Field-scale soil moisture over Hungary under non-stationary drought transfer: a unified account across surface, region, and depth

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Synthesis / overview. This EarthArXiv preprint integrates and establishes the author's priority over three component studies of one field-scale soil-moisture research program over Hungary: a national surface-SSM benchmark (Fehér 2026a, in preparation), a controlled five-region regionalization and dominant-process analysis (Fehér 2026b, submitted), and a depth-resolved observability study (Fehér 2026c, submitted). It states each component result once, cites the detailed sources for full methods and numbers, and develops the cross-cutting laws that unify them. No new simulations were run for this synthesis.

Abstract

Three questions decide whether a satellite-driven soil-moisture estimator is fit for operational drought monitoring over a heterogeneous country: how accurately can the surface layer be recovered, whether the controlling processes differ across the landscape, and how far the surface signal reaches into the profile that actually matters for plants and recharge. The program began with a national surface-moisture benchmark over the 133-station Hungarian OVF *Aszálymonitoring* network and grew from there into a regional and a depth-resolved study; all three fuse Sentinel-1 C-band SAR, harmonized Landsat/Sentinel-2 (HLS) optical data, and a rich ancillary covariate set, evaluated under a single strict protocol that withholds the 2025–2026 drought years for inter-annual transfer. The three component studies map three orthogonal axes. On the horizontal accuracy axis, a tuned gradient-boosted tree ensemble (XGBoost) was the most accurate model for 10-cm surface moisture (RMSE 0.0478 $m^3\ m^{-3}$, R^2 0.735), beating nine deep-learning architectures and the most seed-stable of all. On the spatial-structure axis, the single national model was the best estimator in every one of five contrasting regions – region-specific retraining never lowered error (pooled regionalization gain −0.0019 $m^3\ m^{-3}$) – yet each region carried a distinct dominant control, with selective state-space (Mamba) rewarded by local training only in the recharge-memory Nyírség and a recurrent gate (LSTM) only in the seasonal-memory Tikevir. On the vertical-observability axis, the surface-coupled signal decayed monotonically with depth to an empirical decoupling crossover near 30 cm, governed by a storage-deficit-gated wetting front (≈10 cm penetration per 15–20 mm of rain; ≥45 cm reached in only ~20% of events) rather than static texture (R^2 0.04), and the trees-win result extended down the full profile against a fairly tuned modern deep benchmark. Two laws unify the program: gradient-boosted trees beat deep learning under non-stationary drought transfer because the task is extrapolation, not interpolation; and a single broad-network model is the deployable choice (data synergy) even though the underlying processes differ by region and decay with depth. Remote sensing was redundant given the covariate-rich setting. The three axes together map the full field-scale soil-moisture problem.

Keywords: field-scale soil moisture; Sentinel-1 C-band SAR; temporal transfer; gradient-boosted trees; deep learning; data synergy; dominant processes; vertical observability; relative wetness; Hungary.

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1. Introduction

Soil moisture controls the partitioning of water and energy at the land surface and governs drought onset, plant water stress, and groundwater recharge. For agricultural water management the relevant scale is the field or management zone – tens of metres – and the relevant regime is precisely the dry, anomalous years when the information is most needed. Coarse passive-microwave products (SMAP, SMOS) sample frequently but at tens of kilometres, too coarse for within-field decisions, which motivates finer-resolution Sentinel-1 C-band SAR fused with optical and ancillary data through machine learning. Over the past decade this fusion-plus-learning recipe has matured, but most of the supporting evidence comes from small, homogeneous, densely instrumented experimental sites evaluated by random or interpolating splits. Whether the reported advantages – especially of sequence-aware deep learning – survive transfer to a large heterogeneous domain under a genuine climatic shift has not been established, and three further questions had been left unjoined.

This program began with a single study, and the rest grew out of it: a national surface-soil-moisture benchmark over the 133-station network (Fehér 2026a) is the point of origin. Its motivating question was one of **horizontal accuracy** – over a heterogeneous national domain evaluated under transfer to recent drought years, which model class actually recovers surface moisture most accurately and most reliably? Two findings from that benchmark then set the agenda for everything that followed: under the drought transfer, gradient-boosted trees beat a family of sequence-aware deep-learning models, and static between-site heterogeneity dominated the error budget. Each finding raised a question the original study could not answer.

