https://doi.org/10.5194/egusphere-2026-4516
Preprint. Discussion started: 7 September 2026

Dynamic vegetation-soil-water feedbacks as an under-recognised source of structural uncertainty in digital soil mapping

Odunayo David Adeniyi[1,2,*], Yushu Xia[3], Calogero Schillaci[4], Jamal-Eddine Ouzemou[5,6], Fuat Kaya[7], Abdelhakim Amazirh[5,6], Michael Maerker[8,9,10]

1 Department of Civil and Environmental Engineering, Politecnico di Milano, Milan, Italy
2 CMCC Foundation, Euro-Mediterranean Centre on Climate Change, Viterbo, Italy
3 Lamont-Doherty Earth Observatory, Columbia University, USA
4 European Commission, Joint Research Centre, Ispra, Italy
5 Center for Remote Sensing Applications (CRSA), Mohammed VI Polytechnic University, Ben Guerir 43150, Morocco
6 College of Agriculture and Environmental Sciences, UM6P, Campus Ben Guerir 43150, Morocco
7 Department of Soil Science and Plant Nutrition, Faculty of Agriculture, Isparta University of Applied Sciences, 32260 Isparta, Türkiye
8 Department of Earth and Environmental Sciences, University of Pavia, Via Ferrata 1, 27100 Pavia, Italy
9 Leibniz Centre for Agricultural Landscape Research, Working Group on Soil Erosion and Feedback, Eberswalder Str. 84, 15374 Müncheberg, Germany
10 Consiglio Nazionale delle Ricerche, Institute for Georesources and Geodynamics, Via Ferrata 1, 27100 Pavia, Italy

[*]*Correspondence to*: Odunayo David Adeniyi (odunayodavid.adeniyi@polimi.it)

Abstract

Digital soil mapping (DSM) produces spatially continuous soil information for land-use planning, carbon accounting, and Earth system analysis, resting on the SCORPAN framework and its use of remote-sensing and terrain covariates as indicators of soil-forming processes. Similar approaches estimate ecological and hydrological conditions from vegetation, moisture, and climate data. Two assumptions receive little scrutiny: that soil-covariate relationships stay constant in space and time, and that covariates act as independent predictors. In reality vegetation, soil, and water form a coupled system in which each influences the others, and the strength and even the direction of these interactions vary across landscapes and shift over time. We argue that these dynamic relationships are an important but under-recognised source of structural uncertainty, distinct from the sampling, measurement, and model-fitting error usually partitioned in DSM. Drawing on wetlands, drylands, sloping farmland, burned watersheds, drought-affected forests, and thawing permafrost, we show how the feedbacks break the assumptions behind DSM, why the same problem affects land-surface, ecological, and hydrological models, and how mapping might be made feedback-aware.

Keywords: DSM; prediction uncertainty; ecohydrology; SCORPAN; non-stationarity; transferability; environmental modelling, endogeneity

1 Introduction

Soil information is increasingly needed at finer resolution for food production, carbon accounting, water management, and climate policy (Adhikari & Hartemink, 2016). Conventional surveys cannot meet this demand at scale, so digital soil mapping (DSM) predicts soil properties and classes from environmental covariates using geostatistics or machine learning. SCORPAN expresses soil as a function of other soil properties (s), climate (c), organisms (o), relief (r), parent material (p), age (a), and spatial position (n) (McBratney et al., 2003), represented through raster covariates for DSM. Global products such as SoilGrids now supply pixel-level uncertainty (Poggio et al., 2021), and reviews have consolidated modelling, validation, and uncertainty methods (Wadoux et al., 2020).

Two assumptions underpin routine DSM but are rarely stated. Covariates are usually static, single-date snapshots or long-term averages standing in for fixed soil-forming factors (Adeniyi et al., 2024; Hengl & MacMillan, 2019), describing present conditions but saying little about how they evolve (Xia et al., 2022); and the model is assumed stationary, letting relationships learned in well-sampled areas apply where data

https://doi.org/10.5194/egusphere-2026-4516
Preprint. Discussion started: 7 September 2026

are sparse. These choices make large-scale prediction possible and often work (Hengl et al., 2017), and recur in land-surface, ecological, and hydrological models built on comparable variables.

However, these assumptions sit uneasily with how soils form and evolve. Vegetation, soil, and water are coupled (Li et al., 2022): vegetation builds structure and organic matter and partitions water, soil texture and depth govern water supply, and the hydrological state of the surface, including its extremes, reshapes both (Huang et al., 2025; Jarvis et al., 2024). Ecohydrology and critical-zone science place soil moisture and the root-to-soil-to-rock interface at the centre of landscape evolution (Banwart et al., 2019; Brantley et al., 2017; Moore et al., 2015), and ecology frames the same dynamics as plant-soil feedback (Bardgett & van der Putten, 2014; van der Putten et al., 2013). This coupling is non-stationary: strength and sign differ among climates, soils, and hydrological settings and shift through the year and between years (Frouz, 2024; Pugnaire et al., 2019).

Studies of prediction uncertainty in digital soil mapping have advanced in quantifying and validating uncertainty (Schmidinger & Heuvelink, 2023), attributing it to covariates (Rohmer et al., 2024), comparing how approaches propagate it (Szatmári & Pásztor, 2025), and bounding where a model can be trusted (Meyer & Pebesma, 2021), but they usually trace it to sampling, model choice, or covariate selection. We instead focus on structural uncertainty: the error that arises when the assumed soil-covariate relationship does not match the real soil-vegetation-water system, because that relationship is dynamic and bidirectional rather than fixed. Distinct from the observational and model components already partitioned in DSM (Heuvelink, 2018), it is the least explored. Pedometricians quantify map error but rarely trace it to system dynamics, while ecohydrologists and ecologists describe the feedbacks but seldom follow them into mapping. One mechanism, we argue, underlies both non-stationarity and poor transfer, which these fields treat as separate problems.

