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Hydrology on Solid Grounds? Integration Is Key to Closing Knowledge Gaps Concerning Landscape Subsurface Water Storage Dynamics

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ABSTRACT

Individual approaches to observe water dynamics across our landscape, from the land surface to groundwater, are many though they individually only provide glimpses into the real world due to their specific space–time scales. Comprehensive integration across all available observations is still largely lacking, limiting both our ability to reduce scientific knowledge gaps, and to guide land and water management using the best available scientific evidence. We argue that a stronger focus on integration of observational products, while utilising machine learning and accounting for current perceptual understanding is urgently needed to overcome this limitation. Since Europe is warming faster than any other continent, central Europe is undergoing a dramatic hydroclimatic transition about which such integrated observations would provide timely and valuable insights. Here, we present potential and gaps of current and planned observational methods. We argue that hyperresolution (sub km) integrated estimates of landscape water dynamics are feasible, which could significantly improve our ability to simulate vadose zone and groundwater dynamics, ultimately closing gaps in our current perception of hydrological processes in a temperate region under strong influence from climate change. We close by arguing that an interdisciplinary effort of various scientific communities is needed to enable this advancement.

Abbreviations: AI, artificial intelligence; CRNS, cosmic-ray neutron sensing; CYGNSS, Cyclone Global Navigation Satellite System; GNSS, global navigation satellite system; GRACE, gravity recovery and climate experiment; LSTM, long short-term memory; LSWS, landscape subsurface water storage; ML, machine learning; RZSM, root-zone soil moisture; SAR, synthetic aperture radar; TIR, thermal infrared

1 | Introduction

A plethora of observation-based products that map various aspects of landscape subsurface water storage (LSWS) dynamics is now available. However, each product in isolation provides only a partial picture of LSWS dynamics, and using a single product will also hide substantial variability across products (e.g., Brocca et al. 2024). Here, we argue that advancements must come through integration of current observational products, as well as integration with process- and AI-based models under consideration of our current understanding of LSWS processes and dynamics. Critically, such an effort demands a large interdisciplinary effort in which we shift our focus away from demonstrating the capabilities of individual approaches towards emphasising the full picture and its remaining gaps when considering all available information. LSWS comprises the very dynamic surface soil moisture, water in the root-soil zone, water stored and percolating in the deeper unsaturated zone as well as shallow groundwater. It is this water storage that is decisive for water supply of the vegetation in forests and agricultural areas as well as drinking water, river baseflow and water levels in natural lakes. But is the understanding of this water storage already scientifically sound enough to provide solid ground for such pressing and far-reaching decisions?

Terrestrial Europe is warming faster than any other continent right now (Copernicus Climate Change Service 2023). Climatic gradients across Europe are expected to shift significantly, with great consequences for hydrometeorological conditions as well as for subsequent hydrological services and hazards (see Figure 1). In the coming decades, for example, heat events of outstanding magnitude and large spatial extent, such as the European 2003, 2021 and Russian 2010 events, are more probable to occur over Europe (Barriopedro et al. 2011; Ji and Fan 2023). Such events have dramatic consequences on LSWS (e.g., Boeing et al. 2022) though they may be less obvious and harder to quantify than in surface waters. We lack scientifically robust guidance regarding a wide range of management, planning and adaptation issues related to LSWS that arise from such changes. For example, rain-fed agricultural areas experience drier and hotter summers posing questions if current irrigation practices or even if current crops can be sustained. Do we have sufficient understanding of groundwater renewal under potential future climate and land uses to understand whether a switch to groundwater-based irrigation is sustainable, given that such resources are under increasing stress already (e.g., in the European drought of 2022; Joint Research Centre et al. 2022)? At the same time, regulators tend to reduce water rights and put up more restrictions on consumption to sustain water levels and limit water temperatures in lakes, rivers and groundwater for ecosystem protection among other reasons. Thus, major structural shifts in land cover and water resources management must be expected across central Europe, with decisions to be made by a wide range of actors, from the individual farmer up to national authorities.