First, if static heterogeneity dominates the error budget, are different parts of that heterogeneous domain governed by different dominant processes – and does training a model per region buy any accuracy? This is the **spatial-structure** question, and it touches two literatures that appear to conflict: the data-synergy tradition in large-sample hydrological learning, where a single model pooled over many sites beats locally calibrated ones (Kratzert et al. 2019; Fang & Shen 2022), against the dominant-processes / catchment-similarity tradition, which holds that different controls dominate in different places and models should be matched to them (Grayson & Blöschl 2000; Wagener et al. 2007). Second, because the benchmark – like the satellite it fuses – saw only the top few centimetres (Babaeian et al. 2019), how far does the surface signal it recovers actually propagate down a coupled soil column into the root zone that matters for drought and recharge (Vereecken et al. 2008) before the deep layers decouple and follow their own slow dynamics? This is the **vertical-observability** question. The three studies are therefore not parallel but genealogical: one origin – the national benchmark – and the two branches its findings generated.

Pursued one at a time, these branches left the structure they share invisible. The gap this paper closes is the unification: one network, one strict 2025–2026 drought-transfer protocol, one covariate set, and three axes that are genealogical in origin yet orthogonal in design – horizontal accuracy, spatial structure, vertical observability – read together so that the recurring laws beneath them become visible. I treat the three component studies as the detailed sources of record (Fehér 2026a, 2026b, 2026c) and develop here the synthesis they jointly support. The organizing claim, made explicit in Section 3, is that the same two laws govern all three axes.

The study domain is the OVF *Aszálymonitoring* network, Hungary's operational drought and water-scarcity monitoring system: 133 stations distributed nationally, each carrying locally calibrated FDR capacitance probes at 10, 20, 30, 45, 60, and 75 cm. The window is January 2020 – June 2026, all seasons; the pronounced-drought years 2025–2026 are withheld entirely as the external transfer test, with hyperparameters tuned by forward-chaining temporal cross-validation on 2022/2023/2024. The domain spans a deliberate gradient – from the depleting sandy Danube–Tisza Sand Ridge to clay-dominated lowlands – and sits within a documented multi-decadal decline of groundwater reserves across the Alföld, the regime the hold-out years sharpen.

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2. The three axes

Each axis is the contribution of one component study. To avoid redundancy, every result is stated once, on the axis where it is load-bearing, with the detailed source cited; the synthesis in Section 3 reads across them rather than repeating them.

2.1 The surface / horizontal-accuracy axis

The first study (Fehér 2026a) is a controlled twelve-model benchmark for 10-cm surface soil moisture (the shallowest probe, closest to the satellite-sensed layer) built on a time-aligned 95-feature dataset – Sentinel-1 σ^0 and dual-polarization descriptors, HLS optical bands and indices interpolated to radar overpass times, DEM-5 terrain attributes, static soil texture and properties, meteorology with antecedent-precipitation aggregates over 1–30-day windows, groundwater dynamics, and irregular-time encoding – yielding 46,366 samples. Nine deep-learning architectures (base LSTM and TCN; their feature-, temporal-, and joint feature–temporal-attention variants; and a contemporary selective state-space Mamba model) were compared against three classical baselines (Random Forest, XGBoost, SVR) under one identical protocol.

The headline is a clean inversion of the expected deep-learning advantage. Under transfer to the withheld 2025–2026 drought years, the gradient-boosted tree ensemble was the most accurate model: **XGBoost reached RMSE 0.0478 $m^3\ m^{-3}$, MAE 0.0354, R^2 0.735, KGE 0.834**, with Random Forest a close second (RMSE 0.0485, R^2 0.727). The best deep model, an attention-augmented temporal convolution (FTA-TCN), ranked only third (RMSE 0.0521, R^2 0.685), and even the modern Mamba state-space model ranked fifth (RMSE 0.0555). The advantage was not a lucky configuration: across five random seeds the tree ensembles were the two most accurate models at every seed with negligible variance (SD ≤ 0.0002 $m^3\ m^{-3}$), whereas the strongest single-seed deep model proved seed-sensitive – its third place did not survive re-seeding. The ranking held under the Kling–Gupta efficiency and under a leave-stations-out spatial protocol, where the tree advantage widened rather than closed. Feature attribution located the reason: static between-site heterogeneity – topography (23.7%) and meteorology (23.1%), with satellite features at 21.1% – dominated the cross-site error budget, while the deep models' attention emphasized antecedent precipitation as the within-site temporal driver. The cross-site signal is a static, interaction-rich tabular mapping, the regime in which gradient-boosted trees excel. This axis fixes *which model family to trust as the instrument* and *how accurate the surface layer can be*; it is the accuracy anchor for the other two axes.