2 The vegetation, soil, and water system as a coupled feedback network

We view vegetation, soil, and water as one system evolving through reciprocal feedbacks (Figure 1). Each pair affects the other in both directions, so a relationship in which vegetation predicts soil is only one part of a loop, and non-stationarity means the same predictor can represent different processes under different conditions. Structural uncertainty is the map error from treating these dynamic properties as static and stationary; unlike the usual modelling sense of the term, which concerns choice of algorithm or functional form, here the structure is the soil-forming system itself, so the error persists even with the correct functional form.

https://doi.org/10.5194/egusphere-2026-4516
Preprint. Discussion started: 7 September 2026

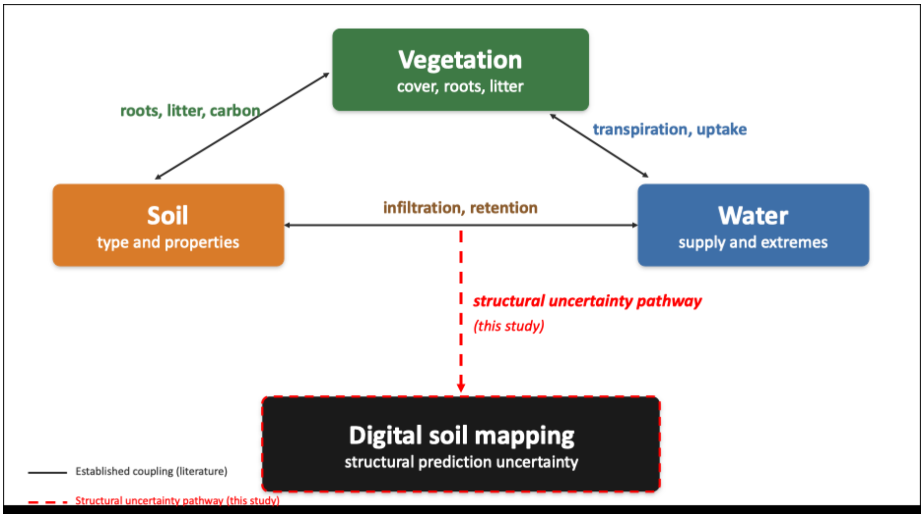

Figure 1. Conceptual model of the bidirectional vegetation, soil, and water feedback system and its propagation into structural uncertainty. Double-headed arrows denote reciprocal influence.

The couplings span scales, from the pore and root-to-soil interface to the region (Fatichi et al., 2016) and from daily leaf exchange to pedogenesis over centuries (Amundson et al., 2015), which is part of why single studies overlook them. They also cross thresholds and leave legacies that persist after the driver is gone (Scheffer et al., 2001): dryland runoff redistribution generates vegetation patterns that shift abruptly as aridity nears a threshold (Berdugo et al., 2020; Meron, 2012), and plant-soil feedbacks steer succession and invasion (Bennett & Klironomos, 2019). Relationships therefore depend on local history rather than a single transferable function.

SCORPAN writes soil as $S = f(s, c, o, r, p, a, n) + e$, usually fitted as $S = f(x) + e$ assuming exogenous predictors, yet several informative covariates are states of the same system. Writing vegetation and hydrological covariates as V and W, Section 3 implies $V = g(S, W, t)$ and $W = h(S, V, t)$, so $x = x(S, t)$ and the fitted relationship becomes implicit, $S = f(x(S, t)) + e$, with no single stationary solution. We call this endogeneity, in a predictive rather than causal-inference sense (Trachsel & Telford, 2016). An endogenous model can pass random cross-validation yet degrade under transfer where the feedback state differs, since applicability diagnostics flag novel predictor values but not shifts in predictor-response relationships (Dutschmann et al., 2024). Such covariates transfer well where feedback regimes are stable, but where strength varies, in-sample accuracy overstates transferability; legacy soil-class maps used as covariates carry the same problem. Endogeneity is the mechanism behind non-stationarity.

3 Evidence for the feedbacks

Vegetation drives soil and water through litter, roots, canopy, and microbes, building structure, adding organic matter, and setting infiltration (Bardgett & van der Putten, 2014; Zhu et al., 2022). Ecology frames this as plant-soil feedback, in which soil communities are themselves partly independent drivers of function (Delgado-Baquerizo et al., 2016, 2018); plants can alter later growth by over a third through the soils they create (Grenzer et al., 2021). Organic-matter inputs, whose quantity and quality depend on vegetation type, set soil carbon (Cotrufo et al., 2015), and vegetation, productivity, and water depth control carbon in coastal and karst wetlands (Guo et al., 2025; Y. Wang et al., 2025). The sign is context-dependent: afforestation

https://doi.org/10.5194/egusphere-2026-4516
Preprint. Discussion started: 7 September 2026

carbon change depends on slope, prior cover, and initial stocks, reversing between carbon-poor and carbon-rich grasslands (Berthrong et al., 2012; Hou et al., 2020). Roots regulate infiltration non-monotonically, organic matter raising it while fine roots clog pores (Rong et al., 2025), and crusts govern infiltration and runoff in drylands (Cantón et al., 2020).

Soil drives vegetation and water in return: texture and depth set plant-available water and the vegetation a site supports. Greenness, rainfall, and soil moisture covaried with soil type in Botswana (Nicholson & Farrar, 1994), and phenology metrics improved soil prediction alongside parent material and topography (Araya et al., 2016; Avalos et al., 2024). Drought-mortality studies point to water-holding capacity, storage, and depth as dominant controls (Cholet et al., 2022; Oucheikh et al., 2025; Stovall et al., 2019), nonlinearly, with mortality low until about half the extractable water is gone (Meir et al., 2015). The coupling runs both ways: adding soil layers cuts soil-moisture modelling error by about a quarter (Fatholoumi & Biswas, 2026), while dryland vegetation has shifted toward deeper water (Liu et al., 2025).

Water and its extremes drive both: drought, flood, waterlogging, and fire reshape vegetation and soil, often abruptly (Adeniyi & Balzarolo, 2026; Cheng et al., 2026; L. Wang et al., 2012). Water level outweighed vegetation type for carbon and microbes in Poyang Lake wetland (Ren et al., 2022), with dry and saturated extremes promoting carbon loss and intermediate moisture favouring storage (Enebe et al., 2025; Hao et al., 2025), while erosion shifts Mollisol infiltration toward preferential flow (Y. Zhang et al., 2025). Fire volatilises organic compounds into a water-repellent layer that sharply cuts infiltration and raises runoff, recovering only with depth, time, and returning vegetation (DeBano, 2000; Gabarrón-Galeote et al., 2013; Hubbert et al., 2012). Thawing permafrost is the sharpest case: thermokarst subsidence alters the water balance over metres and mobilises frozen carbon (Lathrop et al., 2025; Wright et al., 2022).

Three properties recur across these legs, each breaking smooth, reversible mapping: thresholds, where small predictor changes near tipping points give large responses; legacies, where present covariates reflect past states, as with post-fire repellency suppressing establishment; and hysteresis, where recovery follows a different path from degradation, since permafrost and eroded profiles do not simply revert. The relationship between covariates and soil is therefore history-dependent and locally contingent rather than universally transferable.

