m DSM patch (Sect. 2.4) and is therefore free of edge effects. The SVF is assessed at the top of each tree, since the tree would otherwise shade itself in the DSM.

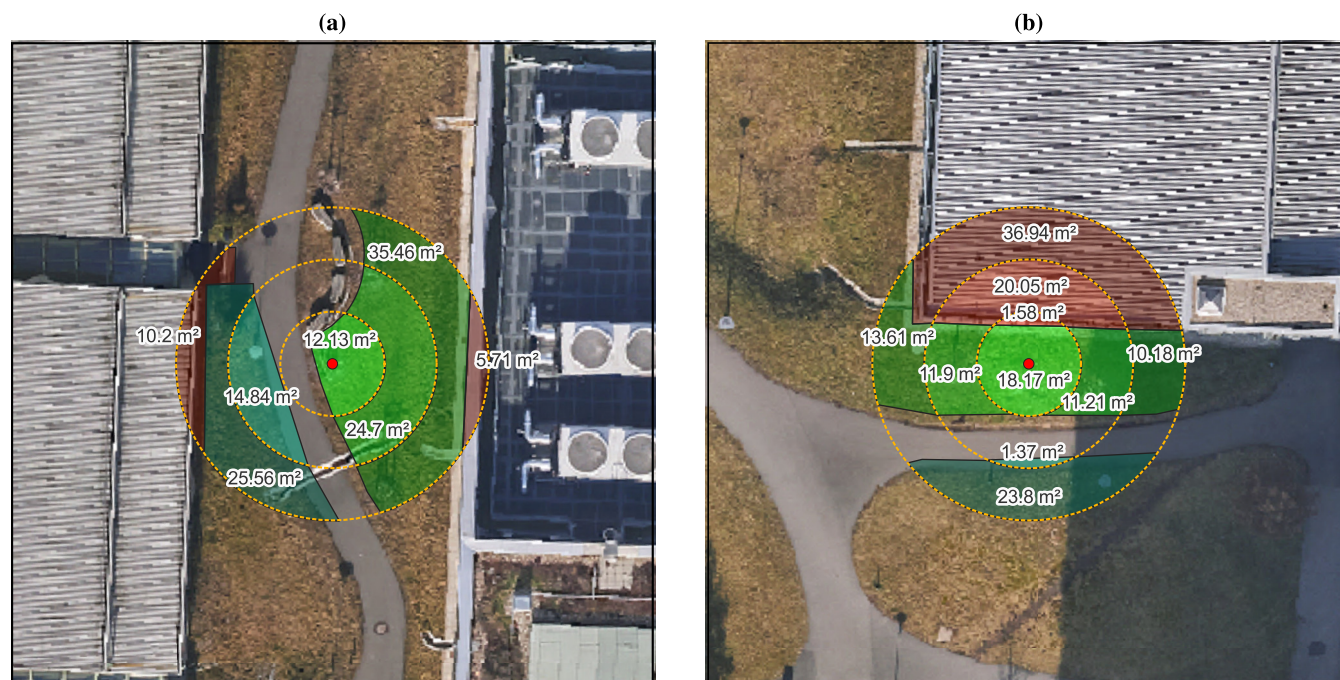


Figure 4. Land-use classification scheme around two instrumented trees in Erlangen, shown on the digital true orthophoto of the City of Erlangen, aerial survey of 2025 (Stadt Erlangen, 2025) with 20 cm ground sampling distance, © Stadt Erlangen, CC BY 4.0. The tree position is marked by the red dot, the dashed circles delimit three concentric annuli with outer radii of 2.5 m, 5 m and 7.5 m. Within each annulus, the surface is digitised manually into the four classes attached green space (green, hydrologically connected to the tree pit), detached green space (blue, permeable but separated, for example by a road), building footprint (red), and sealed surface (unmarked). Polygon areas are given in m². **(a)** Tree in a courtyard between buildings. **(b)** Tree adjacent to a building with a large attached lawn.

305 The tree coordinates were digitised on the satellite images of Sect. 2.4 and do not always coincide with the tree in the DSM,
 so that the observer point can end up beside the tree and the SVF is underestimated. Where the field-measured tree height
 exceeded the LiDAR surface by more than 0.01 m, the DSM value at the observer point was therefore replaced by the DEM
 value plus the measured height. This matters because the instrumented trees are predominantly small or recently planted, and
 would otherwise appear as open sky in a surface model acquired before or shortly after planting. Both the uncorrected and the
 310 corrected value were retained. All SVF values reported and used as model predictors are the corrected variant.

2.6 Time series preprocessing

Soil moisture time series were retrieved per sensor for the three measurement depths 30 cm, 60 cm and 90 cm, together with
 the precipitation and air temperature from the Meteoblue records.

315 WVC measurements were resampled to a uniform 30 min resolution by averaging within each interval, because the stations
 report at intervals between 15 and 240 minutes depending on site and network generation. A common temporal grid is required



to align the three depth channels of one station, to define the per-step increment of the irrigation detector consistently across sensors, and to match the hourly precipitation series. Gaps of up to two steps (1 h) were forward-filled. Precipitation was aggregated to hourly sums with missing intervals set to zero, and air temperature to hourly means with forward-filling of a single step. This is handled differently on purpose. A missing precipitation record is most plausibly interpreted as an absence of rain, whereas soil moisture and temperature are continuous state variables for which short-gap interpolation is physically defensible.

VWC readings outside the plausibility range of 2 %–50 % were discarded, targeting air-gap artefacts at the lower bound, where a probe is not in proper contact with the substrate, and saturation or short-circuit artefacts at the upper bound. The remaining signal was smoothed with a centred rolling median over eight steps (4 h) before the dynamic range $D_{s,d}$ of sensor s at depth d was determined as the difference between the 95th and the 5th percentile of the smoothed series over its full length,

$$D_{s,d} = Q_{0.95}(\text{VWC}_{s,d}^{\text{smooth}}) - Q_{0.05}(\text{VWC}_{s,d}^{\text{smooth}}). \quad (1)$$

Using the full record rather than a single event window fixes the dynamic range of each channel to its long-term behaviour. It serves two purposes in the following, as the normalisation constant of the soil moisture response (Sect. 2.8) and as a predictor in its own right (Sect. 2.9). Sensors for which no valid dynamic range could be computed in any channel were excluded entirely, which was the case for two stations.

No explicit sensor drift correction was applied. The companion paper (Maier et al., 2026) reports a measurement resolution below 1 % VWC, a repeatability of 8 % interquartile range with a 3 % systematic deviation from gravimetric reference in sandy soil, and agreement within about 5 % in field tests against four reference sensor types deployed at urban street trees. Gaps exceeding the forward-fill limits remain undefined and are excluded at the feature level (Sect. 2.9).

2.7 Event detection

Instead of modelling the continuous soil moisture signal, this study analyses discrete wetting events using the two target variables soil moisture increase and drying time. This event-based framing has three advantages over continuous time-series modelling. It makes observations from sites with different installation dates and record lengths directly comparable. It substantially reduces the temporal autocorrelation that would otherwise dominate a half-hourly series. And it isolates physically meaningful response units, namely the arrival and the subsequent depletion of a water pulse in the root zone. The moisture-increase metric thereby acts as an in-situ proxy for infiltration into the root zone, which has been shown to differ measurably between individual urban trees (Rahman et al., 2019).

Two event types are distinguished, rain events and irrigation events. They are detected by different mechanisms and are treated as separate strata throughout the analysis.

2.7.1 Rain events

Rain events were detected from the hourly precipitation time series. An hour was considered wet if it recorded more than 0.1 mm. Consecutive wet hours were defined as events, separated by gaps of at least six consecutive dry hours, consistent with



the storm-separation method of Wischmeier and Smith (1978). In other words, showers separated by less than six dry hours are treated as one event, so a day of intermittent rain enters the analysis as a single input. Wischmeier and Smith included
 350 only events of at least 12.7 mm, since only such events were relevant for erosion. For an urban tree pit, in which canopy interception and the wetting of the surface consume the first millimetres before water reaches the rooting zone, the threshold must be low enough to include events that reach the rooting zone and high enough to exclude those that do not. It was therefore determined empirically. All detected events were grouped into 1 mm classes of event total, and for each class two quantities were determined among the events with a valid record at 30 cm depth, the share of events producing a rise of at least 0.5 %
 355 VWC within 12 h after the event end, and the median normalised response of these responding events (Fig. 5). Below 5 mm, both remain at a baseline, with 12 to 18 % of the events responding and a median response of about 7 to 8 % of the dynamic range. From 5 mm upwards both increase. The share rises to 24 and 28 % in the classes between 5 and 7 mm, to 40 to 44 % between 7 and 10 mm and to between 35 and 70 % for larger events, and the median response of the responding events rises to about 10 % and, for larger events, mostly to 10 to 20 %. Larger events therefore not only reach the rooting zone more often
 360 but also deliver more water to it. The 5 mm threshold removes 68 % of the detected events. Lowering the threshold to 3 mm would enlarge the two model strata by about 44 % and 42 %, but only with events from classes that remain at the baseline, while raising it to 8 mm would shrink them by about 35 % for a modest gain in per-event signal.

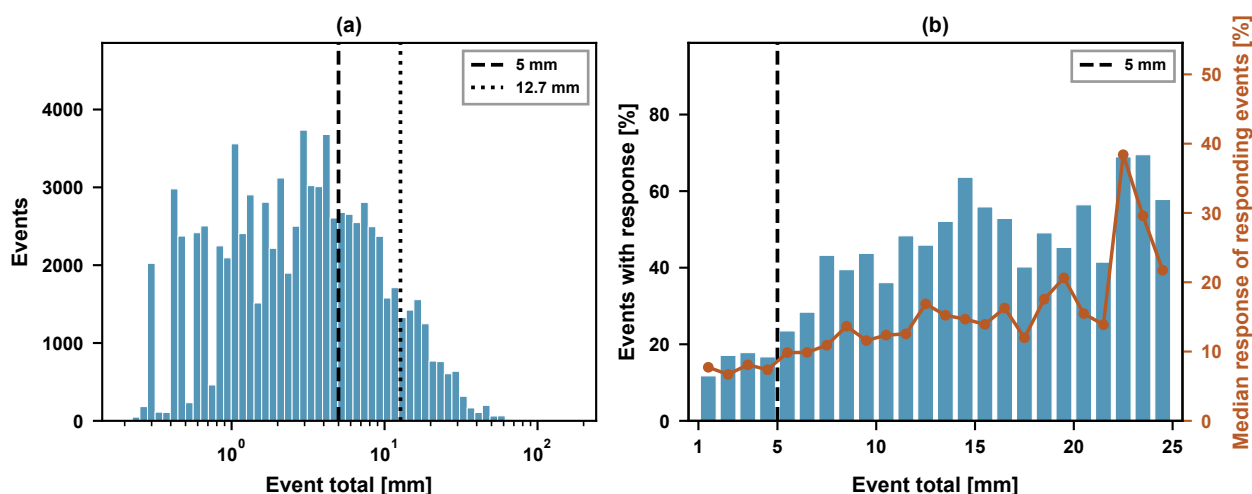


Figure 5. Empirical basis of the 5 mm rain-event threshold. **(a)** Frequency distribution of the 87108 detected events by event total on a logarithmic axis. The dashed line marks the 5 mm inclusion threshold of this study, the dotted line the erosivity threshold of 12.7 mm after Wischmeier and Smith (1978). **(b)** Share of events in each 1 mm class of event total that produce a rise of at least 0.5 % VWC at 30 cm depth within 12 h after the event end (bars, left axis), and the median normalised response of these responding events in percent of the dynamic range (line, right axis), both computed over the events with a valid 30 cm record.



To characterise the temporal structure of each event, two established descriptors were computed. The Huff quartile (Huff, 1967) classifies an event by the dimensionless position of its peak intensity,

$$\text{stac} = \frac{t_{\text{peak}} - t_{\text{start}}}{t_{\text{end}} - t_{\text{start}}}, \quad \text{huff}_Q = \min(4, \lfloor 4\text{stac} \rfloor + 1), \quad (2)$$

assigning events to quartiles Q1 to Q4 for front-, early-, late- and back-loaded storms respectively.

The Binary Shape Code (BSC) (Terranova and Iaquina, 2011) encodes the temporal distribution of rainfall within the event. The standardised rainfall profile is integrated over each of the four event quartiles by the trapezoidal rule and compared to the analytically derived uniform reference values of 0.03125, 0.09375, 0.15625 and 0.21875. Each quartile contributes one bit, set to one if the observed integral exceeds the uniform reference and zero otherwise, yielding a four-character code such as 1011.

Rain events whose onset fell within ± 36 h of a detected irrigation onset at the same tree were suppressed, so that a moisture response driven by irrigation could not be attributed to precipitation. The window is symmetric, spanning 36 h before and 36 h after the irrigation event.