2.2 The regional / spatial-structure axis

The second study (Fehér 2026b) holds the model family and accuracy fixed and asks a structural question across five contrasting regions of the same network: the sandy Homokhátság (43 wells), the heavy-clay Körös–Maros Interfluve (18), the rechargefavoured sandy Nyírség (16), the seasonal-memory Tikevir Tisza-valley lowland (10), and the small lőss/szikes Hajdúság–Hortobágy network (5, transfer-evaluation only). The protocol is strictly controlled and inference-only: each already-trained model is scored on the identical region's 2025–2026 rows with its own training-region scaler, so any difference reflects the training set, not the test sample.

The first finding is that **region-specific training buys nothing**. The single national model was the best estimator in every region: the national XGBoost reached RMSE 0.0422, 0.0498, 0.0520, and 0.0496 $m^3 m^{-3}$ in Homokhátság, Körös–Maros, Nyírség, and Tikevir, and 0.0477 on the entirely unseen Hahó network – in each case at least as good as that region's own region-trained best model. The XGBoost regionalization gain was ≤ 0 in all four trainable regions; a station-paired bootstrap pooled over the 86 stations put the gain at **−0.0019 $m^3 m^{-3}$ (95% CI [−0.0040, +0.0003])**, with the national model at least as accurate in ~95% of resamples. Transferability tracked **donor breadth, not texture similarity**: the pooled national source transferred well everywhere, small-region sources transferred poorly (a Tikevir-trained model degraded to RMSE 0.153 on Homokhátság), and sand-to-sand transfer (Homokhátság→Nyírség, 0.0751) was no easier than sand-to-clay (Homokhátság→Körös–Maros, 0.0674).

The second finding is that "global wins" does **not** mean the regions are the same. When deep models were forced to learn temporal structure rather than read engineered antecedent-precipitation features, exactly one architecture was rewarded by local training in exactly one region: **selective state-space Mamba only in the recharge-buffered Nyírség (+0.0096 $m^3 m^{-3}$)** and negative elsewhere, and a **recurrent LSTM gate only in the seasonal-memory Tikevir (+0.0087)**, where Mamba's long memory hurts. The two static-texture regions were dominated by their per-station structure – Homokhátság by soil texture (permutation share 0.68), Körös–Maros by a groundwater-anomaly-stressed water balance (the strongest groundwater residual association of any region). The per-region controllers are therefore distinct and physics-consistent: static soil texture, static groundwater-stressed balance, long recharge memory, and short seasonal memory. This axis establishes that the spatial structure of the problem is real and classifiable even though it does not change the deployment recommendation.

2.3 The depth / vertical-observability axis

The third study (Fehér 2026c) reframes surface-to-root-zone estimation as a question of physical observability and treats the six FDR depths (10–75 cm) as one hydraulically coupled column under the same drought-transfer protocol. The central data-driven observation is a **monotonic decay of the surface-coupled, satellite-observable signal with depth**: over 10→75 cm the seasonal amplitude fell from 4.15 to 2.80, the lag-1 autocorrelation rose from 0.89 to 0.96 (deeper layers grow smoother and more memory-dominated), and the correlation with 30-day antecedent precipitation fell from +0.18 to +0.08. The empirical decoupling crossover – the shallowest depth where a learned model stops being beaten by the operational filter – sits at a gradual national median near **30 cm**.