4 Consequences for digital soil mapping

SCORPAN itself does not require static or independent proxies; practice settled on both largely because consistent time-series were scarce. Vegetation-to-soil and soil-to-water relationships differ by climate, soil, slope, and hydrological state, and can reverse sign (Kim et al., 2017; Troch et al., 2013; Yetemen et al., 2010). A stationary model fitted across that variation captures an average that is locally wrong, and because these departures track soil, vegetation, and landform, the error is spatially structured, leading to the most consequential kind for a map. Local-coefficient methods respond in part, fitting a relationship per location or separating fixed from spatially varying effects (C. Zhang et al., 2011; Zeng et al., 2016), but treat non-stationarity as spatial when the feedbacks are also temporal. Transferability work is the closest precedent, motivating the area of applicability (Ludwig et al., 2023) and showing that soil-to-environment relationships grow erratic through time as covariates drift (T. Zhang et al., 2024); validation should therefore test transfer across space and time, not average accuracy alone.

Operational covariates are single-date or long-term-average layers, spatial gradients standing in for temporal dynamics. Vegetation status changes seasonally and is obscured by cloud, so dense fused imagery

https://doi.org/10.5194/egusphere-2026-4516
Preprint. Discussion started: 7 September 2026

improves class separability over a few clear scenes (H. Yang et al., 2023; Schillaci et al., 2017), and phenology and time-series covariates, including Fourier harmonics and the bare-soil window, improve carbon mapping (Bueno et al., 2025; L. Yang et al., 2020). Space-and-time DSM now maps soil change at continental scale (Heuvelink et al., 2021; C. Yang et al., 2025), exposing that a model can predict the soil state accurately yet its temporal trend poorly (Broeg et al., 2024).

Covariates are also entangled: a vegetation index partly encodes the soil's water supply, and soil moisture partly reflects the vegetation that transpires it (Pradhan, 2019), so the covariates driving the best estimate need not drive its uncertainty (Rohmer et al., 2024). Topography and near-surface hydrology redistribute water and set feedback direction (Gnann et al., 2025); in discontinuous permafrost, snow and water content controlled the thermal regime more than a 140 km air-temperature gradient, shifting estimated carbon uptake by about 60 percent (Shirley et al., 2022); parent material stays among the top covariates even as vegetation dynamics are added (Avalos et al., 2024); and land-use change resets feedbacks directly (Deng et al., 2014; Gentine et al., 2012). Hydromorphic, transitional, data-scarce, and steep or contrasting-substrate zones are already flagged as high-uncertainty (Alencar Sobrinho et al., 2026); we add that non-stationarity is greatest where feedbacks are strong.

This error survives perfect data and any algorithm, hence a distinct class (Table 1). Misspecification assumes one true relationship approximated imperfectly, but here none exists: the relationship is a function of system state at each location and time, so a flexible learner fits realised states without recovering one that is undefined out of sample. Probabilistic predictions should therefore be checked for reliability and sharpness, since a map can be accurate on average yet over- or under-confident where feedbacks are strong, and direct and indirect mapping propagate uncertainty differently where covariates are entangled (Szatmári & Pásztor, 2025). Since end-users differ in how they want uncertainty represented (Courteille et al., 2025), a map confidently wrong in a predictable zone is riskier than one uniformly uncertain, which is a failure standard cross-validation conceals when validation points share the training feedback state.

Table 1. Sources of prediction uncertainty in digital soil mapping, with the proposed structural (feedback) class. The final row is the contribution of this paper.

Component	Origin	Recognised in DSM?	Relation to feedback-driven uncertainty
Attribute	Measurement and laboratory error in soil observations	Yes	Independent of covariate dynamics
Covariate (input)	Error and selection in predictor layers	Yes	Treats covariates as fixed, possibly noisy inputs
Model (structure)	Algorithm and functional-form misspecification	Yes	Assumes one true relationship exists to approximate
Positional / support	Location error, scale, and support mismatch	Yes	Geometric, not relational
Structural (feedback / endogeneity)	Predictor is an outcome of the target system, so the relationship is bidirectional and non-stationary	Not as a named class	Proposed here; persists with perfect data and algorithm; produces spatially structured residuals

5 Beyond soil mapping: a shared challenge for environmental modelling

Many environmental sciences share these assumptions, predicting targets from vegetation, moisture, climate, and terrain, so the same uncertainty appears wherever predictors are products of the coupled system (Table 2). Land-surface and Earth-system models prescribe soil and vegetation parameters as coarse and

https://doi.org/10.5194/egusphere-2026-4516
Preprint. Discussion started: 7 September 2026

constant (Raoult et al., 2025), yet subgrid heterogeneity, unmodelled subsidence in thawing landscapes, and soil-moisture and vegetation feedbacks each shift estimated land-carbon exchange substantially (Humphrey et al., 2021; Rodenhizer et al., 2023; Shirley et al., 2022). Ecological-niche and species-distribution models face the problem sharply when projecting fitted relationships to new regions and climates (Ludwig et al., 2023; Thuiller, 2024), since plant-soil feedback shows those relationships are not fixed (van der Putten et al., 2013). Hydrological models derive soil hydraulic properties as static pedotransfer parameters (Verhoef et al., 2026), though infiltration swings with roots, fire, and erosion within a season, and reusing DSM layers for soil moisture brings both promise and circularity (Fathololoumi & Biswas, 2026).

Table 2. The same feedback-driven endogeneity across model families that share vegetation, soil, and water predictors.

Model family	Shared predictor	How endogeneity manifests	Mitigation
DSM / pedometrics	Vegetation indices, soil moisture	Greenness encodes the soil's own water supply; structured map residual	Temporal covariates, non-stationary models
Land-surface / Earth-system	Prescribed soil and vegetation parameters	Subgrid feedback heterogeneity averaged away; biased budgets	Dynamic subgrid representation
Ecological / species distribution	Soil, vegetation, and climate layers	Plant-soil feedback alters the fitted niche; poor transfer	Feedback-aware transferability limits
Hydrological	Texture-derived hydraulic properties	Infiltration shifts with roots, fire, and erosion; static parameters miss seasonal swings	State-dependent, time-varying parameters

Four testable predictions follow. Residuals of a static model should carry spatial structure tied to feedback-strength indicators such as phenological variance and disturbance recency; temporal-transfer error should scale with covariate drift; stratifying by feedback regime should cut the structured residual more than adding static covariates; and covariate importance should be unstable in non-stationary zones. Testing whether the residuals of a static organic-carbon model organise along feedback proxies would turn this synthesis into evidence.