How can we provide reliable continuous space–time estimates of landscape subsurface water dynamics and its constituent

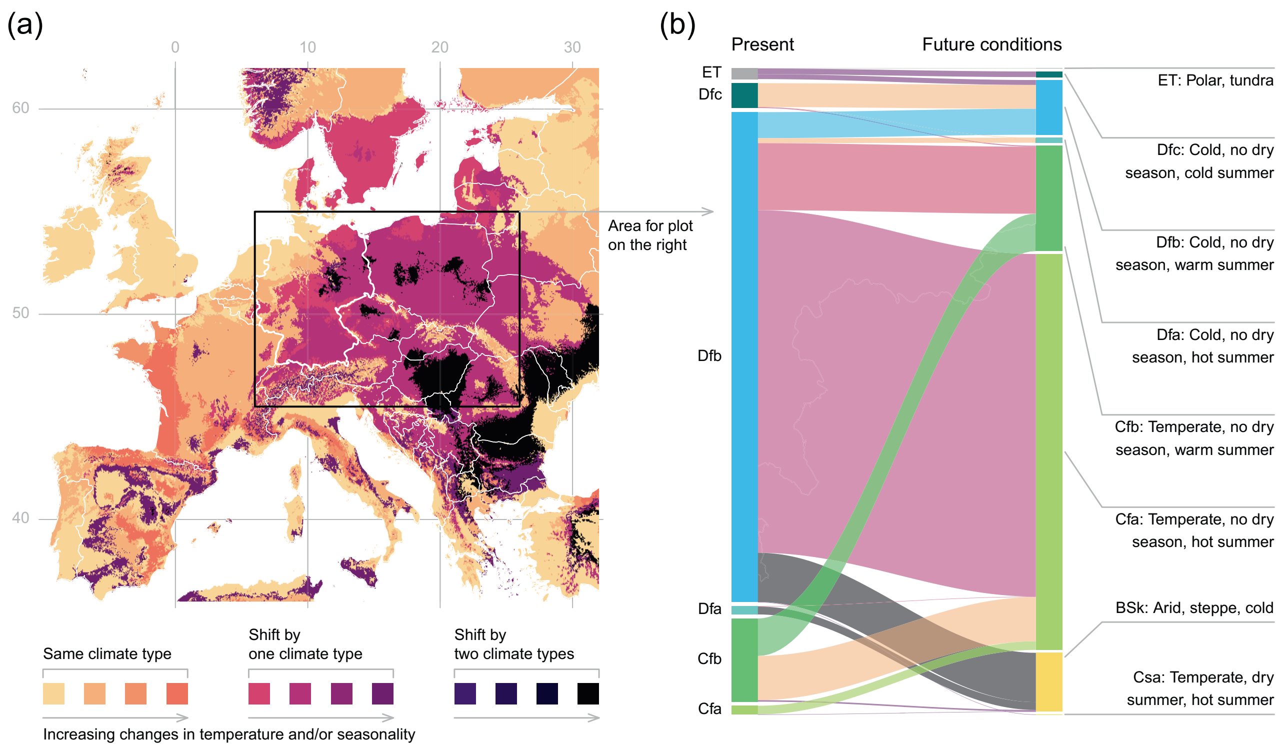

FIGURE 1 | Future climate class change in central Europe. On the left (A): scoring between present-day and degree of change predicted for end of century based on Köppen-Geiger climate classification; adapted from Beck et al. (2018, 2020). The scoring for each 1 km^2 pixel was based on a change of climate group (capital letter) to a neighbouring one giving 1 point, a change of more than one climate group giving 2 points, a change in seasonal precipitation type (first small letter) giving 0.5 points and a change only of the heat level (second small letter) giving 0.25 points. On the right (B): transformation of all pixel areas (1 km^2) from its current to its future class as migration plot.

components at subkilometre and subdaily resolution and from land surface to the top of the saturated zone? We currently still have significant knowledge gaps regarding landscape water dynamics in space and time, and its potential to change with a changing climate. These gaps become visible in our limited ability to predict key subsurface hydrological states and fluxes. Estimates of root-zone soil moisture (RZSM) derived from satellite observations (often in combination with simulation models) reveal large differences between products and real values (Schmidt et al. 2024; Brocca et al. 2024), reducing their reliability and applicability as scientific evidence base for decision-making by stakeholders and local authorities. Long-term change in total water storage of large regions has been assessed by GRACE satellites since 2002 (Schmidt et al. 2006). Thorough tests showed substantial discrepancies between modelled and GRACE-based assessments of long-term trends of groundwater heads (Scanlon et al. 2018). Lischeid et al. (2021) provided evidence that this is due to ignorance of deep vadose zone processes in hydrological models, limiting their ability to predict groundwater levels as well as the complete water storage for the unsaturated zone down to the groundwater surface (Bunting et al. 2022). Groundwater recharge observations are typically scarce and largely biased against humid parts of the world (Gnann et al. 2023) resulting in significant variability and uncertainty of groundwater recharge estimates in hydrological models (Berghuijs et al. 2024).