As the two target variables respond to different aspects of an event, the rain dataset was stratified separately for each, selecting the two ends of the temporal-structure spectrum. For the soil moisture increase, the front-loaded stratum BSC_XX11_Q12 was used. Here, the cumulative rain is above the uniform mass curve in the third and fourth quartile (BSC bits three and four set) and the peak intensity occurs in the first half of the event (Huff Q1 or Q2). Such events deliver most of their water early and approximate a single strong pulse, so that the observed moisture increase reflects the arrival of that pulse rather than a lagged response to continued input. For the drying time, the back-loaded stratum BSC_00XX_Q34 was used. Here, the cumulative rain is below the uniform mass curve in the first half (bits one and two unset) and the peak occurs in the second half (Huff Q3 or Q4) as can be seen for the rain event in Fig. 6. This ensures that drying does not begin before the event has effectively ended. In a front-loaded event, individual depths can begin to dry while rain is still falling, either because the peak has passed at the shallow channels or because the weak late-event input no longer reaches the deeper ones. Beyond this reasoning, the two patterns were an a-priori design choice and not the result of a formal optimisation over the sixteen possible codes.

2.7.2 Irrigation events

The detection exploits a characteristic that distinguishes manual watering from rainfall at these sites. A watering hose or tanker delivers a large volume onto a small area within minutes, producing a near-simultaneous rise at all three measurement depths.

For each 30-minute resampled VWC channel, a rise flag was set where the inter-step increment exceeded 1.5 % volumetric water content. An event was accepted where at least two of the three depth channels triggered simultaneously (majority rule), and where a two-hour persistence check confirmed that the median post-event VWC exceeded the pre-event baseline by at least 0.5 % at the same majority of depths. Detections separated by less than 12 h were merged into a single event. To prevent confusion with rainfall, each detected event was compared with the rain-event catalogue (Sect. 2.7.1). Any VWC jump falling within a confirmed rain window was discarded as an ambiguous mixed signal.

The detector was validated against the irrigation logs provided by the municipal partners. Each documented event was assigned to one of three categories, (A) events for which no concurrent VWC time series existed because the sensor was absent



or the data contained a gap, (B) events coinciding with a BSC-detected rain window, which were discarded as mixed signals, and (C) the assessable subset with clean, rain-free soil moisture observations. Within category C, a documented event counted as detected when a detection fell within a window of ± 48 h around the logged timestamp. Recall was computed as the share of documented events that were detected, and precision as the share of detections with a documented counterpart. Since the logs cover only part of the network, precision is bounded from below by construction. Recall was additionally broken down by irrigation volume and by month to test whether the detector systematically misses particular watering practices or periods. The validation results are reported in Sect. 3.3.

2.8 Target variables

Two response metrics were extracted per event and per measurement depth. The *soil moisture increase* is the rise from the pre-event baseline to the post-event peak, normalised by the dynamic range of Eq. (1),

$$\Delta \text{VWC}_{\text{norm}} = \frac{\text{VWC}_{\text{peak}} - \text{VWC}_{\text{pre}}}{D_{s,d}} \times 100, \quad (3)$$

expressed in percent of the dynamic range. $D_{s,d}$ approximates the available water capacity of the respective channel. Since field capacity and permanent wilting point are unknown for almost all sites (Sect. 2.2), the observed percentile span of a multi-season record is used instead, on the assumption that a sensor observes both near-saturated and strongly depleted conditions over that period. This normalisation makes $\Delta \text{VWC}_{\text{norm}}$ comparable across sites and depths, since the same absolute rise represents a different fraction of the storage available at a sandy and at a clay-rich site. The baseline VWC_{pre} is the median over a 3 h window ending immediately before event onset. The peak was searched from event start until 24 h after event end, truncated at the first subsequent rain hour so that a following event cannot distort the amplitude.

Events without a detectable response ($\Delta \text{VWC}_{\text{norm}} \leq 0$) were excluded from the modelling. The remaining values are strongly right-skewed, with extreme values arising where a sensor's dynamic range is very small and the normalisation therefore becomes numerically unstable. The target was consequently transformed as

$$y_{\text{SM}} = \ln(1 + \Delta \text{VWC}_{\text{norm}}), \quad (4)$$

which stabilises the variance. Feature selection and final models were fitted on the transformed target, so that all reported R^2 values and attributions refer to the same quantity.

The *drying time* t_{dry} is the elapsed time from the moisture peak until the signal first falls below a threshold placed at 10 % of the event amplitude above the pre-event baseline,

$$\text{VWC}_{\text{thr}} = \text{VWC}_{\text{pre}} + 0.10 (\text{VWC}_{\text{peak}} - \text{VWC}_{\text{pre}}). \quad (5)$$

A 10 % rather than a 0 % threshold is used because the tail of the depletion curve approaches the baseline asymptotically, so that the exact return to the pre-event value is not robustly identifiable in a noisy signal. A 10 % threshold is also common in signal processing when the time constant of an impulse response is determined. The elapsed time is measured from the detected moisture peak, not from event onset, so that events with delayed peak responses do not inflate the drying duration. The search



was capped at 168 h (7 d) after the peak, and events not reaching the threshold within this window were excluded. An event was further excluded when more than 5 mm of precipitation fell between the end of the event and the threshold crossing, since such an input constitutes a new event under the same criterion that defines event separation. Precipitation before the end of the event belongs to the event itself and does not trigger this exclusion, even where the moisture peak occurs while precipitation is still ongoing. This rule removes 12 to 17 % of the rain events and about 28 % of the irrigation events from the drying-time strata and restricts the sample to depletion phases that are not interrupted by renewed input of event magnitude. Unlike the moisture increase, the drying time is bounded by construction and free of extreme outliers, and was therefore left untransformed. Rapid responses at depth caused by preferential flow along the stem, cracks or backfill interfaces are not identified separately by the pipeline. They enter the moisture-increase sample like matrix flow, and their possible influence is discussed in Sect. 4.2.

Figure 6 illustrates both targets at the Kapellensteg site in Erlangen (*Populus alba*) for a rain event of late May and an irrigation event in early July. The rain event delivers most of its input within a few hours after onset, and the 30 cm channel responds with a normalised increase of 121 % of its dynamic range, the deeper channels with 104 and 67 % with the peak at 90 cm arriving roughly a day after the peak at 30 cm. A value above 100 % is possible, because the dynamic range is the 5th to 95th percentile span of the multi-season record rather than its absolute extremes, so a single large event can exceed it. The subsequent drying takes 73 to 99 hours depending on depth and is interrupted only by a small shower that stays below the exclusion threshold. The irrigation event produces a rise at all three depths within the same hour, which is the signature the detector relies on, with increases of 74, 72 and 71 % of the respective dynamic range and drying times of 95 to 120 hours. The comparison shows the two properties that motivate the normalisation, the same tree yields responses of different absolute size at the three depths, and irrigation persists longer than rain at this site.

2.9 Predictor variables

Table 3 lists the predictor variables offered to the feature selection. The full set, including the pre-event rainfall windows and the mean air temperature, was offered to every stratum, so that a predictor absent from a final model was rejected by the selection rather than withheld. Land-use, topographic, SVF, groundwater and tree morphological descriptors enter as static site characteristics, identical for all events at a given tree site. Event descriptors and the pre-event soil moisture vary between events at the same tree.

The mean air temperature during the event, $\text{avg_temp}\{d\}$, was computed as the hourly temperature sum accumulated over the drying window divided by the drying time in hours. It describes the conditions the soil actually experienced while drying. Although the target variable drying time appears in its construction, the feature is retained because air temperature is independent of the soil response and does not by itself disclose the target.

Seasonality was encoded as the cosine of the day of year as $\text{day_cos} = \cos(2\pi d/365)$, where d is the day of the year, with missing dates set to $d = 172$ (21 June). The cosine form is continuous across the year boundary and preserves the circular nature of the annual cycle, which matters for tree-based models with axis-aligned splits. The value +1 corresponds to mid-winter and -1 to mid-summer, so a negative contribution of day_cos in the drying-time models means that summer events dry faster. The feature selection screened seasonality as the cosine of the calendar month, $\cos(2\pi m/12)$, and where it was

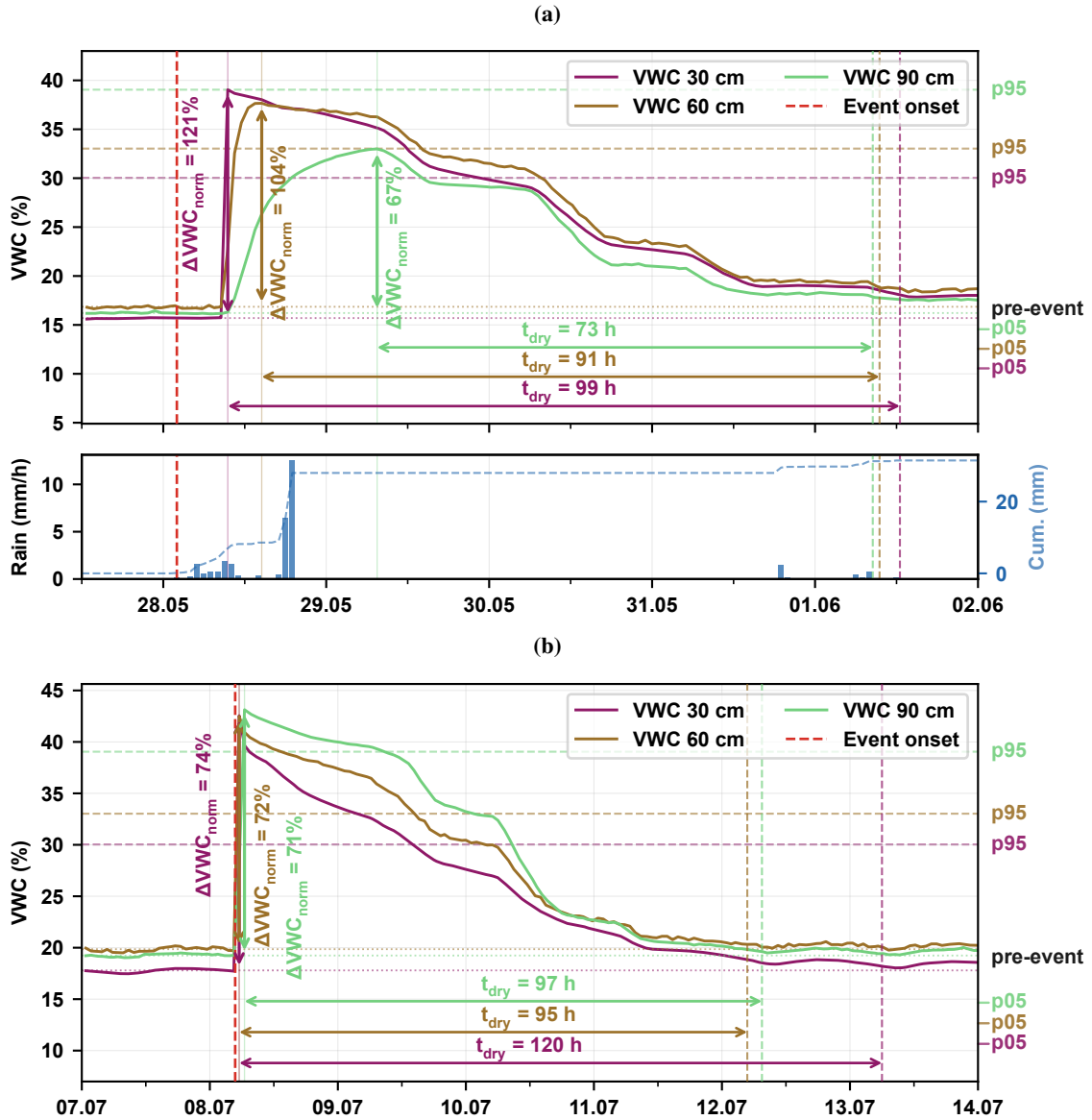


Figure 6. Extraction of the two target variables from the VWC time series at Kapellensteg, Erlangen (*Populus alba*). (a) Rain event BSC 0000, 28 May 2025, where soil moisture increases in a low-pass filtered manner over the measurement depths. (b) Irrigation event, 8 Jul 2026, where the simultaneous sharp rise across all three depths with zero precipitation recorded is the detection criterion. Dashed horizontal lines mark the p_{95} percentile of the 4 h rolling-median smoothed full time series (upper end of the dynamic range). Dotted horizontal lines mark the 3 h pre-event baseline VWC_{pre} . Labelled tick marks on the right axis indicate the p_{05} level (lower end of the dynamic range). Double-headed vertical arrows give ΔVWC_{norm} of Eq. (3) for each depth. Horizontal double-headed arrows give the drying time t_{dry} of Eq. (5) from peak to the 10 % amplitude threshold, with dashed vertical lines at both endpoints. The bottom sub-panel shows hourly precipitation in (a) and confirms zero precipitation in (b).



retained, the final forests were trained on the day-of-year encoding above. The two encodings are monotonically related within a month, and the seven models that retained the monthly variable are exactly those in which `day_cos` appears.

Variables derived from the soil moisture response, which would reveal the target to the model, were excluded before selection, as were sensor and city identifiers. Missing values were imputed with the median of the corresponding event type and depth subgroup. Strata were not modelled in two cases, when they contained fewer than 30 observations, with a reduced threshold of ten for the irrigation strata, or when the feature selection retained fewer than three predictors. No feature scaling was applied, since Random Forests are invariant to monotonic rescaling of individual predictors.