6 Toward feedback-aware mapping and modelling

Replacing single-date layers with time series and phenological metrics addresses the snapshot problem, and spatiotemporal fusion helps where clear scenes are scarce (H. Yang et al., 2023); frameworks such as STEP-AWBH treat the seasonal trajectory as signal (Grunwald et al., 2011), the practical step being to select informative windows such as the bare-soil period. Where the relationship varies in space and time, geographically and temporally weighted approaches (Zeng et al., 2016), models stratified by soil-landscape unit, and hybrids that inject process-model output as covariates all let the fitted function vary. Uncertainty work should separate the structural component from sampling and model terms, report the area of applicability, and draw more on attribution methods, still underused in pedometrics, that separate the drivers of an estimate from its uncertainty (Rohmer et al., 2024). Since the error is spatially organised, sampling can be directed by proxies for feedback strength such as hydrological position, phenological variability, and recent disturbance (Hu et al., 2022; Schweiger et al., 2026), and repeated monitoring at fixed sites constrains the temporal signal that snapshot campaigns miss.

7 Conclusion

DSM has become a rigorous, uncertainty-aware discipline, yet its soil-forming factors stay largely static and its models largely stationary. Evidence from wetlands and afforested slopes to drought-stricken and burned forests and thawing permafrost shows vegetation, soil, and water as a reciprocal, locally contingent, time-varying system whose effects shift with setting, cross thresholds, leave legacies, and sometimes reverse sign. This introduces structural uncertainty intrinsic to the system's encoding, which no added sample or better algorithm removes. Our contribution is to tie a mechanistic reason for shifting covariate-to-soil relationships to a structural error class, distinct from sampling and model error, to show the same logic across model families that share these layers, and to offer a covariate-level diagnostic for sampling and reporting.

Code availability

This work did not develop new code.

Data availability

This work did not generate new data. No new data were created during this study.

Author contribution

ODA conceptualised the perspective and prepared the manuscript with contributions from all co-authors. All authors discussed the synthesis and approved the final manuscript.

Competing interests

The authors declare that they have no conflict of interest.

Acknowledgements

The authors gratefully acknowledge the support of the CMCC Foundation – Euro-Mediterranean Centre on Climate Change and the Department of Civil and Environmental Engineering, Politecnico di Milano, where this work was conducted.

Financial support

This research received no external funding.

References

Adeniyi, O. D. and Balzarolo, M.: Drought influence on carbon assimilation and water use efficiency in Mediterranean ecosystems, Scientific Reports, https://doi.org/10.1038/s41598-026-54809-1, 2026.

Adeniyi, O. D., Bature, H., and Maerker, M.: A Systematic Review on Digital Soil Mapping Approaches in Lowland Areas, Land, 13, 379, https://doi.org/10.3390/land13030379, 2024.

Adhikari, K. and Hartemink, A. E.: Linking soils to ecosystem services - A global review, Geoderma, 262, 101–111, https://doi.org/10.1016/j.geoderma.2015.08.009, 2016.

https://doi.org/10.5194/egusphere-2026-4516
Preprint. Discussion started: 7 September 2026

Alencar Sobrinho, R. J., da Silva, J. O., Santos, L. da S., Farias, F. do C., Lima, A. N. R., Nakakoji, N. K. N., Teixeira, D. D. B., Tavares, R. L. M., Pereira, G. T., Pinheiro, D. P., and Silva-Júnior, J. F. da.: Integrating Tacit Knowledge and AI for Digital Soil Mapping in Eastern Amazonia: Ensemble Learning, Model Performance, and Uncertainty Incorporation, Soil Systems, 10, 41, https://doi.org/10.3390/soilsystems10030041, 2026.

Amundson, R., Berhe, A. A., Hopmans, J. W., Olson, C., Sztein, A. E., and Sparks, D. L.: Soil and human security in the 21st century, Science, 348, https://doi.org/10.1126/science.1261071, 2015.

Araya, S., Lyle, G., Lewis, M., and Ostendorf, B.: Phenologic metrics derived from MODIS NDVI as indicators for Plant Available Water-holding Capacity, Ecological Indicators, 60, 1263–1272, https://doi.org/10.1016/j.ecolind.2015.09.012, 2016.

Avalos, F. A. P., de Menezes, M. D., Acerbi Júnior, F. W., Curi, N., Avanzi, J. C., and Silva, M. L. N.: Evaluation of Synthetic-Temporal Imagery as an Environmental Covariate for Digital Soil Mapping: A Case Study in Soils under Tropical Pastures, Resources, 13, 32, https://doi.org/10.3390/resources13020032, 2024.

Banwart, S. A., Nikolaidis, N. P., Zhu, Y.-G., Peacock, C. L., and Sparks, D. L.: Soil functions: connecting Earth's critical zone, Annu. Rev. Earth Planet. Sci., 47, 333–359, https://doi.org/10.1146/annurev-earth-063016-020544, 2019.

Bardgett, R. D. and van der Putten, W. H.: Belowground biodiversity and ecosystem functioning, Nature, 515, 505–511, https://doi.org/10.1038/nature13855, 2014.

Bennett, J. A. and Klironomos, J.: Mechanisms of plant–soil feedback: interactions among biotic and abiotic drivers, New Phytologist, 222, 91–96, https://doi.org/10.1111/nph.15603, 2019.

Berdugo, M., Delgado-Baquerizo, M., Soliveres, S., Hernández-Clemente, R., Zhao, Y., Gaitán, J. J., Gross, N., Saiz, H., Maire, V., Lehmann, A., Rillig, M. C., Solé, R. V., and Maestre, F. T.: Global ecosystem thresholds driven by aridity, Science, 367, 787–790, https://doi.org/10.1126/science.aay5958, 2020.

Berthrong, S. T., Piñeiro, G., Jobbágy, E. G., and Jackson, R. B.: Soil C and N changes with afforestation of grasslands across gradients of precipitation and plantation age, Ecological Applications, 22, 76–86, https://doi.org/10.1890/10-2210.1, 2012.

Broeg, T., Don, A., Wiesmeier, M., Scholten, T., and Erasmi, S.: Spatiotemporal Monitoring of Cropland Soil Organic Carbon Changes From Space, Global Change Biology, 30, https://doi.org/10.1111/gcb.17608, 2024.

Brantley, S. L., Eissenstat, D. M., Marshall, J. A., Godsey, S. E., Balogh-Brunstad, Z., Karwan, D. L., Papuga, S. A., Roering, J., Dawson, T. E., Evaristo, J., Chadwick, O., McDonnell, J. J., and Weathers, K. C.: Reviews and syntheses: on the roles trees play in building and plumbing the critical zone, Biogeosciences, 14, 5115–5142, https://doi.org/10.5194/bg-14-5115-2017, 2017.