On top of that, no single observational method currently can quantify landscape water storage dynamics and the fluxes between different storage compartments with the necessary areal extent, horizontal, vertical and temporal resolution. Observational methods have very different spatial features, from continuous point measurements with very limited spatial extent in the landscape to subweekly satellite observations with continental extent at kilometre resolution but almost no integration depth. In fact, spatial extent and integration depth are often inversely correlated with temporal resolution (Figure 2). This leaves spatial and temporal gaps in our observations of subsurface water storage dynamics.

We believe that substantially more information than currently utilised would be available if we advanced along three lines: (1) Jointly interpreting diverse existing observations of hydrological states and/or fluxes consistently across scales. Too often observations from specific instruments are assessed in isolation in scientific studies, with insufficient focus on what we could actually know if we used all available observations. (2) Questioning our conceptual understanding of landscape subsurface water dynamics and expanding it to a new perceptual model if necessary. Too often we focus on the direct integration of observations into simulation models (with their specific assumptions and choices) only, without considering what current knowledge and knowledge gaps we have about the real-world system itself. (3) Merging and assessing the value of all observations using AI-based, process-based and hybrid modelling strategies—thus leveraging the value of data for a wide range of models.

In this article, we review recent key developments in the most relevant observational disciplines with respect to landscape water storage dynamics. We then propose and discuss new ideas to close existing knowledge gaps across scales. Our recommendations should support hydrological research to address questions and problems related to subsurface water storage in the landscape and to support current and future management of water resources and landscape productivity.

2 | Opportunities and Limits to Assessing Landscape Water Dynamics in Central Europe

2.1 | Satellite Remote Sensing Observations of Soil Moisture Dynamics

Several satellite soil moisture services are fully operational, relying chiefly on coarse-resolution (10-50 km) microwave observations such as those acquired by the series of Advanced Scatterometre (ASCAT) (Wagner et al. 2013) instruments and the soil moisture and ocean salinity (SMOS), and soil moisture active passive (SMAP) satellites (Kerr et al. 2012; Entekhabi et al. 2010). These missions deliver increasingly reliable soil moisture data (e.g., Gaona et al. 2024) at daily time steps, which allows estimating temporal changes in soil water content down to a depth of about 1 m from the observed surface soil moisture time series (Ceballos et al. 2005). Nonetheless, without ancillary soil data, these microwave satellites are unable to provide absolute soil moisture values, nor can they provide higher-resolution estimates (< 10 km) without further satellite data and modelling approaches. Therefore, recent research has addressed the question of how to disaggregate the coarse-resolution observations using radiative transfer models (Tong et al. 2024) and machine learning algorithms (Alemohammad et al. 2018) that combine the coarse-resolution data with high-resolution information from physically related variables, such as synthetic aperture radar (SAR) data or optical vegetation and surface temperature data (Colliander et al. 2017; Das et al. 2023). However, independent validation efforts have not yet confirmed that disaggregation approaches yield reliable fine-scale patterns (e.g., Brocca et al. 2024).

Another important line of research to improve the spatial heterogeneity of the satellite observations is to retrieve soil moisture directly from SAR data at a much higher spatial resolution. While results obtained at very fine scales (20–100 m) are still experimental, 1 km soil moisture data derived from the C-band SAR instrument onboard of the Sentinel-1 satellites have become available (Balenzano et al. 2021; Quast et al. 2023), over Europe even fully operational (Bauer-Marschallinger et al. 2019). These data have not yet reached the same level of maturity as its coarse-resolution counterparts, but have nonetheless been found to provide valuable information about fine-scale processes related, for example, to irrigation and rainfall (Filippucci et al. 2022; Dari et al. 2023). Upcoming L-band SAR missions such as NISAR (NASA ISRO Synthetic Aperture Radar, Lal et al. (2023)), ROSE-L (Radar Observing System for Europe at L-band, Petrolati et al. (2023)) and possibly also the BIOMASS mission (Miller et al. 2024) can be expected to yield somewhat better soil moisture retrievals than Sentinel-1 due to their longer wavelengths. However, expectations should not be too high, neither regarding the retrieval accuracy nor deeper soil moisture measurements, as the impact of wavelengths keeps on being rather overemphasised compared to other instrument characteristics such as measurement accuracy or spatiotemporal coverage.