Due to the reduced availability and large heterogeneity of groundwater data, median imputation of the missing values in the main models risks attenuating a genuine effect. Two additional model runs were therefore performed for both targets. The first, the coverage subset, is restricted to those trees for which a DTGW value exists, so that no imputation is required. The second is restricted to Potsdam and Berlin, which are covered by a single consistent groundwater dataset and together contribute the largest share of trees in the network, removing heterogeneity at the cost of sample size and geographic distribution. Both subset runs mirror the production pipeline exactly, with the same feature selection, Random Forest configuration, cross-validation, grouped validation and drying-time exclusion. They are evaluated with the same metrics. Both targets of the rain strata are modelled at all three depths, giving twelve subset models. As a control against subsetting artefacts, the analysis is repeated once on a random tree subset of the same size as the coverage subset.

The resulting sample sizes are given in Table 4. They differ between depths because the response filtering is applied per depth. An event enters the moisture-increase stratum of a depth only if that channel shows a valid rise, and the drying-time stratum only if that channel crosses the recovery threshold within the search window, so the same event can be present at 60 cm and absent at 90 cm.

2.10 Feature selection

The predictor set of Table 3 contains groups of strongly correlated variables, in particular the per-annulus land-use descriptors and the multi-radius topographic indices. Feature selection by the Boruta algorithm (Kursa and Rudnicki, 2010) was therefore applied separately to each combination of target, event type and measurement depth.

Boruta compares the importance of each real predictor against that of shadow features, which are copies of the original columns with their values randomly shuffled and therefore carry no information about the target. A predictor is confirmed when its importance exceeds the best shadow feature significantly more often than expected by chance, and rejected when it falls below, decided by a binomial test over the iterations. It was run with an internal Random Forest of 150 trees, for at most 50 iterations, at the default significance level of 0.05. Because the runtime of Boruta grows with the product of observations and iterations, strata with more than 3000 events were represented by a random sample of 3000 events in the selection step only. The final models were fitted on all events.

Across all combinations for the moisture increase target, the attached green area `greenAtta_0to7` within 7.5 m was the only site characteristic confirmed in every stratum. For the drying time target, no predictor was confirmed in all strata. `greenAtta_0to7` was confirmed in the three irrigation models, remained tentative at 30 cm and was rejected at 60 and



Table 3. Predictor variables offered to the feature selection, with their dataset column names. The depth placeholder {d} denotes the modelled measurement depth. Suffixes 2m5, 5m and 7m5 denote the concentric annuli with outer radii of 2.5 m, 5 m and 7.5 m around the trunk, 0to7 the aggregate over the full disc (Fig. 4). Event descriptors marked with an asterisk are available for rain events only.

Group	Variables	Description
Attached green space	greenAtta_2m5, greenAtta_5m, greenAtta_7m5, greenAtta_0to7, greenAttCD	permeable area hydrologically connected to the tree pit: per annulus, aggregated over all three, and within the crown projection
Detached green space	greenDeta_2m5, greenDeta_5m, greenDeta_7m5, greenDeta_0to7, greenDetCD	permeable but hydrologically separated area
Building footprint	buildings_2m5, buildings_5m, buildings_7m5, buildings_0to7, buildingCD	area covered by buildings
Sealed surface	sealedSu_2m5, sealedSu_5m, sealedSu_7m5, sealedSu_0to7, sealedSuCD	impervious area, derived residually per annulus
Topography	twi, tpi_2m5, tpi_5m, tpi_7m5, tpiCD, slope, elevation, flowAcc	topographic wetness index, topographic position indices at several radii, slope in degrees, elevation in m AMSL, flow accumulation
Radiative exposure	SVF	sky view factor, 100 m radius, 16 search directions
Groundwater	DTGW	depth to groundwater in m, available for 15 of 41 locations
Tree morphology	crownDiam, height, stemDiam, age_years, vitality	crown diameter, height and stem diameter in m, age in years, vitality class
Pre-event soil moisture, dynamic range	pre_vwc{d}, dyn_range{d}	baseline VWC before the event and the dynamic range $D_{s,d}$ of Eq. (1) at the modelled depth
Event descriptors	total_mm*, max_intensity_mmh*, duration_h*, rain_pre24h_mm, rain_pre72h_mm, stac*	event total, peak intensity and duration, pre-event rainfall over 24 and 72 h, and dimensionless peak position
Derived	day_cos, avg_temp{d}	seasonality, mean air temperature during the event (Sect. 2.9)



Table 4. Number of events entering the models per target, event type and measurement depth, after all filtering and exclusion steps.

Target	Event type	30 cm	60 cm	90 cm
Moisture increase	BSC_XX11_Q12	4499	4867	4464
	IRRIGATION	3051	3057	3055
Drying time	BSC_00XX_Q34	1358	1726	1501
	IRRIGATION	1131	1075	1040
Moisture increase, coverage subset	BSC_XX11_Q12	1452	1487	1407
	IRRIGATION	369	372	368
Drying time, coverage subset ^a	BSC_00XX_Q34	585	653	584
	IRRIGATION	216	218	208

^a Upper bounds, before the post-event rain exclusion of Sect. 2.8.

495 90 cm for rain events, so it enters four of the six drying-time models, ranked sixth to tenth with 2.6 to 6.2 % of the mean
 absolute attribution. Refitting these four models without it changes the cross-validated R^2 by at most 0.011 and the ranking
 of the remaining predictors only by adjacent swaps. Predictors still tentative after the maximum number of iterations were
 retained. Boruta was chosen over a correlation-based reduction because it decides relevance in the presence of all other pre-
 dictors, whereas a correlation filter removes redundancy without asking whether a variable carries signal. The selection serves
 500 interpretability, not predictive performance, which is set by the log transform of the moisture increase and by the sample size.

2.11 Random Forest models

The multivariate analysis serves to identify which of the event, tree and site characteristics govern the two response metrics,
 and to quantify the direction and the magnitude of their contributions under the simultaneous presence of all other predictors.
 Random Forest regression (Breiman, 2001) was chosen for the multivariate analysis, as it is appropriate for the following three
 505 characteristics of the analysed dataset:

- the predictors mix continuous, count-like and bounded quantities on very different scales (no transformation required)
- the expected relationships are non-linear and involve interactions (specification in advance not necessary)
- the smaller strata have moderate sample sizes (tolerated without severe overfitting, while remaining interpretable through permutation importance and SHAP attribution).

510 One model was fitted per combination of target, event type and measurement depth, twelve models in total. Each forest
 comprised 150 trees. At every split, $\sqrt{p}$ predictors were drawn at random from the p predictors retained for the respective
 stratum. With p between 7 and 13, two predictors were considered per split in the two drying-time rain models with seven
 predictors and three in all other models. Bootstrap resampling was enabled, the minimum leaf size was three observations,



and the depth of the individual decision trees, that is the number of successive splits, was left unconstrained. These settings were fixed a priori on three grounds. 150 trees are sufficient for the ensemble error of a regression forest to stabilise while keeping cross-validation and SHAP computation across all strata tractable. The $\sqrt{p}$ rule decorrelates the trees more strongly than considering all predictors at each split, which matters for a predictor set with the correlation structure of Table 3. The minimum leaf size of three is the only explicit regularisation and suppresses single-observation leaves in the smaller strata. Identical settings were used for the internal Boruta forest, so that importance estimates from the selection and from the final fitting step refer to the same model.

Sensitivity to the two main target variables was assessed on three representative strata (the soil moisture increase for BSC rain events and for irrigation events at 30 cm, and the drying time for BSC rain events at 60 cm). Increasing `n_estimators` from 150 to 500 changed cross-validated R^2 by at most 0.02. Varying `min_samples_leaf` across {1, 3, 10} showed that the chosen value of 3 performs close to the less-regularised setting of 1 ($|\Delta R^2| \leq 0.02$) while avoiding the degradation seen at 10 ($|\Delta R^2| \leq 0.06$). The results are therefore not sensitive to these choices within a practical range.

2.11.1 Model evaluation

Model performance was assessed by three-fold cross-validation with shuffling, reporting the mean and the standard deviation of R^2 across folds. The training R^2 on the full stratum is reported alongside, as an indication of the gap between fitted and generalised performance. After cross-validation, the final model of each stratum was refitted on all available observations for the attribution analysis.

The cross-validation folds were drawn at random over events and were not blocked by tree or by city. Consecutive events at the same tree share all static site characteristics, and their soil moisture states are autocorrelated in time, so observations within and across folds are not strictly independent. A random fold assignment therefore leaks these site characteristics from the training folds into the test fold. The reported values must therefore be read as within-network interpolation performance and not as an estimate of predictive skill at a tree the model has never seen. This is taken up again in Sect. 4.2. To quantify how much of the reported performance originates from this dependence, every model was additionally evaluated with a grouped split in which all events from the same sensor, identified by its devEUI, were assigned to the same fold (`GroupKFold` of scikit-learn (Pedregosa et al., 2011), $k = 3$). The grouped split enforces strict site holdout and therefore estimates the ability of a model to generalise to sensors that were not present during training. Both estimates are reported in Sect. 3.4.

Predictor influence was quantified with SHAP values (Lundberg and Lee, 2017), computed with the exact tree explainer, which decompose each prediction into signed, additive feature contributions per observation. Where a stratum exceeded 2000 observations, a random subsample of that size was drawn for the SHAP computation. For the combined presentation across depths, SHAP values of each depth were normalised by the mean observed target of that depth and expressed in percent, so that contributions from different depths can be displayed on a common axis. Features are ranked by their mean absolute SHAP value, and the Spearman rank correlation between feature value and SHAP value is reported per feature as an indicator of the direction and monotonicity of the effect. Permutation importance with ten repetitions per feature was computed in parallel and ranks the features in the same order, so only the SHAP attribution is presented.



2.11.2 Software

The analysis was implemented in Python 3. Time series handling and event detection use `numpy` and `pandas`. The models, the cross-validation and the permutation importance use `scikit-learn`, feature selection uses `boruta`, and attribution uses `shap`. Raster and vector data handling use `rasterio`, `geopandas`, `shapely` and `pyproj`, the sky view factor uses `rvt` (Kokalj et al., 2025), and figures use `matplotlib`. A single random seed governs all stochastic steps, namely the forest construction, the cross-validation splits, the Boruta runs and the SHAP subsampling, so that the reported results are exactly reproducible.

The processing chain is executed as a fixed sequence of scripts. The terrain, sky view factor, groundwater and land-use derivations produce the static site characteristics. The rain and irrigation detectors produce the event tables. These are joined into the event feature matrix, which is then passed to feature selection and to model fitting with attribution, separately for each target. The code and the processed event tables are available in the project repository (Maier, 2026).

3 Results

3.1 Descriptive statistics of trees and sites

The current dataset contains in total 555 urban tree sites, distributed over 41 locations. Figure 7 gives an overview of selected tree and site characteristics. The cities with the largest number of measured tree sites are Potsdam (134), Erlangen (99) and Lemgo (35). The trees belong to 63 genera and 123 species, with the highest abundance of *Tilia* (79), *Quercus* (63) and *Acer* (54). Tree age, estimated as described in Sect. 2.3.3, ranges from 1 to 286 years. The value of 286 is a strong outlier and the overall median and mean are 14 and 19 years. The crown diameter ranges from less than 1 to 27 m and correlates with tree height and stem diameter. Tree size distribution differs between the cities, with mainly larger trees in Bremen, a wide range of sizes in Dresden and Pillnitz and mainly small trees in Bamberg, Hannover and Lemgo, among others. These differences reflect the cities' varying motivations to monitor urban trees.

The attached green area of the monitored tree sites covers mostly the entire 7.5 m circle in Bremen, Dresden, Salzburg and Vienna, is rather small in Hagen, Hannover and Nürnberg and covers the whole possible range in Bamberg, Berlin, Celle, Erlangen, Garbsen, Kassel and Potsdam.

Mean TWI is 4.1 with a standard deviation of 1.8. The five trees in Hannover show the highest mean TWI (6.2), and the highest values, up to 13.8, are remote outliers at nine trees in Biberach, Heidelberg and Pforzheim. TPI at the 7.5 m radius ranges roughly between -1 and 1 , with a mean of 0.03 and a standard deviation of 0.17. The seven Salzburg trees show the highest median TPI ($+0.18$), driven by two Alpine sites, and among the cities with at least ten trees, Bamberg leads ($+0.07$).

Regarding SVF, the values cover the full possible range of 0–1, with the mean at 0.7 and a standard deviation of 0.2. The trees in Bremen, Hildesheim, Kassel and Vienna have the highest mean SVF, while those in Hannover and Hassfurt have the lowest mean SVF. DTGW varies most in Hagen and Lemgo. Bremen stands out with very shallow groundwater, with DTGW always smaller than 1.9 m. Among the attribute fields, the core tree-biological variables were complete for 87 to 99 % of trees,



580 with the exception of the vitality assessment at 43 %. The GIS-derived topographic and land-use variables reached a median completeness of 98 %, because they are computed automatically from public DEMs and remote-sensing products, with the depth to groundwater available for 52 % of trees. The soil-analytical parameters required laboratory analysis of soil cores and were available for about 20 % of trees, concentrated in sites where soil characterisation was part of the project scope.