Bueno, M., Loayza, H., Ninanya, J., Rinza, J., Briceño, P., Silva, L., Mestanza, C., Otiniano, R., Kreuze, J., and Ramírez, D. A.: Can a history of crop rotations improve the prediction of soil organic carbon in the Andes? integrating machine learning multi-annual crop classification as a proxy of soil management, bioRxiv [preprint], https://doi.org/10.64898/2025.12.06.692759, 2025.

Cantón, Y., Chamizo, S., Rodriguez-Caballero, E., Lázaro, R., Roncero-Ramos, B., Román, J. R., and Solé-Benet, A.: Water Regulation in Cyanobacterial Biocrusts from Drylands: Negative Impacts of Anthropogenic Disturbance, Water, 12, 720, https://doi.org/10.3390/w12030720, 2020.

Cheng, X., Zhan, C., De Kauwe, M. G., Hildebrandt, A., and Orth, R.: Global vegetation responses to wet and dry soil moisture extremes, EGUsphere [preprint], https://doi.org/10.5194/egusphere-2026-1199, 2026.

Cholet, C., Houle, D., Sylvain, J.-D., Doyon, F., and Maheu, A.: Climate Change Increases the Severity and Duration of Soil Water Stress in the Temperate Forest of Eastern North America, Frontiers in Forests and Global Change, 5, https://doi.org/10.3389/ffgc.2022.879382, 2022.

Cotrufo, M. F., Soong, J. L., Horton, A. J., Campbell, E. E., Haddix, M. L., Wall, D. H., and Parton, W. J.: Formation of soil organic matter via biochemical and physical pathways of litter mass loss, Nature Geoscience, 8, 776–779, https://doi.org/10.1038/ngeo2520, 2015.

Courteille, L., Tardieu, L., Boukhelifa, N., Lutton, E., and Lagacherie, P.: What is the best way to communicate the uncertainty of a digital soil mapping product? Some lessons from an end-users survey, Geoderma, 459, 117302, https://doi.org/10.1016/j.geoderma.2025.117302, 2025.

DeBano, L. F.: The role of fire and soil heating on water repellency in wildland environments: a review, Journal of Hydrology, 231–232, 195–206, https://doi.org/10.1016/S0022-1694(00)00194-3, 2000.

Delgado-Baquerizo, M., Maestre, F. T., Reich, P. B., Jeffries, T. C., Gaitan, J. J., Encinar, D., Berdugo, M., Campbell, C. D., and Singh, B. K.: Microbial diversity drives multifunctionality in terrestrial ecosystems, Nat. Commun., 7, 10541, https://doi.org/10.1038/ncomms10541, 2016.

https://doi.org/10.5194/egusphere-2026-4516
Preprint. Discussion started: 7 September 2026

Delgado-Baquerizo, M., Oliverio, A. M., Brewer, T. E., Benavent-González, A., Eldridge, D. J., Bardgett, R. D., Maestre, F. T., Singh, B. K., and Fierer, N.: A global atlas of the dominant bacteria found in soil, Science, 359, 320–325, https://doi.org/10.1126/science.aap9516, 2018.

Deng, L., Shangguan, Z., and Sweeney, S.: "Grain for Green" driven land use change and carbon sequestration on the Loess Plateau, China, Scientific Reports, 4, 7039, https://doi.org/10.1038/srep07039, 2014.

Dutschmann, T., Schlenker, V., and Baumann, K.: Chemoinformatic regression methods and their applicability domain, Molecular Informatics, 43, e202400018, https://doi.org/10.1002/minf.202400018, 2024.

Enebe, M. C., Ray, R. L., and Griffin, R. W.: Carbon sequestration and soil responses to soil amendments – A review, Journal of Hazardous Materials Advances, 18, 100714, https://doi.org/10.1016/j.hazadv.2025.100714, 2025.

Fathololoumi, S. and Biswas, A.: Incorporating digital soil mapping-derived soil properties for enhanced soil moisture prediction, Soil and Tillage Research, 256, 106901, https://doi.org/10.1016/j.still.2025.106901, 2026.

Fatichi, S., Pappas, C., and Ivanov, V. Y.: Modeling plant–water interactions: an ecohydrological overview from the cell to the global scale, WIREs Water, 3, 327–368, https://doi.org/10.1002/wat2.1125, 2016.

Frouz, J.: Plant-soil feedback across spatiotemporal scales from immediate effects to legacy, Soil Biology and Biochemistry, 189, 109289, https://doi.org/10.1016/j.soilbio.2023.109289, 2024.

Gabarrón-Galeote, M. A., Martínez-Murillo, J. F., Quesada, M. A., and Ruiz-Sinoga, J. D.: Seasonal changes in the soil hydrological and erosive response depending on aspect, vegetation type and soil water repellency in different Mediterranean microenvironments, Solid Earth, 4, 497–509, https://doi.org/10.5194/se-4-497-2013, 2013.

Gentine, P., D'Odorico, P., Lintner, B. R., Sivandran, G., and Salvucci, G.: Interdependence of climate, soil, and vegetation as constrained by the Budyko curve, Geophysical Research Letters, 39, https://doi.org/10.1029/2012GL053492, 2012.

Gnann, S., Baldwin, J. W., Cuthbert, M. O., Gleeson, T., Schwanghart, W., and Wagener, T.: The Influence of Topography on the Global Terrestrial Water Cycle, Reviews of Geophysics, 63, https://doi.org/10.1029/2023RG000810, 2025.

Grenzer, J., Kulmatiski, A., Forero, L., Ebeling, A., Eisenhauer, N., and Norton, J.: Moderate plant–soil feedbacks have small effects on the biodiversity–productivity relationship: A field experiment, Ecology and Evolution, 11, 11651–11663, https://doi.org/10.1002/ece3.7819, 2021.

Grunwald, S., Thompson, J. A., and Boettinger, J. L.: Digital Soil Mapping and Modeling at Continental Scales: Finding Solutions for Global Issues, Soil Science Society of America Journal, 75, 1201–1213, https://doi.org/10.2136/sssaj2011.0025, 2011.

Guo, M., Yang, L., Zhang, L., Shen, F., Meadows, M. E., and Zhou, C.: Hydrology, vegetation, and soil properties as key drivers of soil organic carbon in coastal wetlands: A high-resolution study, Environmental Science and Ecotechnology, 23, 100482, https://doi.org/10.1016/j.ese.2024.100482, 2025.