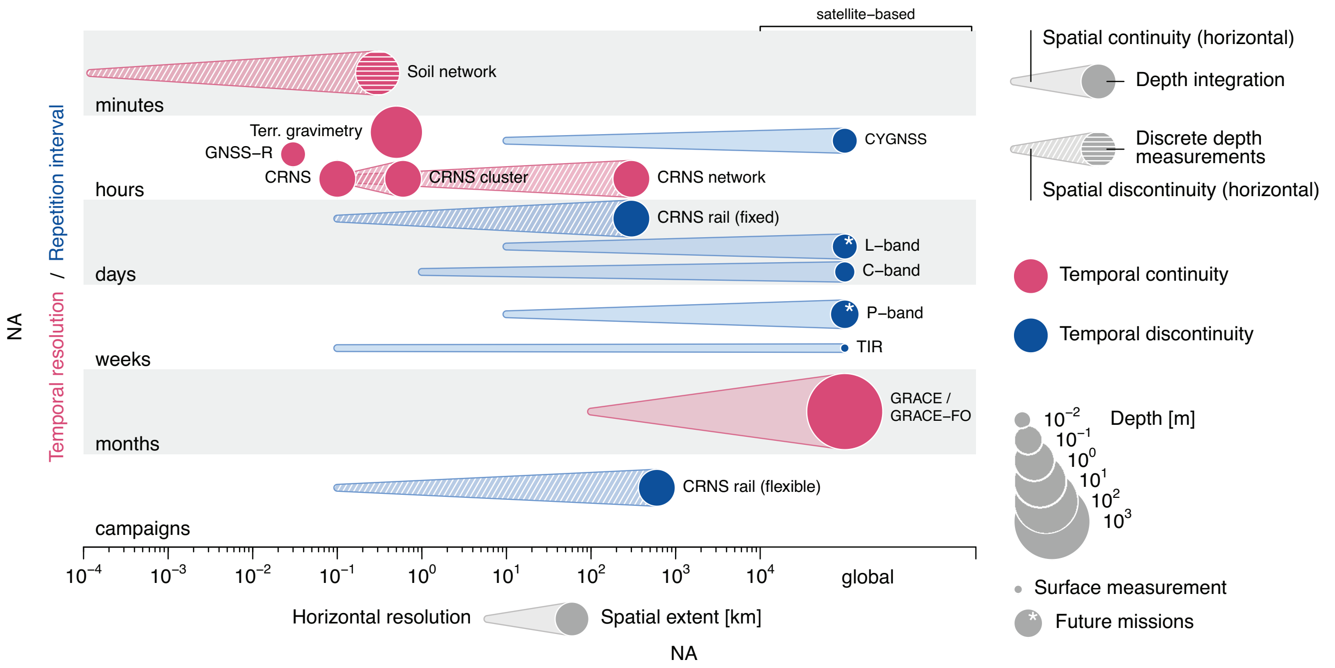

FIGURE 2 | Spatial and temporal resolution and scales of methods for observing soil moisture or subsurface water storage as field-scale average or above. Remote sensing observations are grouped together by bands, including active and passive ones. Derived products combining different observations or observations and modelling approaches are not shown. Terrestrial gravimetry could also be installed as a network but is not included as it has not yet been implemented, opposed to CRNS.

Spaceborne global navigation satellite systems reflectometry (GNSS-R) has recently emerged as a powerful new microwave technique for observing soil moisture (Clarizia et al. 2019). Though it will not help to improve the spatial resolution, we can expect big advances in improving the spatiotemporal coverage at the 10 km scale due to the large number of satellites carrying the sensor. Finally, the SigNals of Opportunity P-band investigation (SNOOPI) will use transmissions from telecommunications satellites reflected at the land surface with the potential to determine RZSM but with varying quality depending on vegetation cover (Garrison et al. 2024).