Unconditional Spearman rank correlations between the actionable site characteristics and both response variables are weak
 585 throughout ($|\rho| < 0.2$), which is expected, since the site characteristics act jointly and conditionally in the multivariate models and their isolated effect is diluted by the event-to-event variability that dominates both targets.

The predictors of Table 3 are correlated within groups, in particular between the annuli of one land-use class and between the radii of TPI (Fig. 8).

3.2 Event characteristics

590 Figure 9 shows a summary of the percentage contributions of monitored tree sites, sensor days and rain and irrigation events.

Sensor data collection began in April 2023, and the detected events analysed here span 4 February 2024 to 22 July 2026, since precipitation data prior to 1 February 2024 was not logged in the database. Of the 555 trees in the database, 510 contribute at least one BSC rain event. Event detection yields 25 819 BSC rain events in total, of which 12 967 lie above the uniform mass curve in both first-half quartiles (codes 11xx), 7117 below it (00xx) and 5735 are mixed (10xx and 01xx) (Fig. 10). 8397 events
 595 (32.5 %) reach the classical erosivity threshold of 12.7 mm. The Huff quartiles are populated almost evenly, with 6841, 6969, 6536 and 5473 events in Q1 to Q4. The two model strata comprise 10911 events for the moisture increase and 5961 events for the drying time, together 16 872 events before the per-depth response filtering of Sect. 2.9. The median event delivers 9.3 mm of precipitation over 14 hours, with interquartile ranges of 6.9 to 15.0 mm and 9 to 21 hours and a maximum event total of 173 mm. The median tree contributes 56 events, with a range of 1 to 123. Deployments per city range from 1 to 134 sensors.

600 3.3 Validation of the irrigation event detector

Eighteen municipal partners provided partial irrigation logs comprising timestamps and volumes, 1548 documented events across 121 trees at the time of writing. Of these, 119 events (8 %) fell into periods without concurrent VWC data and 93 (6 %) coincided with a BSC-detected rain window and were discarded as mixed signals, leaving 1336 assessable events (86 %, Table 5).

605 Within this subset, 1019 events (76 %) were matched to a detection within the 48 h window, yielding a recall of 0.76. The 317 undetected events are concentrated in June and July, consistent with wetter pre-event conditions that reduce the relative magnitude of a watering pulse. Recall is stable across volume classes below 150 L (0.77 to 0.78) and across the growing season (0.70 to 0.82 from April to October), so the detector does not systematically miss a particular watering practice or period. Precision over the assessable subset was 0.31. Because the reference records are incomplete, the majority of unmatched
 610 detections occur at trees or in time windows of partners who submitted no documentation at all, so this value is a conservative lower bound of the detector's precision rather than an estimate of its false-alarm rate. Applied to the full network, the detector yields 5242 irrigation detections across 379 trees.

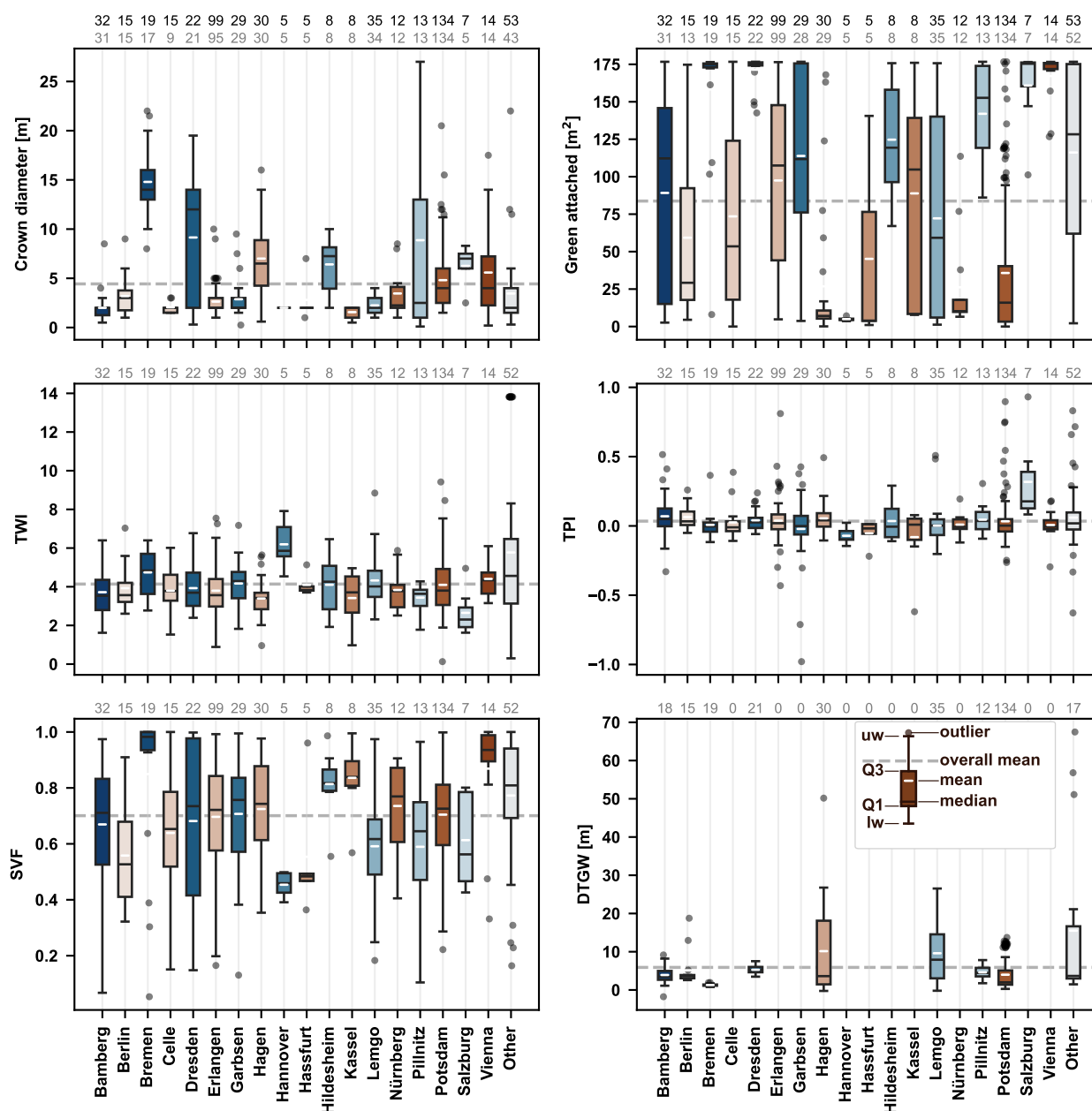


Figure 7. Boxplots showing the distribution of tree and site characteristics: crown diameter, attached green land cover, topographic wetness index (TWI), topographic position index (TPI), sky view factor (SVF) and depth to groundwater (DTGW). Number of trees per city in black, number of available features per tree in grey above the boxplots.

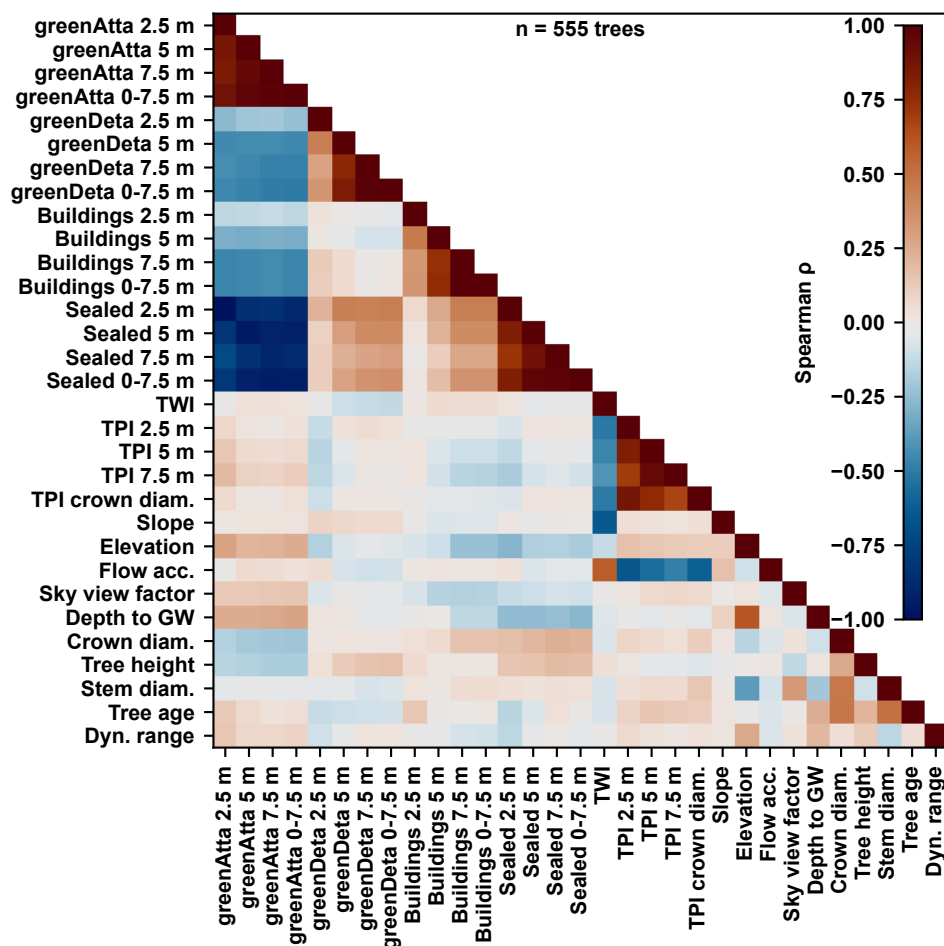


Figure 8. Spearman rank correlations among the static site characteristics of the tree locations ($n = 555$ trees, pairwise complete observations) and the dynamic range at 30 cm, taken as the per-tree median across rain events. Same-radius descriptors of the four land-use classes correlate strongly with each other, the aggregated 0 to 7.5 m descriptors correlate strongly with their ring components, the topographic position indices cluster across radii, and the tree-morphology variables form a positively correlated group. Sealed surface and building cover are negatively correlated with the green-cover descriptors, a structure taken up in Sect. 3.7.

3.4 Model performance and feature importance

Table 6 summarises the twelve models together with their grouped-by-sensor validation. The cross-validated R^2 ranges from 0.40 to 0.69. The moisture increase is predicted best for irrigation events, with R^2 between 0.63 and 0.69 across depths, followed by the rain stratum with 0.51 to 0.55. The drying time ranges from 0.51 to 0.55 for irrigation events and from 0.40 to 0.45 for rain events, with the weakest model at a depth of 90 cm for rain events. Training R^2 ranges between 0.76 and 0.85

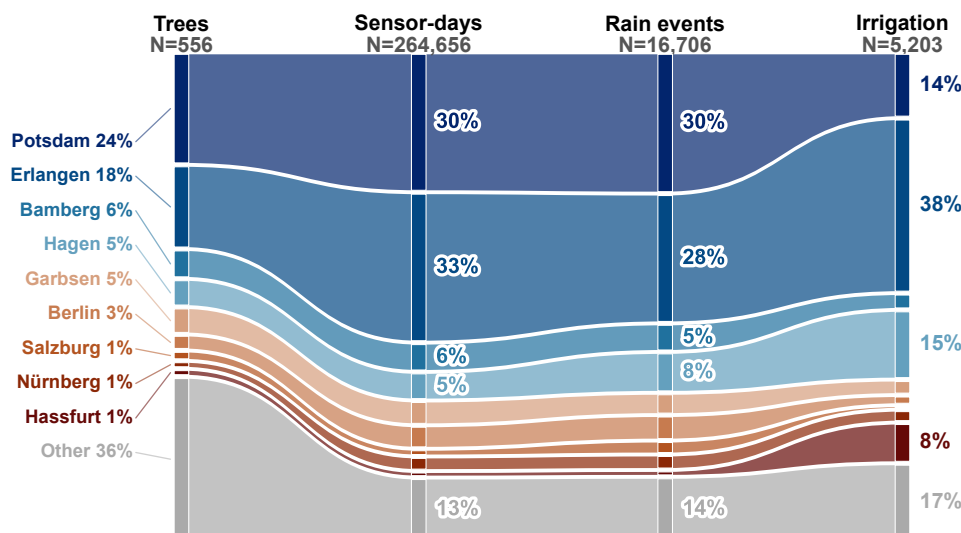


Figure 9. Contribution of the cities to the tree stock, the measurement volume and the two event populations. Each axis is normalised to 100 % of its own total, given as N above the axis: trees in the database, sensor-active days with valid readings, BSC rain events of the two model strata with a city assignment, and documented irrigation events. One ribbon per city connects its share on consecutive axes, the stacking order is identical on all axes, so ribbon widths alone encode how a city's share changes from one quantity to the next. The nine largest contributors are named, all remaining cities are merged into Other.