Hao, Y., Mao, J., Bachmann, C. M., Hoffman, F. M., Koren, G., Chen, H., Tian, H., Liu, J., Tao, J., Tang, J., Li, L., Liu, L., Apple, M., Shi, M., Jin, M., Zhu, Q., Kannenberg, S., Shi, X., Zhang, X., and Dai, Y.: Soil moisture controls over carbon sequestration and greenhouse gas emissions: a review, Npj Climate and Atmospheric Science, 8, 16, https://doi.org/10.1038/s41612-024-00888-8, 2025.

Hengl, T. and MacMillan, R. A.: Predictive Soil Mapping with R, OpenGeoHub foundation, www.soilmapper.org, 2019.

Hengl, T., Mendes de Jesus, J., Heuvelink, G. B. M., Ruiperez Gonzalez, M., Kilibarda, M., Blagotić, A., Shangguan, W., Wright, M. N., Geng, X., Bauer-Marschallinger, B., Guevara, M. A., Vargas, R., MacMillan, R. A., Batjes, N. H., Leenaars, J. G. B., Ribeiro, E., Wheeler, I., Mantel, S., and Kempen, B.: SoilGrids250m: Global gridded soil information based on machine learning, PLOS ONE, 12, e0169748, https://doi.org/10.1371/journal.pone.0169748, 2017.

Heuvelink, G. B. M.: Uncertainty and uncertainty propagation in soil mapping and modelling, in: Pedometrics, edited by: McBratney, A. B., Minasny, B., and Stockmann, U., Progress in Soil Science, Springer, Cham, Switzerland, 439–461, https://doi.org/10.1007/978-3-319-63439-5_14, 2018.

Heuvelink, G. B. M., Angelini, M. E., Poggio, L., Bai, Z., Batjes, N. H., Bosch, R., Bossio, D., Estella, S., Lehmann, J., Olmedo, G. F., and Sanderman, J.: Machine learning in space and time for modelling soil organic carbon change, European Journal of Soil Science, 72, 1607–1623, https://doi.org/10.1111/ejss.12998, 2021.

Hou, G., Delang, C. O., and Lu, X.: Afforestation changes soil organic carbon stocks on sloping land: The role of previous land cover and tree type, Ecological Engineering, 152, 105860, https://doi.org/10.1016/j.ecoleng.2020.105860, 2020.

Hu, Z., Dakos, V., and Rietkerk, M.: Using functional indicators to detect state changes in terrestrial ecosystems, Trends in Ecology & Evolution, 37, 1036–1045, https://doi.org/10.1016/j.tree.2022.07.011, 2022.

Huang, X.-D., Luo, G.-M., Han, P.-P., Liu, J., and Zhang, J.: Editorial: Vegetation–soil–hydrology interactions and ecohydrological processes, Frontiers in Environmental Science, 13, https://doi.org/10.3389/fenvs.2025.1705595, 2025.

Hubbert, K. R., Wohlgemuth, P. M., Beyers, J. L., Narog, M. G., and Gerrard, R.: Post-Fire Soil Water Repellency, Hydrologic Response, and Sediment Yield Compared between Grass-Converted and Chaparral Watersheds, Fire Ecology, 8, 143–162, https://doi.org/10.4996/fireecology.0802143, 2012.

Humphrey, V., Berg, A., Ciais, P., Gentine, P., Jung, M., Reichstein, M., Seneviratne, S. I., and Frankenberg, C.: Soil moisture–atmosphere feedback dominates land carbon uptake variability, Nature, 592, 65–69, https://doi.org/10.1038/s41586-021-03325-5, 2021.

Jarvis, N., Coucheney, E., Lewan, E., Klöffel, T., Meurer, K. H. E., Keller, T., and Larsbo, M.: Interactions between soil structure dynamics, hydrological processes, and organic matter cycling: A new soil-crop model, European Journal of Soil Science, 75, https://doi.org/10.1111/ejss.13455, 2024.

Kim, J. H., Fourcaud, T., Jourdan, C., Maeght, J., Mao, Z., Metayer, J., Meylan, L., Pierret, A., Rapidel, B., Roupsard, O., de Rouw, A., Sanchez, M. V., Wang, Y., and Stokes, A.: Vegetation as a driver of temporal variations in slope stability: The impact of hydrological processes, Geophysical Research Letters, 44, 4897–4907, https://doi.org/10.1002/2017GL073174, 2017.

Lathrop, E., See, C., Walker, X., Falvo, G., Axler, Z., Ebert, C., Kadej, S., Kelley, A., Ledman, J., Opfergelt, S., Rodenhizer, H., and Schuur, E. A. G.: Permafrost Thaw Accelerates Old Soil Carbon Release, Outpacing New Plant Inputs During a 13-Year Tundra Warming Experiment, Global Change Biology, 31, https://doi.org/10.1111/gcb.70609, 2025.

Li, Z., Li, X., Zhou, S., Yang, X., Fu, Y., Miao, C., Wang, S., Zhang, G., Wu, X., Yang, C., and Deng, Y.: A comprehensive review on coupled processes and mechanisms of soil-vegetation-hydrology, and recent research advances, Science China Earth Sciences, 65, 2083–2114, https://doi.org/10.1007/s11430-021-9990-5, 2022.

Liu, C., Jia, X., Ren, L., Zhao, C., Bai, X., and Shao, M.: Relationship of vegetation stand age to soil water dynamics and use in artificial shrublands and grasslands in a semiarid region, Agricultural Water Management, 313, 109487, https://doi.org/10.1016/j.agwat.2025.109487, 2025.

Ludwig, M., Moreno-Martinez, A., Hölzel, N., Pebesma, E., and Meyer, H.: Assessing and improving the transferability of current global spatial prediction models, Global Ecology and Biogeography, 32, 356–368, https://doi.org/10.1111/geb.13635, 2023.

McBratney, A. B., Mendonça Santos, M. L., and Minasny, B.: On digital soil mapping, Geoderma, 117, 3–52, https://doi.org/10.1016/S0016-7061(03)00223-4, 2003.

Meir, P., Wood, T. E., Galbraith, D. R., Brando, P. M., Da Costa, A. C. L., Rowland, L., and Ferreira, L. V.: Threshold Responses to Soil Moisture Deficit by Trees and Soil in Tropical Rain Forests: Insights from Field Experiments, BioScience, 65, 882–892, https://doi.org/10.1093/biosci/biv107, 2015.