Remote sensing estimates of water storage and fluxes below the surface will always rely on modelling frameworks (Wood et al. 2011), which will lead to uncertainties despite using observational constraints. Current assimilation work finds that although soil moisture assimilation improves soil moisture characterisation, the characterisation of groundwater levels or evapotranspiration does at best improve to a limited extent (e.g., Hung et al. 2022) or all improve less for droughts than for wet conditions (Li et al. 2024). The latter may be related to the finding that surface soil moisture estimates can show different levels of accuracy over dry and wet soil surfaces (Li et al. 2021). Furthermore, dense vegetation continues to be an obstacle to detect the soil signal from satellites (Liu et al. 2021). This is especially the case for forested areas (Przeździecki et al. 2023).

Many remote sensing applications could greatly benefit from temporally varying quality information to provide bias and uncertainty estimates at different time scales as retrieval accuracy can be expected to vary strongly between seasons (Gruber et al. 2020). Due to the lack of dense in situ soil moisture data, the validation of high-resolution soil moisture patterns is a largely unsolved problem. So far, there is no hard evidence to assume that AI predicted fine-scale soil moisture maps, for example, presented by Singh and Gaurav (2023) make much sense beyond the limited in situ dataset with which the AI model was trained.

2.2 | Ground-Based Observations of Water Dynamics in Soil and the Unsaturated Zone

In recent years, various initiatives have been launched to make existing soil water storage data available to a wider scientific community, for example, the International Soil Moisture Network (ISMN) provides data from at least 2842 stations worldwide, though mainly from invasive point-scale measurements and with sparse coverage in central Europe (Dorigo et al. 2021). Wireless sensor network (WSN) technology has evolved significantly over the last decades and can now cover plot-to-field-scale areas with frequencies in the subgigahertz range, for example, LoRa or NB-IoT technologies. They provide detailed spatiotemporal soil moisture data in near real-time, for example, to support flood management (Bogena, Weuthen, and Huisman 2022). However, also several noninvasive soil moisture measurement techniques are now available at the field scale, for example, cosmic-ray neutron sensing (CRNS), GNSS reflectometry, ground-based microwave radiometry, gamma-ray spectroscopy, and hydrogravimetry (Bogena et al. 2015). Besides stationary use, some noninvasive methods have been applied in a flexible way at a regional scale, for example, to instrument small catchments with different types of land use including forest and cropped fields (Fersch et al. 2020; Heistermann et al. 2022), as an airborne variant, (e.g., Zribi et al. 2022), or as mobile roving measurements of RZSM or snow water equivalents for potentially hundreds of kilometres using rail-CRNS (Schrön et al. 2021).

More representative soil moisture observations are now moving up the scales with respect to total averaging size and extent, as permanent CRNS clusters are about to produce continuous times series over years for an area of about 0.5 km^2 or more (Heistermann et al. 2023), reaching the averaging area of high-resolution satellite observations. As observational networks in central Europe, they could be established at the extent of federal states or provinces, a development that could gain more momentum if the strong drop in costs of CRNS devices with basic features continues. Permanent mobile CRNS systems on rails as recently established by Altdorff et al. (2023) could be installed on long-haul trains and reveal the dynamics of spatial soil moisture patterns along its tracks across federal states or even nations as automated measurements (Figure 2).

Continuous in situ or noninvasive ground measurement of soil moisture is currently only carried out in limited regions with high spatial density (e.g., in terrestrial observatories such as TERENO; Zacharias et al. 2024). These observations are about to reach larger and larger scales but will still provide patchy information at these scales, not continuous as is the case for satellite remote sensing. Also, continuous soil moisture measurements at greater depths, that is, deeper than 2 m, will continue to be extremely rare. Noninvasive ground observation techniques can only provide information on vertical variability of water storage in the unsaturated zone if applied in combination with methods at different integration depths (e.g., GNSS reflectometry, CRNS, and hydrogravimetry).

2.3 | Observations of Groundwater-Level Dynamics

The increasing instrumentation of groundwater observation wells with automatic, continuous water-level recording creates a more comprehensive basis for larger-scale assessment of temporal changes of groundwater heads. However, Lischeid et al. (2021) have shown via principal component analysis for a larger region in Germany that predicting trends and fluctuations of groundwater heads over years and decades may by illusive when directly related to changes in precipitation because of the diverse and poorly known damping in the unsaturated zone. Other options for noninvasive longer-term observation of terrestrial water storage changes in central Europe are via satellite gravimetry data (Güntner et al. 2023). So far, GRACE/GRACE-FO data have been used mainly for observing longer-term changes in larger-scale aquifers. However, assimilating total water storage variations can be a valuable constraint for the overall water storage variations in models as well as for the dynamics of individual storage compartments and for water balance closure (e.g., Gerdener et al. 2022).