Table 5. Validation of the irrigation event detector against field-documented irrigation records (1548 events across 121 trees at the time of writing). Events are categorised by data availability and overlap with independently detected rain periods (BSC method). Performance metrics are computed over the assessable subset only.

Category	Description	N	%
<i>Documented events (1548 total)</i>			
A. No sensor data	No VWC time-series available during event window	119	8
B. Mixed signal	Event coincides with BSC-detected rain, excluded	93	6
C. Assessable	Clean window, VWC data present	1336	86
<i>Detection performance (assessable subset, $N = 1336$)</i>			
True positive (TP)	Irrigation detected within ± 48 h	1019	76
False negative (FN)	Documented event not detected	317	24
False positive (FP)	Detection without documented counterpart	2300	–
Recall	$TP / (TP + FN)$	0.76	
Precision	$TP / (TP + FP)$	0.31	

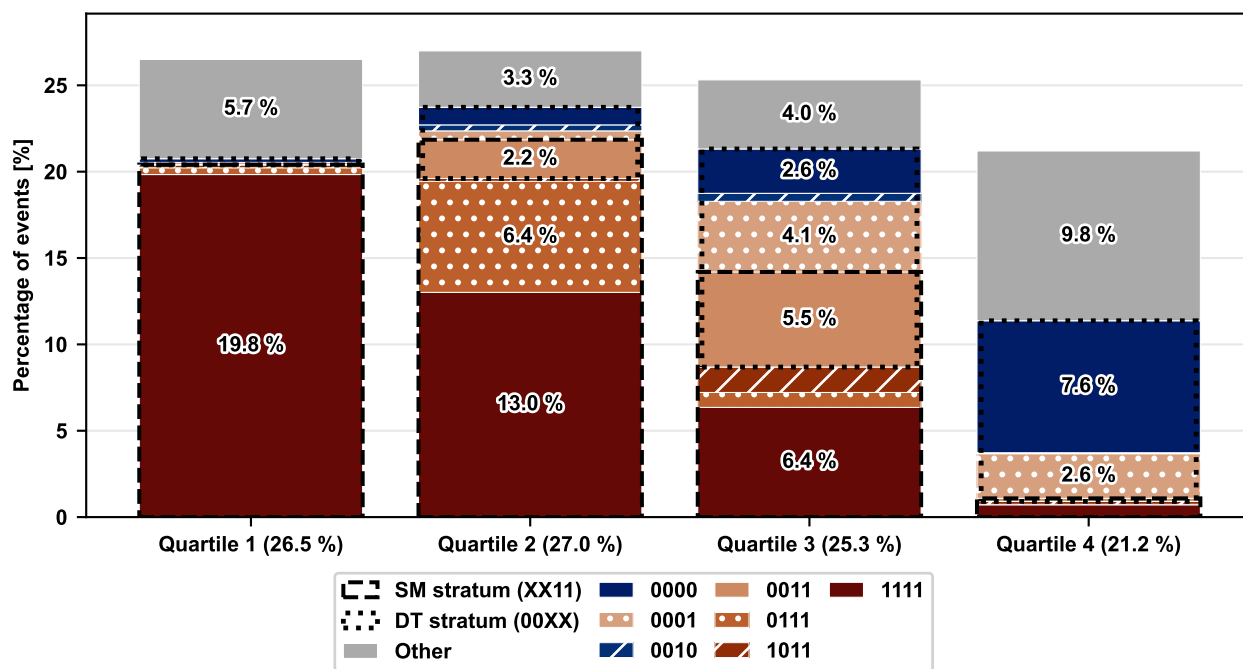


Figure 10. Internal temporal structure of the detected rain events. Frequency of the Binary Shape Code patterns after Terranova and Iaquina (2011), with the two pattern groups used as model strata highlighted.

throughout, so the gap to the cross-validated values indicates the moderate optimism that is expected for Random Forests on correlated event data. The models use 7 to 13 of the offered predictors per stratum.

620 The grouped variant of Sect. 2.11.1 assigns all events of one sensor to the same fold. For the rain strata, the grouped estimates match the random ones within 0.03 for the moisture increase and within 0.01 for the drying time. For the irrigation strata, the R^2 drops by 0.21 to 0.37.

3.5 Drying time

3.5.1 Rain events

625 The mean drying time after back-loaded rain (BSC_00XX_Q34) amounts to 30.0, 17.8 and 16.7 h at 30, 60 and 90 cm (medians 14.5, 4.0 and 4.0 h in Fig. 11, left). Each point in Fig. 11 is one event at one depth, and its position on the horizontal axis gives the contribution of that feature to the predicted drying time of that event, expressed in percent of the mean observed drying time at the respective depth. A point at +20 therefore means that the value of this feature lengthened the predicted drying time of this event by 20 % of the depth-specific mean, a point at -20 that it shortened it by the same amount, and a point near zero that the feature was irrelevant for this particular event. As the normalisation is applied per depth before pooling them together
 630 in one plot, the three depths are directly comparable despite their different mean drying times. Accordingly, horizontal spread



Table 6. Model performance per target, event type and measurement depth. Reported are the number of events, the cross-validated R^2 of the random three-fold split as mean $\pm$ standard deviation over the folds, the training R^2 , the grouped-by-sensor estimate in which all events of one sensor fall into the same fold (GroupKFold , $k = 3$) so that strict site holdout is enforced, the difference ΔR^2 between the grouped and the random estimate, and the number of predictors entering the final model.

Target	Event type	Depth	n	R^2_{CV}	R^2_{train}	$R^2_{grouped}$	ΔR^2	Feat.
Moisture increase	BSC_XX11_Q12	30 cm	4499	0.51 ± 0.01	0.84	0.51 ± 0.03	0.00	11
		60 cm	4867	0.55 ± 0.01	0.85	0.54 ± 0.02	-0.01	9
		90 cm	4464	0.52 ± 0.02	0.84	0.49 ± 0.02	-0.03	12
	IRRIGATION	30 cm	3051	0.63 ± 0.03	0.84	0.34 ± 0.08	-0.29	13
		60 cm	3057	0.69 ± 0.03	0.83	0.35 ± 0.14	-0.34	11
		90 cm	3055	0.69 ± 0.03	0.84	0.34 ± 0.16	-0.35	11
Drying time	BSC_00XX_Q34	30 cm	1358	0.45 ± 0.03	0.80	0.44 ± 0.06	-0.01	9
		60 cm	1726	0.45 ± 0.02	0.79	0.46 ± 0.01	+0.01	7
		90 cm	1501	0.40 ± 0.02	0.76	0.39 ± 0.02	-0.01	7
	IRRIGATION	30 cm	1131	0.51 ± 0.05	0.79	0.30 ± 0.12	-0.21	12
		60 cm	1075	0.53 ± 0.06	0.80	0.28 ± 0.08	-0.25	12
		90 cm	1040	0.55 ± 0.02	0.79	0.18 ± 0.12	-0.37	12

Values for the moisture increase target refer to the log-transformed target of Eq. (4) and are therefore not directly comparable to those of the drying time target, which is modelled untransformed and in a different unit.

of a feature row shows its influence, and features are ordered by the mean absolute contribution across all events, which is the number given in percent below. The colour of a point encodes the feature value itself relative to its median, so for example an entry with all red colours on the right and all blue colours on the left indicates a monotonic effect. This is quantified by the annotated Spearman rank correlation ρ between feature value and SHAP value, which gives the direction and the monotonicity of an effect but not its size. Importance and monotonicity are independent here. A feature can rank high in attribution while its effect is non-monotonic, and a feature with a clear direction can still contribute little.

The mean air temperature during the event is by far the strongest predictor (34.5 % of the mean drying time, $\rho = -0.73$), warm recession phases being associated with shorter drying times. Seasonality ranks second (16.3 %, $\rho = +0.41$), with winter events drying slowest. The 24 h pre-event rainfall ranks third in magnitude (14.7 %) and shows the most consistently monotonic effect of all predictors ($\rho = +0.82$), prolonging drying. The 72 h pre-event rainfall acts in the same direction (8.1 %, $\rho = +0.65$). High peak intensities shorten drying (10.3 %, $\rho = -0.42$), whereas the event total (5.5 %, $\rho = +0.21$) and the event duration (5.6 %, $\rho = -0.13$) contribute only marginally. The pre-event soil moisture at the sensor itself is the weakest of all retained predictors (2.2 %, $\rho = +0.31$), ranking below both pre-event rainfall sums. With respect to RQ2, drying after rain is governed by the thermal and seasonal regime during the recession, and by the pre-event rainfall. The cross-validated R^2 is 0.40 to 0.45 (Table 6).

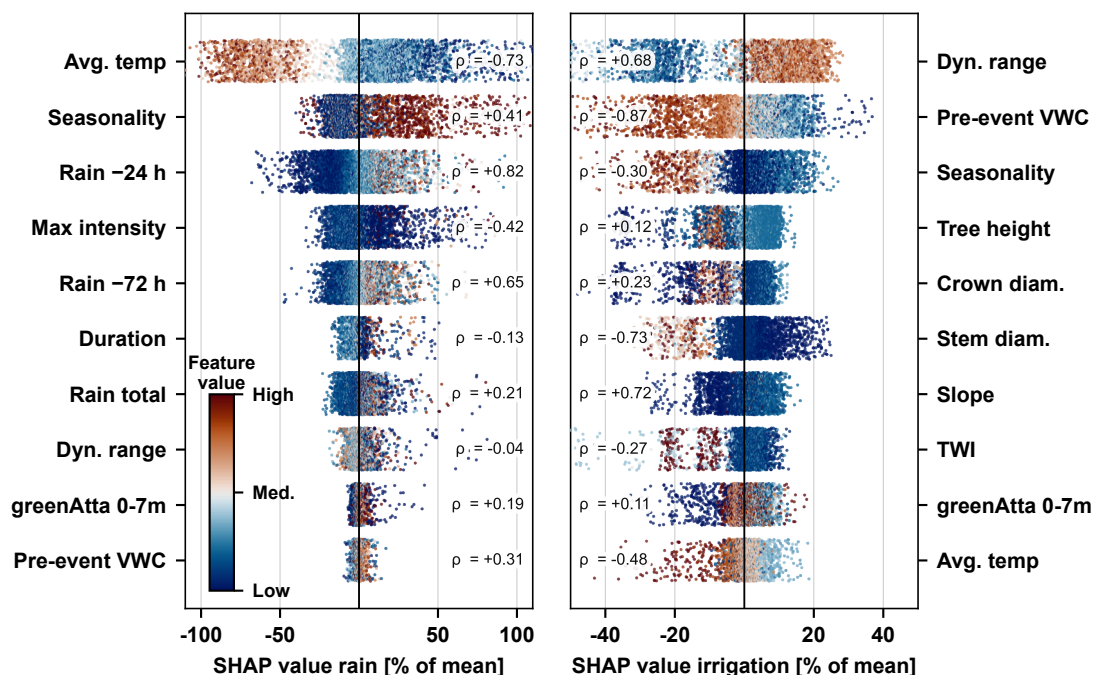


Figure 11. SHAP attribution for the drying time model, pooled over the three measurement depths and expressed in percent of the depth-specific mean drying time. The left panel shows rain events (BSC_00XX_Q34) and the right panel irrigation events. Each point is one event sample, coloured by the feature value relative to its per-feature median, with up to 600 points per feature row. Features are ordered by mean absolute contribution, and the annotated value is the Spearman rank correlation ρ between feature value and SHAP value, which gives the direction and the monotonicity of an effect rather than its strength.

3.5.2 Irrigation events

The mean drying time after irrigation amounts to roughly 62 hours at all three depths, approximately three times the post-rain values (Fig. 11, right). This comparison contrasts typical irrigation inputs of 100 to 200 litres per tree with rain events of at least 5 mm over the whole site, not equal water amounts, so the longer persistence reflects the input regime as much as the site. The dynamic range is the dominant predictor ($\rho = +0.68$). Trees in high-capacity substrates retain irrigation water substantially longer, with an interquartile effect of roughly 9 to 15 hours depending on the depth. The pre-event soil moisture ranks second ($\rho = -0.87$), so watering an already wet pit produces no measurable persistence. Such events were retained deliberately, since the detector cannot know the soil state in advance and their inclusion is what makes this effect visible. Seasonality follows in attribution, though with a weaker linear association ($\rho = -0.30$), with summer irrigation drying faster under high evaporative demand. Tree size is modelled through the stem diameter ($\rho = -0.73$), with larger trees extracting the water more rapidly, while tree height and crown diameter contribute little, and slope shows a positive association ($\rho = +0.72$) at modest attribution. With

respect to RQ2, drying after irrigation is governed by the dynamic range, the pre-event soil moisture, seasonality and tree size, a driver profile that differs fundamentally from the rain stratum, which indicates that irrigation as currently practised does not reproduce the moisture dynamics of natural rain events.