The control is dynamic, not static. An event-scale analysis of **13,733 rainfall events** identified a **storage-deficit-gated wetting front**: penetration of ≈10 cm per 15–20 mm of rain, with ≥45 cm reached in only ~20% of events, a layer responding two-to-four times more often when rain exceeded the unfilled capacity above it. No static property predicted the between-site decoupling depth (texture $R^2 = 0.04$, not significant; groundwater only a weak, non-replicating signal), so the decoupling is best read as an event-driven regime change set by the time-varying soil-water state. A process-constrained differentiable-Richards model – an input-dependent, per-depth generalization of the operational Exponential-Filter / Soil Water Index – beat that filter floor at every depth (mean ubRMSE 0.0516 $m^3 m^{-3}$ over 20–75 cm), with its margin widening with depth, where the single-timescale filter loses its grip.

Crucially, the surface trees-win result **extended down the full profile** against a deliberately strong, fairly tuned deep benchmark. A gradient-boosted tree family (LightGBM and XGBoost, statistically indistinguishable at ≈ 0.047 $m^3 m^{-3}$ mean ubRMSE) beat every deep model: the strongest deep models formed a tight, statistically tied cluster – **Informer 0.0512, differentiable-Richards 0.0516, Entity-Aware LSTM 0.0517** – with the feature-attention FA-LSTM (0.0557), Mamba (0.0546), the FT-Transformer (0.0573), and the forecasting-oriented iTransformer (0.0923) further back, all trailing the trees by a station-paired-bootstrap-significant margin (the gap widened to ≈ 0.19 in the scale-free anomaly correlation). The Entity-Aware LSTM – the canonical large-sample hydrological architecture and the literature's winning data-synergy recipe, fed raw daily forcings plus static attributes – was the KGE-leading deep model yet still lost to the trees on ubRMSE under the drought transfer. Finally, per-prediction SHAP attribution placed the **Sentinel-1 SAR contribution at 0.4–1.0% at every depth** (Sentinel-2 optical under 3%): given high-resolution soil maps, weather, and groundwater, the satellite channels added only noise-level skill – a real but directionally consistent spatial signal already absorbed by the covariates, not an absolute irrelevance. This axis measures *how far the observed signal reaches and what governs that reach*.

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3. Synthesis

Read together, the three axes are not three results but one structure seen from three sides. Two laws recur on every axis.

3.1 First law: trees beat deep learning under non-stationary transfer because the task is extrapolation

The same family – gradient-boosted trees – was the most accurate on all three axes: at the surface (XGBoost 0.0478 $m^3 m^{-3}$), across every region (national XGBoost best estimator everywhere), and down the full profile (LightGBM/XGBoost ≈ 0.047 ubRMSE at every depth). This was not a weak-baseline artifact. The deep field spanned the modern architecture classes – recurrent (LSTM, Entity-Aware LSTM), convolutional with attention (FTA-TCN), tabular-attention (FT-Transformer), multivariate-attention (iTransformer), long-sequence transformer (Informer), and selective state-space (Mamba) – each tuned at full budget under the identical protocol, with several reaching cross-validation fits competitive with the best models. They lost anyway, and the loss was seed-stable for the trees and seed-sensitive for the strongest deep models.

The mechanism is the evaluation regime, not the data domain. By holding out the 2025–2026 drought years, every axis poses a problem of **non-stationary extrapolation**, not interpolation: the test data leave the training support along the moisture axis (and, under leave-stations-out, along the spatial axis too). Trees and neural networks diverge precisely there. A piecewise-constant tree ensemble clamps every prediction to the range of leaf values seen in training and is robust by construction under distribution shift, whereas a rectified-linear network converges to linear behaviour along any direction that exits the training manifold and cannot reliably extrapolate a nonlinear target beyond it (Xu et al. 2021). This is consistent with the broader tabular-learning evidence that gradient-boosted trees remain hard to beat on heterogeneous tabular data even by purpose-built deep architectures (Grinsztajn et al. 2022), and specifically that they lead under *temporal* distribution shift – the closest published analogue to a drought hold-out (Rubachev et al. 2024). The one regime in which deep learning reliably wins in hydrology is the opposite of this one: large-sample, raw-forcing recurrent models that learn temporal memory directly and exploit data synergy across many diverse sites (Kratzert et al. 2019; Fang & Shen 2022). The depth axis tested exactly that architecture on its own terms – an Entity-Aware LSTM on raw forcings plus static attributes – and even it lost to the trees under transfer, which is the decisive evidence that the result is intrinsic to the non-stationary regime rather than a model-choice accident.