Increasingly, add-on information from the unsaturated zone is used to constrain groundwater recharge estimates. Spatiotemporal changes in stable isotopes can help distinguish mobile and less mobile water pools in soil (Sprenger et al. 2018) or seasonally changing water pools in root water uptake (Floriancic, Allen, and Kirchner 2024), and also to directly estimate groundwater recharge fluxes (Boumaiza et al. 2023). Levels of degradable pollutants can help assessing young water fractions in carbonate rock regions (Hartmann et al. 2021). First studies have shown that CRNS-derived soil moisture observation can be used successfully for estimating groundwater recharge at the field scale (Barbosa et al. 2021; Scheiffele et al. 2024). CRNS data very recently have been assimilated into larger-scale land surface-subsurface models (Li et al. 2024) and though soil moisture estimates could be improved this did not transfer to a similar degree into improvements of fluxes, which may indicate that the density of observations was still too low.

Thus, we are now in a better position to address the dynamics of groundwater recharge beyond the water table fluctuation method or water balance calculations based on precipitation and evapotranspiration fluxes with their individual and often high uncertainties. By that also the transport times between the net groundwater recharge, that is percolation fluxes, from the soil zone to the groundwater table will play a larger role and can locally be derived as time lags between net and actual groundwater recharge. Also, by observing water storage dynamics in soil on the field-scale net groundwater recharge can be estimated on this scale as being more representative than point-scale observations including lysimeters. Both principal component analysis and GRACE data provide strong evidence that trends of groundwater head cannot be understood without explicit consideration of changes in the water storage in the deep vadose zone. The role of the soil's memory in regard to buffering atmospheric inputs is well known (e.g., Rahmati et al. 2024). This holds more for the deep vadose zone. Low-pass filtering of hydrological signals in the subsurface results in substantial shifts in the frequency spectrum of groundwater head time series compared to that of the input signal (Lischeid et al. 2021), which needs to be considered when groundwater head dynamics is linked to atmospheric and topsoil processes, for example, via wavelet coherence.

Using CRNS state-level networks representing hydrological units will enable us to estimate observation-based dynamic groundwater recharge, if combined with unsaturated-zone flow models even in larger catchments. This directly links to groundwater recharge simulations over decades to determine trends by climate change or land use change. Being able to observe soil water storage dynamics for regions with larger depth to the groundwater table will enable us to derive the percolation that will eventually form groundwater recharge in some years or decades.

Although considerable progress has been made, the scale gap between measurements on the ground, such as CRNS or terrestrial gravimetry, and from space, such as GRACE-FO, is still far from being bridged. However, given a multitude of both natural and anthropogenic factors affecting hydrological processes, a spatially extensive assessment of the drivers and the dynamics and time lags between infiltration, percolation and actual groundwater recharge is indispensable. Moreover, current monitoring programmes and field campaigns hardly cover the extended time scales of groundwater recharge dynamics. Overall, the heterogeneous, diverse and time-lagged response of shallow groundwater levels pose still a big challenge to address changes in recharge, storage and discharge.

3 | Approaches to Estimate LSWS Dynamics

The lack of robust and high-resolution estimates of landscape water dynamics limits both our ability to reduce scientific knowledge gaps and guide land and water management using the best available scientific evidence. Practical applications in water, forest, agriculture and environmental management could benefit greatly if water storage could be estimated at daily (or higher) and kilometre (or higher) resolutions with national extent, thus providing accurate insight into water states and fluxes in the subsurface. However, no single method, may it be new or advancing rapidly, is the golden bullet to provide such a comprehensive dataset. Therefore, a strategy to achieve this goal will have to integrate contributions of a range of different methods, compensate for individual shortcomings, fill gaps in space and time and transfer this into observation-driven models.

3.1 | Integration of Methods for Ground-Based Observations and Combination of Several Data Products With Diverse Range of Scales, Resolutions and Depth Contributions

The growing number, wealth and potential of modelling, remote sensing and AI supported products of soil moisture and other parts of landscape water storage should not mislead us to believe that we know or soon will know the distribution and dynamics of subsurface water storage at the landscape scale and with national or (sub)continental extent. On the contrary, knowledge gaps still have to be closed, for example (i) differentiating and disentangling different depth components of landscape water storage, (ii) closing the scale gap between in situ measurements and modelling or remote sensing resolution hinged at the kilometre scale and (iii) moving from assessments that are biased towards relative changes (temporal dynamics, pure spatial patterns, relative soil moisture indices, anomalies addressed with large spatial and temporally averaged values) to absolute values such as percentage of field capacity, volumetric water content or even pressure values.