3.6 Soil moisture increase

3.6.1 Rain events

The mean normalised response amounts to 85, 69 and 56 % of $D_{s,d}$ at 30, 60 and 90 cm, corresponding to absolute rises of 2.2, 1.8 and 1.7 percentage points of VWC. SHAP contributions are expressed in percent of this depth-specific mean response (Fig. 12, left). The axes read as in Fig. 11, with a point at +20 meaning that the feature increased the predicted moisture response of that event by 20 % of the depth-specific mean response. The mean air temperature during the event is the dominant predictor ($\rho = -0.38$), with warm events producing smaller normalised responses. The dynamic range ranks second and acts through the normalisation of Eq. (3) ($\rho = -0.89$). The pre-event water input follows closely, with the 24 h pre-event rainfall amplifying the response ($\rho = +0.92$) and the 72 h pre-event rainfall acting in the same direction ($\rho = +0.89$), since prior wetting primes the profile for transmission and activates preferential flow paths. Larger and longer events drive larger increases ($\rho = +0.87$ for the event total and $+0.71$ for duration), while high peak intensities show a weaker positive association ($\rho = +0.62$). The pre-event soil moisture lowers the increment ($\rho = -0.66$), reflecting the field-capacity ceiling. Among the site characteristics the attached green area is the leading descriptor and reduces the response ($\rho = -0.36$), with the signal carried by the aggregate disc rather than by any individual ring (Sect. 3.7). With respect to RQ1, the magnitude of the moisture response is therefore set by the mean air temperature during the event, the pre-event rainfall and soil moisture and the size of the event, while the attached green area modulates it secondarily.

3.6.2 Irrigation events

For irrigation events, the pre-event soil moisture dominates ($\rho = -0.92$), so drier soils respond more strongly to the same water input, and the dynamic range ranks second ($\rho = -0.80$), again acting through the normalisation (Fig. 12, right). Seasonality contributes with larger normalised responses in summer ($\rho = -0.85$), and the mean air temperature during the event shows a positive association ($\rho = +0.47$) that plausibly reflects the drier baseline conditions of warm irrigation days. The remaining site characteristics, wetness index, tree size, topographic position and sky view factor, contribute less, slope shows a positive association ($\rho = +0.53$) at small attribution, and the attached green area is effectively irrelevant ($\rho = -0.05$), since irrigation is applied directly to the pit and bypasses both the canopy and the surrounding surface. The pre-event rainfall windows were offered to the irrigation models but retained by the feature selection in only one of the six irrigation models, the 72 h window of the moisture-increase model at 30 cm, since irrigation is scheduled independently of recent rainfall and the pre-event soil moisture already carries the relevant information.

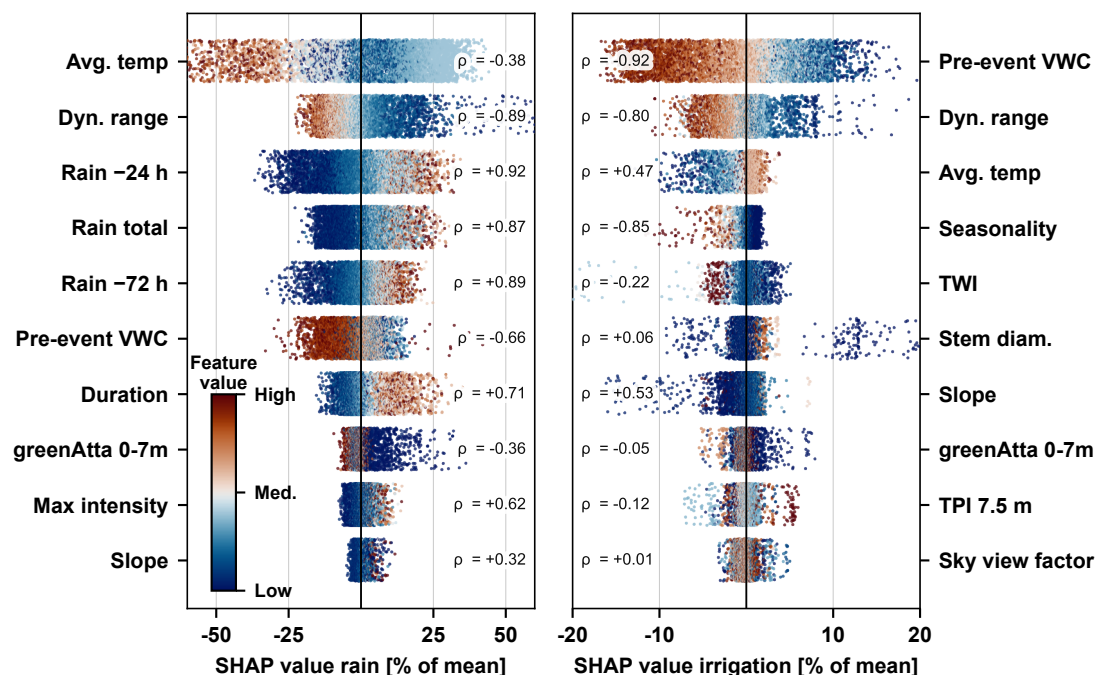


Figure 12. SHAP attribution for the normalised soil moisture increase model, pooled over the three measurement depths and expressed in percent of the depth-specific mean response. The left panel shows rain events (BSC_XX11_Q12) and the right panel irrigation events. Contributions refer to the log-transformed target of Eq. (4). Point colours, ordering and the annotated Spearman rank correlation ρ follow Fig. 11.

3.7 Spatial scale of the land use effect

Each land-use class was offered to the feature selection both per annulus and as the aggregate over the full 7.5 m disc (Table 3), so the rings and the aggregate competed in the same selection. If the effect of the attached green area depended on its distance from the trunk, an individual annulus should be retained in preference to the aggregate. This is not the case. Across all strata and depths, no individual annulus is retained, while the aggregate `greenAtta_0to7` enters all six moisture-increase models and four of the six drying-time models (Sect. 2.10). The land-use signal is therefore carried by the attached green area as a whole, and a radial gradient is not resolvable with the present data, which is plausible for the predominantly young trees of the network whose rooting zone is small relative to the digitised radius. The detached green fraction is not retained in any model.

3.8 Groundwater subsets

The coverage subset comprises 291 tree sites in 15 locations, of which 261 carry a numeric value, the remaining only an interval statement from the source map and were excluded from the subset models. The Potsdam and Berlin subset contributes the



majority with 149 tree sites. After all filters, the moisture-increase models train on over 1400 events per depth in the coverage
 700 subset and over 500 in the Potsdam and Berlin subset, the drying-time models on over 500 and 180 events. The moisture-
 increase performance matches the full models, with a cross-validated R^2 of 0.50 to 0.57 in the coverage subset and 0.53 to 0.60
 in the Potsdam and Berlin subset, against 0.51 to 0.55 in the full stratum, while the drying-time models lose accuracy with depth
 (0.28 to 0.42 and 0.25 to 0.53), consistent with their small post-exclusion samples. The depth to groundwater is not retained by
 the feature selection in any of the twelve subset models. Among the production models it survives only in the moisture-increase
 705 irrigation model at 30 cm, where it ranks last with imputed values for most events (Table B4). The univariate association persists
 for the moisture increase, with Spearman ρ between -0.13 and -0.15 at $p < 10^{-6}$ across all depths and deeper groundwater
 associated with smaller responses, while it is weak and inconsistent for the drying time ($|\rho| \leq 0.09$, significant at the 30 cm
 channel only). The control run on a random tree subset of the same size reproduces the subset performance within a cross-
 validated R^2 of 0.015, so the restriction itself introduces no artefact. Details on these numbers are available at the data repository
 710 (Maier, 2026).

4 Discussion

4.1 Importance of event, tree and site characteristics (RQ1 and RQ2)

The central pattern across both target variables is that the meteorological regime and the pre-event soil moisture outweigh any
 other site characteristic. For the rain events, the mean air temperature during the event ranks highest, followed by the dynamic
 715 range and the pre-event rainfall for the moisture increase and by seasonality and the pre-event rainfall for the drying time. For
 irrigation events, the pre-event soil moisture and the dynamic range dominate. This is consistent with the physical constraints
 on urban soils, where compaction, disturbance and restricted volumes make infiltration and storage the limiting processes
 (Scalenghe and Ajmone Marsan, 2009; Livesley et al., 2016; Endreny, 2018), and with the general behaviour of soil moisture,
 reflecting the accumulated inputs and losses of the preceding days rather than the current conditions alone.

720 Within the site characteristics, the attached green area is the most relevant for the rain response. It acts simultaneously
 as a proxy for infiltration area, evapotranspiration, attached green area and the absence of compaction over the rooting zone
 (Weltecke and Gaertig, 2012; Fini et al., 2017). The negative sign of its attribution is consistent with a runoff mechanism. At
 strongly sealed sites, the small unsealed pit collects concentrated surface runoff and receives a larger local pulse, whereas at
 green sites the water spreads over a wider area. The practical recommendation therefore concerns the total attached green area
 725 around the pit rather than its distance from the trunk (Sect. 3.7).

The topographic indices should be read with care. They contribute little, appear mainly in the irrigation plots, and their
 implications, such as shorter post-irrigation drying at high wetness-index locations, resist a routing interpretation. The strongest
 of them, slope, is discussed as a probable proxy for city membership in Sect. 4.2. TWI and TPI were designed for natural
 catchments (Beven and Kirkby, 1979; Weiss, 2001). In sealed urban terrain, small-scale structures such as kerbs, edging stones
 730 and the rim of the tree pit determine where surface water actually flows. They are not resolved by a digital elevation model

with a resolution of one metre. Their modest contributions are therefore best understood as coarse morphological context rather than as resolved hydrological routing, and they inherit the resolution and algorithm dependence stated in Sect. 2.5.

The sky view factor illustrates the limits of static geometric descriptors for dynamic processes. In the final attribution it contributes little, with 0.4 to 3.0 % of the mean absolute attribution in the panels where it appears (Appendix B), so the radiative exposure of a site leaves no direct imprint at the event level. Several reasons are plausible. The sky view factor describes the hemispherical openness at a point and thus the diffuse radiation, whereas direct radiation depends on the position of the sun and the surrounding building geometry over the course of a day. Tams et al. (2023) combined both and found a substantial effect of shading on evapotranspiration and water availability, which suggests that the descriptor rather than the process is the limitation here. In addition, radiative exposure acts cumulatively on the water balance, so its effect may be diluted at the scale of single events of a few hours to days. Furthermore, the observer point of the sky view factor was placed at the top of the tree. A point within the crown, for example at two thirds of the tree height, would be closer to the radiation actually received by the leaf area, but would require the DSM to be adjusted over the whole crown area. The strong micrometeorological impact of canyon conditions on the transpiration of street trees (Rahman et al., 2017) supports keeping an exposure descriptor in the feature set, but a time-resolved shading model would be required to interpret it better.

The groundwater result is a statement about the heterogeneity of the available data rather than about the ecological relevance of groundwater access. The variable covers only part of the network and comes from sources with reference dates two decades apart (Sect. 2.4), a heterogeneity that no further modelling step can repair. The feature selection discards the variable in every subset model and retains it in a single production model, where it ranks last. This might also imply that within this network the groundwater level is hydraulically decoupled from the upper 90 cm, with no capillary connection that would be visible at the event scale, which is consistent with the depths recorded for most sites. Whether a given tree reaches the water level also depends on its species-specific rooting depth and on barriers in the subsoil, neither of which is captured by a distance in metres, so a reachability classification would require assumptions that the present data do not support.

Rain and irrigation events represent different parts of the urban water balance, and the attribution emphasises the contrast. Rain occurs across larger areas and has diverse temporal patterns, so the rain models are governed by the thermal and seasonal regime, the pre-event rainfall, soil moisture and the event properties. Irrigation delivers a concentrated volume directly to the root zone, so the irrigation models are governed by the storage capacity of the substrate, the pre-event soil moisture and tree size, with a post-irrigation persistence around three times longer than after rain. Two field studies on routing stormwater to street trees point in the same direction. Infiltration trenches that direct kerbside runoff to established street trees reduced runoff but did not reduce drought stress, which Szota et al. (2019) attribute to the trees already having adequate soil water within their rooting volume, consistent with the dominant role of the pre-event soil moisture in this study. Biofiltration tree pits with a sandy filter substrate delivered more water to the root zone immediately after rain, but drained and dried so quickly that the trees showed no reduction in water stress (Gebert et al., 2019), consistent with the dominant role of the storage capacity of the substrate in the post-irrigation drying of this study. In both cases, delivering water to a tree was not sufficient, whether it benefits the tree depends on the soil moisture state it meets and on how long the substrate can hold it.