A subtlety sharpens rather than weakens the law. The accuracy ranking is metric-dependent at depth: clear on ubRMSE but narrow under KGE, where the EA-LSTM (0.812) is on par with the tree family, because KGE rewards the recurrent model's capture of temporal variability. And the trees win for a reason that is silent about dynamics – engineered antecedent-precipitation aggregates pre-bake temporal memory into tabular features, so the tree never learns a temporal kernel; the accuracy ranking and the process classification therefore live on different axes. That separation is what makes the second law possible.

3.2 Second law: one broad model is deployable (data synergy) while the processes differ by region and decay with depth

The second recurring law is that **a single broad-network model is the deployable choice, yet the structure beneath it is not uniform** – it varies across space and decays with depth. The regional axis shows the data-synergy half directly: pooling regularizes data-poor regions and borrows strength across the network, so the national model is the best estimator everywhere and region-specific retraining is, at best, a wash. The same axis shows the dominant-processes half: each region maps cleanly to a distinct controller, exposed only when the deep models are forced to learn temporal structure (Mamba rewarded only in the recharge region, LSTM only in the seasonal region). These are not in tension – "global wins" is a statement about the estimator, not a claim that the regions are hydrologically identical, exactly the resolution the large-sample literature anticipates (Kratzert et al. 2019; Wagener et al. 2007).

The depth axis is the same law rotated 90 degrees from horizontal to vertical. Where the regional axis shows structure varying *across space* beneath a globally optimal model, the depth axis shows structure varying *with depth*: the surface-forced, weather-driven signal that dominates at 10 cm (SHAP weather share 42%) gives way to a static-soil-governed, slow-storage regime at 75 cm (soil share 67%), with the surface-coupled signal decaying monotonically and the operational filter's predictive grip falling away past the ≈30-cm crossover. The deployable single model still wins on accuracy at every depth – coupling the column helps within the deep-learning family but never overturns the trees – yet the *process* it is fitting changes character down the profile, just as it changes across regions. Data synergy (one model wins) and structured heterogeneity (processes differ by place and by depth) hold simultaneously on both the spatial and the vertical axis.

3.3 The orthogonality of the three axes, and the remote-sensing redundancy theme

The three axes are orthogonal: each isolates one dimension of the problem while holding the others fixed. The surface axis varies the model class at fixed (surface) depth and pooled (national) extent. The regional axis varies the spatial extent at fixed depth and fixed model family. The depth axis varies the vertical position at fixed extent and fixed (transfer) regime. Because they share the network, the protocol, and the covariate set, a result on one axis transfers cleanly as a fixed premise to the others – the surface axis hands the regional and depth axes their model family; the regional axis hands the depth axis the motivation that the distinguishing processes (recharge memory, groundwater stress) live deeper than the satellite can see; the depth axis confirms that the trees-win and data-synergy laws are not surface artifacts. Together they span the field-scale soil-moisture estimation problem: how accurate (horizontal), where it differs (spatial), and how deep it reaches (vertical).

A single theme cuts across all three: **remote sensing is redundant given a covariate-rich setting**. On the surface axis, satellite features contributed a meaningful but non-dominant 21.1% of cross-site importance, secondary to terrain and soil. On the depth axis, the per-prediction SAR contribution was 0.4–1.0% at every depth, and a direct ablation showed that adding Sentinel-1/2 recovered only 0.0002 of the 0.0064 ubRMSE lost by removing the high-resolution soil maps – the satellite cannot substitute for the maps, and once they (plus weather and groundwater) are present, its channels are intrinsically redundant for this point-estimation task. This is a scoped claim, not a dismissal: the spatial-downscaling value of satellites is real and directionally consistent under leave-stations-out, and on stations dominated by unmodeled dynamic anomalies (irrigation, ponding, bypass flow) the satellite value is expected to be larger because those events leave a signature only a direct surface observation carries. In the covariate-rich, lightly irrigated retrospective regime studied here, however, the high-resolution soil maps already encode the sub-field heterogeneity that Sentinel-1/2 would otherwise resolve.