The components missing so far were ground-based observations at the field to regional scales. We believe that several methods are now able to close this gap. Examples of field-scale observation methods are (cf. Figure 2)

i. Cosmic-ray neutron sensing networks at a regional or province scale that aim to represent RSZM within hydrological units in the landscape with a larger number of CRNS devices (per area) than have been realised so far in national networks (the United States and United Kingdom). First examples in central Europe start to exist, at least in several federal states in Germany with about 10–15 CRNS sensors each.

ii. Ground-based terrestrial gravimetres that can be deployed within such networks as a data source for total water storage dynamics, which would go deeper in integration than the typical monitoring of RSZM.

iii. Mobile cosmic-ray neutron sensors carried by regular transportation, such as trains or trucks, could close the spatial gap between stationary networks across hydrological units. The method has been tested with manual car-borne roving campaigns (Schrön et al. 2018; Jakobi et al. 2020), cross-country public trains (Schrön et al. 2021) and with a first permanent installation on a locomotive engine along a fixed track (Altdorff et al. 2023).

We do not know yet what density of network locations will be needed to improve regional water dynamics in land surface or other models (e.g., Patil et al. 2021; Li et al. 2024, in the case of CRNS). But especially when combining the results from these ground-based methods it is becoming feasible to create a daily RZSM product at the regional scale, if observed data can be interpolated via machine learning, as has been tested recently with mobile CRNS data (Dega et al. 2023).

However, the bigger potential is combining ground-based observation networks, each individual measurement representing a field-scale average, with satellite remote sensing, from electromagnetic bands to gravimetry. There will be different ways to do so, from triple collocation with ground observation-based products and satellite remote sensing to machine learning, This could even comprise the distinction of different parts of the landscape water storage on top of its spatiotemporal development, which is to resolve separate values and dynamics for different vertical zones. For example, by applying and expanding the methods used to create soil moisture products from satellite remote sensing observations of surface soil moisture (SSM), for example, exponential filtering (Wagner, Lemoine, and Rott 1999), it should be possible to create products based on CRNS observations of RZSM (up to half a metre) that cover the whole soil water storage (several metres) if not the whole unsaturated zone down to the groundwater table. Or it may include an AI-based spatial downscaling, for example, of large-scale terrestrial water storage observations (from satellite gravimetry, i.e., GRACE-FO) to the dynamics of the individual storage compartments in different soil depths and in groundwater aided with complementary observations; this may also include terrestrial gravimetry (e.g., Güntner et al. 2017).

The establishment and expansion of ground observation networks should be accompanied by enhancement and long-term operation of validation sites that deliver a field-scale estimate of subsurface water storage at different depths as individual time series with daily or subdaily resolution. This could also only be achieved by a combination of methods, a high-end version combining, for example, meteostation, eddy-covariance, GNSS reflectometry, CRNS, soil sensor networks, terrestrial gravimetry and groundwater-level observations.

3.2 | Machine Learning Could Provide the Glue Between Observations and Across Scales to Derive Integrated LSWS Dynamics Products

Machine learning (ML) is rapidly changing our ability to analyse complex datasets or to make predictions across the Earth Sciences, including hydrology (Reichstein et al. 2019). This includes examples related to LSWS dynamics. For example, ML-based extrapolation of soil moisture in different depths using gridded meteorological data and in situ observations has recently been introduced at both European (Sungmin et al. 2022) and global levels (Sungmin and Orth 2021). However, these studies still stress that the scale gap between meteorological data and in situ observations reduces accuracy and that soil moisture observations to test against at larger scales are sparse. Other ML approaches such as convolutional neural network (CNN) models have been used to generate different multidimensional, multivariate, nationwide soil data products taking into account distributed information on climate, vegetation indices, topography, and parent material (Ließ and Sakhaee 2024). While methodological issues around ML still remain to be solved, such as equifinality in the explanatory power of different input features (e.g., Lischeid et al. 2022), rapid advancements in areas such as explainable AI (XAI) (Wang et al. 2024) improve our ability to identify how strongly different factors such as precipitation, temperature, or soil characteristics influence predictions, for example, of soil moisture dynamics derived by an LSTM (Ley, Bormann, and Casper 2024). These approaches offer an agnostic strategy to assess the value of different pieces of information outside the context of established hydrological models.