765 The tree size variables return contradictory results. Tree size enters the post-irrigation drying model through the stem diameter, whose contribution declines consistently with increasing diameter ($\rho = -0.73$), while crown diameter and tree height carry comparable attribution (6.4 and 6.7 % of the mean drying time against 6.3 % for the stem diameter) but almost no monotonic direction ($\rho = +0.23$ and $+0.12$). Since the crown governs transpirational demand, the opposite ordering would be expected. Three explanations are plausible and cannot be separated with the present data. The network is dominated by young trees with small crowns, whose crown diameter varies over a narrow range and is measured with a larger relative error than the stem diameter. The trees span 63 genera whose crown architecture differs systematically at equal stem diameter, so a single crown-diameter axis pools species with very different leaf areas. Also, we measured crown diameter in the field with a measuring tape at ground level and from aerial imagery, whereas stem diameter is always a higher-precision tape measurement. Stratifying by size class or by genus, rather than offering crown diameter as a continuous predictor across the whole network, might be more promising if the number of large trees per genus permits it.

Three approaches in previous work address urban tree water availability, and the event-based framing used here belongs to none of them. Process-based models simulate growth and ecosystem services continuously and require parameterisation per species and site (Rötzer et al., 2021). Water-balance studies close the budget over a greenspace and a season (Cleugh et al., 2005). Single-city monitoring campaigns observe continuously at few sites, most closely the Hamburg study of Schütt et al. (2022a). Event-based analysis is established in erosivity research (Wischmeier and Smith, 1978; Huff, 1967; Terranova and Iaquina, 2011), from which the present event definition is taken, but we are not aware of its application to soil moisture at urban tree sites across cities. It makes an event at a Bremen park tree and one at an Erlangen street tree two rows of the same table, which is what makes the grouped transfer analysis of Table 6 possible at all.

4.2 Limitations of the study

785 The limitations of this study fall into three groups. The first concerns the data. The substrate was characterised in only two cities, the cities contribute very unevenly to the event population, and influences such as subsurface infrastructure, undocumented irrigation and root or hydrological barriers remain uncaptured. Soil moisture varies strongly over short distances, so a single probe represents one point of a heterogeneous tree pit rather than its mean. Reference profiles at the same site would quantify this but are not practicable at network scale, and for the same reason no site-specific calibration was performed, so the accuracy reported by Maier et al. (2026) describes the instrument rather than a site-validated uncertainty.

The second concerns the event definition and the response metrics. The dynamic range approximates the available water capacity and becomes unstable for sensors with a small range, which motivated the log transform of the moisture response. The drying time is evaluated only for depletion phases that receive no more than 5 mm of precipitation before the threshold crossing, so the drying-time sample represents dry conditions. Events were not filtered by their pre-event soil moisture, so irrigation applied to an already wet pit and rain falling on a saturated profile both enter the samples, and the reported responses average over dry and wet starting conditions. Restricting the samples to events below a defined pre-event threshold would sharpen the estimate of what an irrigation achieves under dry conditions, once the record is long enough to afford the loss of events. Preferential flow along stems, cracks or backfill interfaces can produce rapid deep responses to rain events that might



be misinterpreted as irrigation events, although the simultaneity criterion and the cross-check against the rain catalogue absorb
 800 them partially. Finally, cutting the records into events discards the periods between them, which is the price of making events
 at different trees and cities comparable.

The third concerns the transfer of the irrigation models to trees outside the training data. While the rain models transfer to
 unseen trees with almost no loss (Sect. 3.4), the R^2 of the irrigation models drops by 0.21 to 0.37 when all events of a tree
 are held out together. Their information therefore originates largely from characteristics that are fixed per tree, in particular the
 805 dynamic range and the local terrain. The main cause is the composition of the irrigation sample. Erlangen's share grows from
 18 % of the trees to 38 % of all documented irrigation events, and the three largest cities hold 66 % (Fig. 9), so the models are
 dominated by few cities with their tree populations and irrigation practices. Slope shows a consistent positive association in
 both irrigation models ($\rho = +0.72$ for the drying time, $+0.53$ for the moisture increase) but none in the rain models, which
 points to a proxy for city membership rather than a hydrological mechanism, and we refrain from a physical interpretation of
 810 slope for that reason. In addition, occasional rises from undocumented rain, leaks or cleaning water may enter the irrigation
 sample, an effect bounded by the validation with a recall of 0.76 and a precision of at least 0.31 (Sect. 3.3). The cross-validated
 R^2 of the irrigation models therefore describes how well responses can be ranked among the trees of the present network and
 must not be read as a prediction for new planting sites, for which the grouped values of 0.34 to 0.35 for the moisture increase
 and 0.18 to 0.30 for the drying time are the more realistic estimate. This limitation should ease as irrigated sensors in further
 815 cities join the network.

4.3 Implications for the monitoring and maintenance of urban tree sites (RQ3)

First, the storage capacity of the substrate is the primary controllable design variable. Among the site characteristics, the
 storage capacity of the substrate prolongs the drying time after irrigation the most, with a difference of roughly 9 to 15 hours
 in post-irrigation persistence between trees. In contrast, the storage capacity of the substrate contributes little to drying time
 820 after rain, where the mean air temperature during the event dominates, and it lowers the normalised moisture increase for both
 event types, since the same absolute rise is a smaller fraction of a larger storage. Storage capacity and the attached green area
 around the trunk, which together determine how much water the rooting zone can take up and hold, are fixed at installation and
 cannot be enlarged afterwards without replacing the pit, so both have to be secured at planting.

Second, soil moisture monitoring enables event-level irrigation scheduling, since the pre-event soil moisture alone answers
 825 both operational questions, whether an irrigation will produce a measurable benefit at all and when it needs to be repeated.
 Watering a pit that is still sufficiently supplied yields no measurable persistence, so the same information that improves the
 supply of the trees also avoids water, fuel and working time spent without effect, which matters where municipal irrigation
 budgets and staff are the constraint.

Third, the mean air temperature during the event is among the leading predictors in both rain models, with warmer events
 830 producing smaller normalised increments and faster drying. If this pattern holds under a warming climate, each event would
 add less water to the soil, and that water would be depleted sooner. Irrigation could then be timed according to temperature
 and adapted to tree size, with smaller and more frequent applications for young trees, whose roots are confined to the pit, and



larger applications at longer intervals for mature trees. The present data support the attribution on which this suggestion rests, but not the irrigation protocol itself, which would have to be tested experimentally.

835 4.4 Outlook

Several further research questions remain. An application-oriented analysis of drought resilience and irrigation demand would be a suitable follow-up study. A coarse functional grouping of species, for example ring- versus diffuse-porous or deciduous versus evergreen, would allow the species information to enter the models without a botanical assessment per tree. Spatially blocked validation beyond the sensor level, the continuing growth of the network and the integration of remote sensing products offer further possibilities. These include deep-learning approaches to species mapping from combined multispectral and LiDAR data (Hartling et al., 2019), UAV-based individual-tree crown detection (Troles et al., 2023, 2024), and complementary IoT tree-monitoring systems such as accelerometer-based stability sensing (Fiorentino et al., 2024) and stem-radius variation as a proxy of tree water status (Ziegler et al., 2024). Soil moisture describes the supply side only, and tree-based methods such as sap flow or dendrometer measurements would capture drought stress at the plant itself. They could answer questions this dataset cannot. However, they would increase instrumentation costs and exposure to vandalism.

5 Conclusions

This study introduced an operational and continuously growing database of in-situ soil moisture observations at urban tree sites across Central European cities, together with an event-based analysis pipeline that turns heterogeneous multi-year records into comparable response units. Returning to the three research questions, we can conclude the following:

- 850 RQ1: the magnitude of the soil moisture increase is determined primarily by the conditions at the time of the event rather than by characteristics of the site. For rain events, the mean air temperature during the event leads, followed by the dynamic range and the pre-event rainfall, and for irrigation events the pre-event soil moisture ranks first, followed by the dynamic range. The models explain 51 to 55 % of the variance for rain and 63 to 69 % for irrigation events in cross-validation. Among the site characteristics that a municipality can influence, the attached green area around the tree is the only consistently relevant one.
- 855 RQ2: drying after rain is determined by the thermal and seasonal regime and by the pre-event rainfall, and it is less predictable than the moisture increase, with an R^2 of 0.40 to 0.45 against 0.51 to 0.55. Drying after irrigation persists around 62 hours on average, roughly three times longer than after rain, and is governed by the storage capacity of the substrate, with an interquartile effect of roughly 9 to 15 hours, by the pre-event soil moisture and by tree size, while the attached green area contributes little to the drying time.
- 860 RQ3: three practical conclusions follow. The storage capacity of the substrate is decisive for the drying time after irrigation and the attached green area for the moisture increase after rain. Both are fixed at planting. Continuous soil moisture monitoring supports event-level irrigation management, since the pre-event soil moisture indicates whether an irrigation is likely to produce a measurable benefit and when it may need to be repeated. As warming coincides with smaller per-event moisture gains and faster drying, the attribution results suggest that temperature-informed scheduling and size-differentiated irrigation protocols



865 are worth testing in operational practice, with the caveat that the irrigation models have so far been trained on few cities and their transfer to new sites remains to be demonstrated as the database grows.

The present database continues to grow, so every result stated here can be sharpened as new data is assessed at the present tree sites and as new cities and trees join the network. This study shows that continuous in-situ soil moisture monitoring produces insights into the soil moisture dynamics of urban tree sites, which can be used to complement the experience-driven practice
870 of horticultural professionals with measurable evidence.

Code and data availability. The soil moisture time series, the derived event feature tables, the tree and site metadata, and all analysis scripts are available in the project repository (Maier, 2026). Sensor data were accessed through the climavi platform API (<https://app.climavi.eu>). The digital elevation and surface models, the groundwater data and the climate normals used as external input are publicly available from the sources cited in Sect. 2.4.



875 Appendix A: Terrain indices

The local slope at the tree pixel was estimated by central finite differences on the 1 m DEM, following the four-neighbour formulation of Zevenbergen and Thorne (1987),

$$\beta = \arctan \sqrt{\left(\frac{z_{i,j+1} - z_{i,j-1}}{2\Delta x}\right)^2 + \left(\frac{z_{i-1,j} - z_{i+1,j}}{2\Delta y}\right)^2}, \quad (\text{A1})$$

with β being the local slope angle, $z_{i,j}$ the DEM elevation at the raster cell containing the tree, $z_{i,j\pm 1}$ and $z_{i\pm 1,j}$ the elevations of its four direct neighbours along the column and row direction of the grid, and $\Delta x = \Delta y = 1$ m the cell spacing. For use as a model predictor, β is stored in decimal degrees. Where a neighbour was an edge pixel or carried no data, the elevation of the tree cell itself was substituted, which is conservative in the sense that it pushes the estimate towards zero slope.

A steepest-descent D8 routing scheme was applied across the 200 m DEM patch, with the eight cardinal and diagonal directions weighted by distances of 1 m and $\sqrt{2}$ m respectively. Cells were processed in descending order of elevation, each routing its accumulated area to its single steepest downslope neighbour. The resulting variable `flowAcc` is the dimensionless count of upstream contributing cells.

TWI was computed in the standard formulation of Beven and Kirkby (1979),

$$\text{TWI} = \ln\left(\frac{a + \varepsilon}{\tan \beta + \varepsilon}\right), \quad (\text{A2})$$

where a is the specific upslope contributing area in m^2 , obtained as the flow accumulation multiplied by the cell area. β is the local slope angle of Eq. (A1) entered in radians, and $\varepsilon = 10^{-6}$ prevents division by zero on flat cells. Higher TWI values indicate a greater potential for water accumulation.

No pit filling or depression filling was applied to the DEM. The 200 m local window restricts the routing to the immediate surroundings of the tree and therefore avoids the watershed-scale artefacts that would make hydrological conditioning necessary. The consequence is that TWI here describes the local convergence of surface flow towards the planting site rather than a catchment-scale wetness, which is the quantity of interest for an individual tree pit.

TPI describes the relative elevation of a point compared to its surrounding terrain, with positive values indicating a ridge, negative values a depression and values near zero a flat or uniformly sloping surface (Weiss, 2001). It was computed as the elevation at the tree cell minus the mean elevation of all cells within a circular neighbourhood, the centre cell excluded,

$$\text{TPI}_r = z_0 - \frac{1}{N_r} \sum_{(i,j) \in C_r} z_{i,j}, \quad (\text{A3})$$

where C_r is the set of cells whose Euclidean distance to the tree cell is strictly less than the radius r and N_r its cardinality, with nodata pixels excluded from the mean. Neighbourhoods were realised as binary circular masks pre-computed at the DEM resolution, following the `numpy` sliding-window implementation of Čučković (2021). TPI was evaluated at three fixed radii of 2.5 m, 5 m and 7.5 m, and at a fourth variable radius equal to half the measured crown diameter, capped at the available coverage, yielding the variables `tpi_2m5`, `tpi_5m`, `tpi_7m5` and `tpiCD`.



905 Appendix B: Selected predictors per model

Tables B1 to B4 list every predictor retained by the feature selection in the twelve production models, separated by target and event type and ranked by mean absolute SHAP value normalised by the depth-specific mean target. Both the Pearson r and the Spearman ρ between feature value and SHAP value are given, since the two differ by 0.17 on average and by up to 0.58 for individual features, and the value annotated in Figs. 11 and 12 is ρ . The quartiles of the feature values in the respective training
 910 sample allow the attribution to be read against the range the model actually saw. Features not listed were offered to the feature selection but not retained. For the drying-time models, SHAP values were computed on the complete training sample, for the moisture-increase models on a random subsample of 2000 events per depth.