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4. Conclusions and outlook

One coherent field-scale soil-moisture program over Hungary, evaluated under a single strict 2025–2026 drought-transfer protocol, yields a unified picture along three orthogonal axes. **Horizontal accuracy:** a tuned gradient-boosted tree ensemble

(XGBoost, RMSE 0.0478 $m^3 m^{-3}$, R^2 0.735) is the most accurate and most seed-stable model for surface moisture, beating nine deep architectures. **Spatial structure:** the single national model is the best estimator in every one of five contrasting regions (regionalization gain ≤ 0; pooled −0.0019 $m^3 m^{-3}$), transferring by donor breadth not texture, even though each region carries a distinct, classifiable dominant control. **Vertical observability:** the surface-coupled signal decays monotonically to a ≈30-cm decoupling crossover governed by a storage-deficit-gated wetting front (not static texture, R^2 0.04), and the trees-win result extends down the full profile against a fairly tuned modern deep benchmark.

Two laws unify the program. First, gradient-boosted trees beat deep learning under non-stationary drought transfer because the task is extrapolation, not interpolation – trees clamp to the training range while ReLU networks run off-manifold (Xu et al. 2021; Grinsztajn et al. 2022; Rubachev et al. 2024) – a result that survived even giving deep learning its best hydrological architecture and the data-synergy recipe. Second, a single broad-network model is the deployable choice (data synergy; Kratzert et al. 2019; Fang & Shen 2022) while the underlying processes differ by region and decay with depth (dominant processes; Grayson & Blöschl 2000; Wagener et al. 2007). Across all three axes, Sentinel-1/2 added only noise-level skill once high-resolution soil maps, weather, and groundwater were present.

The operational recommendation is concrete: deploy the single national tree model for drought monitoring over any of these landscapes, and do not regionalize for accuracy. The scientific payoff is a map of where additional physics and additional depth will help. The per-region controllers and the depth-dependent observability decay point the same way – toward water stored below the satellite-observed skin (Babaeian et al. 2019; Vereecken et al. 2008), whose surface coupling is state-dependent rather than fixed. The event-driven decoupling carries a climate-vulnerability implication that ties the program together: deep recharge in these soils depends on winter and snowmelt water passing deep fronts, whereas summer convective rain is shallow-confined, so declining winter precipitation starves deep-soil and groundwater recharge – the very 2025–2026 depletion regime the hold-out years capture. Natural extensions are a mass-conserving finite-volume differentiable-Richards solver, process-aware estimators matched to each region's dominant control, spatial downscaling to unmonitored locations where the soil maps and satellites should finally earn their keep, and longer-wavelength (L-band) SAR for deeper sensitivity. The honest scope is that "trees win" is a verdict about this non-stationary, covariate-rich, tabular transfer regime, not a universal claim – and stating that scope is what makes the unifying laws defensible. The Area of Applicability framework (Meyer & Pebesma 2021) bounds where these verdicts hold; representativeness of point probes for field-scale pixels remains a structural validation limit throughout.

References

Component works (detailed sources of record for this synthesis):

- Fehér, Z.Z. (2026a). *Sequence-Aware Deep Learning and Classical Machine Learning for Field-Scale Surface Soil Moisture Estimation from Sentinel-1, HLS, and Ancillary Data over Hungary.* In preparation. (National surface-SSM benchmark over the OVF *Aszálymonitoring* network – the horizontal-accuracy axis.)
- Fehér, Z.Z. (2026b). *One National Model, Five Distinct Controls: Data Synergy Beats Regionalization yet Dominant Soil-Moisture Processes Differ Across Hungarian Landscapes.* Submitted. (Controlled five-region regionalization and dominant-process analysis – the spatial-structure axis.)
- Fehér, Z.Z. (2026c). *Observability Decay and a Storage-Deficit-Gated Limit on Surface-to-Root-Zone Soil-Moisture Propagation Across a National Network.* Submitted. (Depth-resolved coupled-profile observability study – the vertical-observability axis.)

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