How well we might use such ML-based estimates in the context of scenario analysis under climate or land use change is another area that requires more study. We might for example find that ML models provide high predictive performance even without including system characteristics (as input features) that we believe should be important. We might, for example, argue that in addition to the effect of surface and subsurface heterogeneities, the complexity of memory processes (e.g., Rahmati et al. 2024) needs to be considered for simulating long-term landscape water dynamics. We expect this to be relevant especially for thick vadose zones with extended memory effects. Thus, there is need for joint analyses of large datasets both of hydrological behaviour (stream discharge, groundwater head, or soil moisture dynamics) and sets of potential drivers. Promise also lies in hybrid models based on ML that can ingest both diverse hydrological observations and physical laws/constraints such as the water balance (see e.g., Kraft et al. 2022). ML tools also enable new approaches to integrate in situ observations in physically based models, for example, through the calibration of parameters using ML algorithms (Chaney et al. 2016) or using differentiable models (Shen et al. 2023).

3.3 | Integrated Representation of Location-Specific Understanding and Knowledge Gaps Regarding LSWS

To our knowledge, a (community) perceptual model of landscape water dynamics has not yet been built for central Europe. Perceptual models are knowledge models which integrate the current state of hydrologic knowledge of a specific location derived from past observations, models or experiments. Such models can be more generalised or highly complex and personal, and can be representative of the aggregated knowledge of a community (e.g., Wagener et al. 2021) or of individuals (Beven and Chappell 2021). Importantly, any perceptual model is independent of any subsequent simulation model implementation where simplifying choices have to be made. Perceptual models are not limited by any subsequent assumption of spatial or temporal averaging, or by our (in)ability to parameterise a particular hydrologic process. Importantly, perceptual models should also reflect uncertainties and knowledge gaps. Advancements in hydrology science can come in terms of advancing theory such as Darcy's law (does not happen very often), or in our understanding of the hydrology of specific places (happens more often). The latter could be considered as an advancement of our perceptual model of a specific location, for example, of specific experimental catchments (Aulenbach et al. 2021; McGlynn, McDonnel, and Brammer 2002).

Initial attempts have been made to compile available perceptual models—for groundwater systems (Zipper et al. 2023) and for hydrologic catchments (McMillan et al. 2023). These efforts are currently still in their infancy and opportunities for developing community based perceptual models as an explicit strategy to share knowledge (and knowledge gaps) have yet to be realised. If such models would exist, they could be used to ensure a consistent basis for subsequent model development, they could be used for hypothesis generation, or to guide targeted monitoring to close knowledge gaps (Wagener et al. 2021). Having such an evolving and shared perceptual model, for example, at km-resolution, as a common knowledge base would provide a significant advancement for hydrology and a new opportunity to pool community understanding.

4 | Conclusions

The integration issues and opportunities we discussed in the previous sections place the focus on how we can best advance our scientific understanding regarding LSWS dynamics. We often focus our research on assessing what can be achieved with a specific new model or method. A question we can assess as individuals or small groups. However, we additionally have to ask how much we could advance our knowledge if we integrate all available elements—observations, models and understanding—regardless of how much is contributed by what approach. And what knowledge gaps remain if we do so. Only if we reasonably achieve such integration, we can argue about what we can really observe, model, or understand. Such integration requires us to come together as scientific communities—given that it is infeasible to expect smaller groups to contain the necessary expertise or experience. What do we need to enable this coming together and to achieve such integration? Well, there might be at least three requirements:

1. A change in mindset, that is, moving away from demonstrating mainly a particular model or method, towards understanding how much can be contributed to the overarching picture.
2. Digital platforms that enable integration of observational datasets, model outputs, and current understanding (sometimes called soft data). Importantly, not just a static data repository but as an evolving knowledge hub.
3. Protocols in which we define harmonisation of (soft and hard) data, so that different datasets can be combined and compared, as well as new ways to perpetuate current understanding and address knowledge gaps.

Following this route, we see significant opportunity not just for advancing our scientific understanding of LSWS dynamics, but also to achieve a step-change in practical and operational applications of these new observations, models and insights.

Author Contributions

All authors contributed to writing the text. Lisa Angermann designed the illustrations with other authors contributing to their concepts.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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