Table B1. Selected predictors of the drying-time model, rain events (BSC_00XX_Q34). Ranked by mean |SHAP| normalised by the depth-specific mean target. r is the Pearson and ρ the Spearman correlation between feature value and SHAP value. Quartiles are in physical units.

Depth	Feature	Rank	mean SHAP [%]	r	ρ	Q25	Median	Q75
30	Day of year	1	15.3	+0.74	+0.76	-0.912	-0.577	0.598
30	Avg. temp	2	12.7	-0.79	-0.70	7.419	14.717	18.419
30	Max intensity	3	10.5	-0.15	-0.67	1.6	2.4	4.5
30	Rain -24 h	4	8.6	+0.74	+0.80	3.8	7.075	10.595
30	Rain -72 h	5	7.1	+0.55	+0.65	7.5	11.91	18.428
30	Duration	6	5.6	+0.09	-0.13	8	14	21
30	Rain total	7	4.2	+0.46	+0.47	6.845	9.445	14.5
30	greenAtta 0-7 m	8	2.6	+0.02	+0.19	19.83	80.51	147.99
30	Pre-event VWC	9	2.2	+0.24	+0.31	18.1	26.87	36.22
60	Avg. temp	1	44.1	-0.82	-0.78	9.896	17.218	24.247
60	Day of year	2	17.1	+0.62	+0.30	-0.932	-0.744	0.342
60	Rain -24 h	3	17.1	+0.65	+0.82	1.5	5.89	10
60	Max intensity	4	9.5	+0.07	-0.51	1.6	2.5	4.7
60	Rain -72 h	5	8.2	+0.44	+0.66	6.393	10.8	17.4
60	Rain total	6	5.3	+0.23	+0.26	6.65	9.44	14.9
60	Dyn. range	7	4.1	-0.09	-0.10	10.96	15.88	20.64
90	Avg. temp	1	43.2	-0.85	-0.80	9.705	17.038	23.4
90	Rain -24 h	2	17.4	+0.68	+0.84	1.7	6	10
90	Day of year	3	16.3	+0.51	+0.13	-0.919	-0.744	0.342
90	Max intensity	4	11.0	+0.14	-0.14	1.6	2.5	4.3
90	Rain -72 h	5	8.8	+0.48	+0.60	6.44	10.9	17.4
90	Rain total	6	6.9	+0.31	-0.03	6.7	9.5	14.9
90	Dyn. range	7	3.5	-0.14	+0.06	8.52	14.08	18.59



Table B2. Selected predictors of the drying-time model, irrigation events. Columns as in Table B1.

Depth	Feature	Rank	mean SHAP [%]	r	ρ	Q25	Median	Q75
30	Dyn. range	1	17.5	+0.80	+0.72	11.15	16.5	20.69
30	Pre-event VWC	2	11.2	-0.89	-0.86	19.285	27	34.62
30	Day of year	3	9.8	-0.72	-0.39	-0.98	-0.778	-0.398
30	Stem diam.	4	7.2	-0.62	-0.78	0.064	0.078	0.103
30	Tree height	5	5.8	-0.21	+0.03	5	5	6
30	Crown diam.	6	4.6	-0.41	+0.16	2	2	3
30	Slope	7	4.1	+0.23	+0.64	1.038	1.87	3.794
30	Avg. temp	8	3.3	-0.45	-0.24	14.676	19.637	22.151
30	TWI	9	3.2	-0.54	-0.09	3.021	3.689	4.515
30	greenAtta 0-7 m	10	2.6	-0.12	-0.13	43.41	95.97	139.25
30	Sky view factor	11	2.2	+0.52	+0.52	0.579	0.696	0.843
30	TPI 7.5 m	12	2.1	-0.35	-0.25	-0.018	0.034	0.105
60	Dyn. range	1	18.8	+0.73	+0.61	9.775	15.14	19.16
60	Pre-event VWC	2	12.1	-0.82	-0.86	21.44	28	37.875
60	Day of year	3	7.4	-0.70	-0.26	-0.984	-0.767	-0.413
60	Crown diam.	4	6.8	+0.01	+0.27	2	2	3
60	Tree height	5	5.6	-0.13	+0.08	5	5	6
60	Stem diam.	6	5.1	-0.67	-0.74	0.063	0.078	0.103
60	Slope	7	4.3	+0.41	+0.80	1.033	1.87	3.748
60	TWI	8	4.3	-0.59	-0.29	2.996	3.689	4.515
60	greenAtta 0-7 m	9	3.4	+0.14	+0.05	45.3	112.13	138.63
60	Avg. temp	10	3.2	-0.63	-0.60	15.052	19.634	22.464
60	Sky view factor	11	2.5	+0.65	+0.66	0.577	0.683	0.829
60	TPI 7.5 m	12	2.3	-0.01	+0.11	-0.018	0.034	0.096
90	Dyn. range	1	12.5	+0.73	+0.71	7.38	13.26	17.37
90	Tree height	2	8.8	+0.05	+0.24	5	5	6
90	Crown diam.	3	8.1	-0.02	+0.32	2	2	3.5
90	Pre-event VWC	4	7.7	-0.83	-0.86	24.73	33.235	39.72
90	Stem diam.	5	6.6	-0.76	-0.63	0.064	0.078	0.103
90	greenAtta 0-7 m	6	6.2	+0.47	+0.30	43.41	112.13	139.25
90	Day of year	7	6.2	-0.71	-0.22	-0.984	-0.767	-0.398
90	Slope	8	6.0	+0.32	+0.72	1.038	1.87	3.81
90	TWI	9	6.0	-0.67	-0.43	3.021	3.689	4.515
90	Avg. temp	10	3.1	-0.51	-0.56	14.63	19.445	22.356
90	Sky view factor	11	3.0	+0.73	+0.78	0.577	0.683	0.829
90	TPI 7.5 m	12	2.5	+0.00	+0.12	-0.018	0.034	0.096



Table B3. Selected predictors of the soil-moisture increase model, rain events (BSC_XX11_Q12). Columns as in Table B1.

Depth	Feature	Rank	mean SHAP [%]	r	ρ	Q25	Median	Q75
30	Avg. temp	1	13.8	-0.53	-0.45	9.662	12.726	15.8
30	Dyn. range	2	8.5	-0.59	-0.95	13.04	17.57	21.57
30	Rain -24 h	3	7.1	+0.84	+0.93	4.815	7.5	12.262
30	Rain total	4	6.7	+0.80	+0.91	7.3	10.6	17.7
30	Rain -72 h	5	6.0	+0.73	+0.91	8.9	13.63	20.323
30	Pre-event VWC	6	5.0	-0.34	-0.28	19.498	27.92	37.273
30	Duration	7	3.9	+0.76	+0.62	9	15	24
30	Max intensity	8	2.2	+0.47	+0.68	1.7	2.5	4.1
30	TPI 7.5 m	9	1.7	+0.50	+0.26	-0.022	0.014	0.086
30	greenAtta 0-7 m	10	1.5	-0.05	+0.25	21.61	76.86	147.09
30	Sky view factor	11	1.0	-0.49	-0.54	0.561	0.713	0.871
60	Avg. temp	1	18.8	-0.53	-0.43	10.021	14.35	17.95
60	Dyn. range	2	12.8	-0.67	-0.96	11.505	15.88	20.52
60	Rain -24 h	3	11.5	+0.82	+0.94	3.64	7	11.808
60	Rain total	4	6.9	+0.78	+0.87	7.2	10.8	17.7
60	Pre-event VWC	5	6.2	-0.74	-0.78	20.457	29.775	38.072
60	Rain -72 h	6	6.1	+0.77	+0.89	8	13	19.6
60	Duration	7	5.0	+0.76	+0.69	9	15	24
60	Max intensity	8	2.0	+0.51	+0.63	1.7	2.515	4.1
60	greenAtta 0-7 m	9	1.5	-0.46	-0.49	22.21	79.7	142.473
90	Avg. temp	1	20.4	-0.54	-0.39	9.908	14.5	17.441
90	Dyn. range	2	12.9	-0.55	-0.95	8.89	14.77	18.59
90	Rain -24 h	3	11.9	+0.79	+0.92	3.3	7.105	11.928
90	Rain total	4	9.0	+0.78	+0.84	7.3	11	18
90	Duration	5	5.9	+0.81	+0.81	9	15	25
90	Pre-event VWC	6	5.8	-0.67	-0.84	23.145	33.3	40.595
90	Rain -72 h	7	5.2	+0.78	+0.89	8.2	13.2	20.578
90	greenAtta 0-7 m	8	4.2	-0.61	-0.70	18.08	69.5	148.35
90	Max intensity	9	2.1	+0.51	+0.54	1.7	2.5	4.293
90	Slope	10	1.7	+0.43	+0.32	1.234	2.51	4.126
90	Tree height	11	1.4	+0.61	+0.24	5	5	6
90	TWI	12	1.3	-0.14	-0.41	2.983	3.704	4.664



Table B4. Selected predictors of the soil-moisture increase model, irrigation events. Columns as in Table B1.

Depth	Feature	Rank	mean SHAP [%]	r	ρ	Q25	Median	Q75
30	Pre-event VWC	1	5.2	-0.90	-0.95	18.567	25.375	32.285
30	Dyn. range	2	2.7	-0.62	-0.82	13.182	17.34	20.905
30	Avg. temp	3	1.1	+0.72	+0.56	18.914	18.914	18.914
30	Day of year	4	1.0	-0.83	-0.85	-0.973	-0.819	-0.444
30	Slope	5	1.0	+0.20	+0.51	1.131	2.411	3.947
30	Stem diam.	6	0.9	+0.03	+0.19	0.062	0.073	0.095
30	TWI	7	0.9	-0.41	-0.20	2.994	3.689	4.515
30	greenAtta 0-7 m	8	0.5	-0.20	-0.17	43.41	93.24	145.9
30	TPI 7.5 m	9	0.5	-0.00	-0.01	-0.02	0.034	0.102
30	Sky view factor	10	0.4	+0.21	+0.14	0.575	0.711	0.844
30	Tree height	11	0.4	+0.71	+0.46	5	5	6
30	Rain -72 h	12	0.3	+0.05	+0.16	0	1.875	10.1
30	DTGW	13	0.1	-0.26	-0.24	3.19	3.19	3.19
60	Pre-event VWC	1	5.5	-0.92	-0.95	19.678	26.38	33.172
60	Dyn. range	2	2.8	-0.54	-0.81	11.52	15.815	19.27
60	TWI	3	1.1	-0.33	-0.28	2.996	3.689	4.533
60	Slope	4	1.1	+0.16	+0.60	1.08	2.411	3.947
60	Avg. temp	5	1.1	+0.72	+0.58	19.244	19.244	19.244
60	Stem diam.	6	0.8	+0.02	+0.04	0.063	0.073	0.091
60	TPI 7.5 m	7	0.5	-0.22	-0.34	-0.022	0.034	0.106
60	greenAtta 0-7 m	8	0.5	-0.34	-0.26	43.42	93.24	147.16
60	Sky view factor	9	0.5	+0.15	+0.17	0.577	0.711	0.844
60	Tree height	10	0.4	+0.51	+0.30	5	5	6
60	Crown diam.	11	0.3	+0.05	-0.04	2	2	3
90	Pre-event VWC	1	6.4	-0.90	-0.93	22.297	31.27	38.712
90	Dyn. range	2	3.7	-0.65	-0.88	8.38	14.09	17.85
90	Avg. temp	3	1.4	+0.68	+0.43	18.927	18.927	18.927
90	Stem diam.	4	1.1	+0.03	-0.04	0.063	0.073	0.094
90	TWI	5	0.9	-0.18	-0.19	2.996	3.689	4.515
90	TPI 7.5 m	6	0.7	+0.40	-0.00	-0.022	0.033	0.102
90	Slope	7	0.6	+0.12	+0.46	1.155	2.411	4.039
90	greenAtta 0-7 m	8	0.6	+0.03	+0.28	44.93	93.24	145.9
90	Tree height	9	0.5	+0.19	-0.13	5	5	6
90	Sky view factor	10	0.5	-0.45	-0.31	0.577	0.711	0.844
90	Crown diam.	11	0.3	+0.39	+0.09	2	2	3



Author contributions. T.Ma. conceived the study, developed and set up the sensor network, implemented the analysis pipeline and wrote the manuscript (conceptualisation, methodology, software, formal analysis, visualisation, writing of the original draft). S.D. contributed the external spatial data workflows, the depth to groundwater and sky view factor derivation and the descriptive analysis (methodology, formal analysis, visualization, writing, review and editing). B.M.E. supervised the research and acquired funding (supervision, funding acquisition, writing, review and editing).

P.D.S. and S.R. carried out the exploratory studies on automated land use classification and remote sensing, co-supervised by N.V.S.J.J. (investigation, supervision, writing, review and editing). U.F. digitised the land use classes around the monitored trees (data curation, investigation). P.L.C. carried out the field surveys of the tree dimensions (investigation, data curation).

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