Meron, E.: Pattern-formation approach to modelling spatially extended ecosystems, Ecological Modelling, 234, 70–82, https://doi.org/10.1016/j.ecolmodel.2011.05.035, 2012.

Meyer, H. and Pebesma, E.: Predicting into unknown space? Estimating the area of applicability of spatial prediction models, Methods in Ecology and Evolution, 12, 1620–1633, https://doi.org/10.1111/2041-210X.13650, 2021.

Moore, G., McGuire, K., Troch, P., and Barron-Gafford, G.: Ecohydrology and the critical zone: processes and patterns across scales, in: Principles and Dynamics of the Critical Zone, edited by: Giardino, J. R. and Houser, C., Developments in Earth Surface Processes, 19, Elsevier, Amsterdam, the Netherlands, 239–266, https://doi.org/10.1016/B978-0-444-63369-9.00008-2, 2015.

Nicholson, S. and Farrar, T.: The influence of soil type on the relationships between NDVI, rainfall, and soil moisture in semiarid Botswana. I. NDVI response to rainfall, Remote Sensing of Environment, 50, 107–120, https://doi.org/10.1016/0034-4257(94)90038-8, 1994.

Oucheikh, R., Arampola, N., Zhao, P., and Mansourian, A.: Understanding drought related tree responses using deep learning approaches and satellite based proxy, Science of Remote Sensing, 12, 100317, https://doi.org/10.1016/j.srs.2025.100317, 2025.

Poggio, L., de Sousa, L. M., Batjes, N. H., Heuvelink, G. B. M., Kempen, B., Ribeiro, E., and Rossiter, D.: SoilGrids 2.0: producing soil information for the globe with quantified spatial uncertainty, SOIL, 7, 217–240, https://doi.org/10.5194/soil-7- 217-2021, 2021.

Pradhan, N. R.: Estimating growing-season root zone soil moisture from vegetation index-based evapotranspiration fraction and soil properties in the Northwest Mountain region, USA, Hydrological Sciences Journal, 64, 771–788, https://doi.org/10.1080/02626667.2019.1593417, 2019.

Pugnaire, F. I., Morillo, J. A., Peñuelas, J., Reich, P. B., Bardgett, R. D., Gaxiola, A., Wardle, D. A., and van der Putten, W. H.: Climate change effects on plant-soil feedbacks and consequences for biodiversity and functioning of terrestrial ecosystems, Science Advances, 5, https://doi.org/10.1126/sciadv.aaz1834, 2019.

https://doi.org/10.5194/egusphere-2026-4516
Preprint. Discussion started: 7 September 2026

Raoult, N., Douglas, N., MacBean, N., Kolassa, J., Quaife, T., Roberts, A. G., Fisher, R., Fer, I., Bacour, C., Dagon, K., Hawkins, L., Carvalhais, N., Cooper, E., Dietze, M. C., Gentine, P., Kaminski, T., Kennedy, D., Liddy, H. M., Moore, D. J. P., and Zobitz, J.: Parameter Estimation in Land Surface Models: Challenges and Opportunities With Data Assimilation and Machine Learning, Journal of Advances in Modeling Earth Systems, 17, https://doi.org/10.1029/2024MS004733, 2025.

Ren, Q., Yuan, J., Wang, J., Liu, X., Ma, S., Zhou, L., Miao, L., and Zhang, J.: Water Level Has Higher Influence on Soil Organic Carbon and Microbial Community in Poyang Lake Wetland Than Vegetation Type, Microorganisms, 10, 131, https://doi.org/10.3390/microorganisms10010131, 2022.

Rodenhizer, H., Natali, S. M., Mauritz, M., Taylor, M. A., Celis, G., Kadej, S., Kelley, A. K., Lathrop, E. R., Ledman, J., Pegoraro, E. F., Salmon, V. G., Schädel, C., See, C., Webb, E. E., and Schuur, E. A. G.: Abrupt permafrost thaw drives spatially heterogeneous soil moisture and carbon dioxide fluxes in upland tundra, Global Change Biology, 29, 6286–6302, https://doi.org/10.1111/gcb.16936, 2023.

Rohmer, J., Belbeze, S., and Guyonnet, D.: Insights into the prediction uncertainty of machine-learning-based digital soil mapping through a local attribution approach, SOIL, 10, 679–697, https://doi.org/10.5194/soil-10-679-2024, 2024.

Rong, Q., Yang, M., Deng, Y., Zhao, M., Liao, Y., Tan, Q., Pan, T., Yang, G., Yu, X., and Huang, Y.: Influence of the root– soil complex on soil infiltration stages and their temporal changes in Cunninghamia lanceolata plantations, Geoderma, 464, 117606, https://doi.org/10.1016/j.geoderma.2025.117606, 2025.

Scheffer, M., Carpenter, S., Foley, J. A., Folke, C., and Walker, B.: Catastrophic shifts in ecosystems, Nature, 413, 591–596, https://doi.org/10.1038/35098000, 2001.

Schillaci, C., Acutis, M., Lombardo, L., Lipani, A., Fantappiè, M., Märker, M., and Saia, S.: Spatio-temporal topsoil organic carbon mapping of a semi-arid Mediterranean region: the role of land use, soil texture, topographic indices and the influence of remote sensing data to modelling, Sci. Total Environ., 601–602, 821–832, https://doi.org/10.1016/j.scitotenv.2017.05.239, 2017.

Schmidinger, J. and Heuvelink, G. B. M.: Validation of uncertainty predictions in digital soil mapping, Geoderma, 437, 116585, https://doi.org/10.1016/j.geoderma.2023.116585, 2023.

Schweiger, A. H., Garthen, A., Bahn, M., Chalcraft, D., Schtickzelle, N., Larsen, K. S., and Kreyling, J.: How to optimally allocate sampling effort in experimental ecology, Scientific Reports, 16, 6503, https://doi.org/10.1038/s41598-026-38541-4, 2026.

Shirley, I. A., Mekonnen, Z. A., Wainwright, H., Romanovsky, V. E., Grant, R. F., Hubbard, S. S., Riley, W. J., and Dafflon, B.: Near-Surface Hydrology and Soil Properties Drive Heterogeneity in Permafrost Distribution, Vegetation Dynamics, and Carbon Cycling in a Sub-Arctic Watershed, Journal of Geophysical Research: Biogeosciences, 127, https://doi.org/10.1029/2022JG006864, 2022.

Stovall, A. E. L., Shugart, H., and Yang, X.: Tree height explains mortality risk during an intense drought, Nature Communications, 10, 4385, https://doi.org/10.1038/s41467-019-12380-6, 2019.

Szatmári, G. and Pásztor, L.: The impact of direct and indirect digital soil mapping approaches on spatial uncertainty, Geoderma, 460, 117448, https://doi.org/10.1016/j.geoderma.2025.117448, 2025.

Thuiller, W.: Ecological niche modelling, Current Biology, 34, R225–R229, https://doi.org/10.1016/j.cub.2024.02.018, 2024.

Trachsel, M. and Telford, R. J.: Technical note: estimating unbiased transfer-function performances in spatially structured environments, Climate of the Past, 12, 1215–1223, https://doi.org/10.5194/cp-12-1215-2016, 2016.

Troch, P. A., Carrillo, G., Sivapalan, M., Wagener, T., and Sawicz, K.: Climate-vegetation-soil interactions and long-term hydrologic partitioning: signatures of catchment co-evolution, Hydrology and Earth System Sciences, 17, 2209–2217, https://doi.org/10.5194/hess-17-2209-2013, 2013.

van der Putten, W. H., Bardgett, R. D., Bever, J. D., Bezemer, T. M., Casper, B. B., Fukami, T., Kardol, P., Klironomos, J. N., Kulmatiski, A., Schweitzer, J. A., Suding, K. N., Van de Voorde, T. F. J., and Wardle, D. A.: Plant–soil feedbacks: the past, the present and future challenges, Journal of Ecology, 101, 265–276, https://doi.org/10.1111/1365-2745.12054, 2013.

Verhoef, A., Zeng, Y., Agam, N., Best, M., Bonetti, S., Boussetta, S., Chaney, N., Cuntz, M., Edwards, J., Gupta, S., Heitman, J., Huang, M., Jarvis, N., Jiang, S., Kandala, R., Kiałka, F., Lian, T., Mu, M., Nemes, A., and Weihermüller, L.: Rethinking Soils in Land Surface Models, Bulletin of the American Meteorological Society, 107, E665–E674, https://doi.org/10.1175/BAMS-D-26-0003.1, 2026.

Wadoux, A. M. J. C., Minasny, B., and McBratney, A. B.: Machine learning for digital soil mapping: Applications, challenges and suggested solutions, Earth-Science Reviews, 210, https://doi.org/10.1016/j.earscirev.2020.103359, 2020.

Wang, L., Liu, J., Sun, G., Wei, X., Liu, S., and Dong, Q.: Preface "Water, climate, and vegetation: ecohydrology in a changing world", Hydrology and Earth System Sciences, 16, 4633–4636, https://doi.org/10.5194/hess-16-4633-2012, 2012.

https://doi.org/10.5194/egusphere-2026-4516
Preprint. Discussion started: 7 September 2026

Wang, Y., Dai, J., Jiang, F., Wan, Z., and Zhang, S.: Coupled Effects of Water Depth, Vegetation, and Soil Properties on Soil Organic Carbon Components in the Huixian Wetland of the Li River Basin, Land, 14, 584, https://doi.org/10.3390/land14030584, 2025.

Wright, S. N., Thompson, L. M., Olefeldt, D., Connon, R. F., Carpino, O. A., Beel, C. R., and Quinton, W. L.: Thaw-induced impacts on land and water in discontinuous permafrost: A review of the Taiga Plains and Taiga Shield, northwestern Canada, Earth-Science Reviews, 232, 104104, https://doi.org/10.1016/j.earscirev.2022.104104, 2022.

Xia, Y., McSweeney, K., and Wander, M. M.: Digital Mapping of Agricultural Soil Organic Carbon Using Soil Forming Factors: A Review of Current Efforts at the Regional and National Scales, Frontiers in Soil Science, 2, https://doi.org/10.3389/fsoil.2022.890437, 2022.

Yang, C., Shen, F., Li, X., Cui, W., Zhang, L., Yang, L., and Zhou, C.: Spatio-temporal mapping reveals changes in soil organic carbon stocks across the contiguous United States since 1955, Communications Earth & Environment, 6, 615, https://doi.org/10.1038/s43247-025-02605-6, 2025.

Yang, H., Wang, Q., Ma, X., Liu, W., and Liu, H.: Digital Soil Mapping Based on Fine Temporal Resolution Landsat Data Produced by Spatiotemporal Fusion, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 16, 3905–3914, https://doi.org/10.1109/JSTARS.2023.3267102, 2023.

Yang, L., He, X., Shen, F., Zhou, C., Zhu, A.-X., Gao, B., Chen, Z., and Li, M.: Improving prediction of soil organic carbon content in croplands using phenological parameters extracted from NDVI time series data, Soil and Tillage Research, 196, 104465, https://doi.org/10.1016/j.still.2019.104465, 2020.

Yetemen, O., Istanbulluoglu, E., and Vivoni, E. R.: The implications of geology, soils, and vegetation on landscape morphology: Inferences from semi-arid basins with complex vegetation patterns in Central New Mexico, USA, Geomorphology, 116, 246–263, https://doi.org/10.1016/j.geomorph.2009.11.026, 2010.

Zeng, C., Yang, L., Zhu, A.-X., Rossiter, D. G., Liu, J., Liu, J., Qin, C., and Wang, D.: Mapping soil organic matter concentration at different scales using a mixed geographically weighted regression method, Geoderma, 281, 69–82, https://doi.org/10.1016/j.geoderma.2016.06.033, 2016.

Zhang, C., Tang, Y., Xu, X., and Kiely, G.: Towards spatial geochemical modelling: Use of geographically weighted regression for mapping soil organic carbon contents in Ireland, Applied Geochemistry, 26, 1239–1248, https://doi.org/10.1016/j.apgeochem.2011.04.014, 2011.

Zhang, T., Huang, L.-M., and Yang, R.-M.: Evaluation of digital soil mapping projection in soil organic carbon change modeling, Ecological Informatics, 79, 102394, https://doi.org/10.1016/j.ecoinf.2023.102394, 2024.

Zhang, Y., Pang, Z., Chen, J., Chen, X., and Wang, E.: Root-mediated regulation of soil infiltration dynamics in eroded Mollisols, Geoderma, 462, 117508, https://doi.org/10.1016/j.geoderma.2025.117508, 2025.

Zhu, H., Gong, L., Luo, Y., Tang, J., Ding, Z., and Li, X.: Effects of Litter and Root Manipulations on Soil Bacterial and Fungal Community Structure and Function in a Schrenk's Spruce (Picea schrenkiana) Forest, Frontiers in Plant Science, 13, https://doi.org/10.3389/fpls.2022.849483, 2022.