Hoppenbrock, J., Beyer, M., Gerchow, M., and Bücker, M.: Technical note: Monitoring diel soil water variations below trees using high-resolution electrical resistivity tomography, EGUsphere [preprint], https://doi.org/10.5194/egusphere-2026-4818, 2026.

The global demand for development has driven rapid urbanization across the world. However, human infrastructure remains inherently bound to the natural climate system. To mitigate and pacify the climate alterations caused by rapid urban expansion, various counter-measures have been introduced. Among these, urban trees play a critical role, acting as both biological filters and natural fans that provide microclimate cooling and carbon dioxide sequestration.

Despite their benefits, urban trees are frequently planted without a sufficient understanding of the underlying subsurface system, specifically within the complex unsaturated zone. To address this critical knowledge gap, the authors utilize Electrical Resistivity Tomography (ERT) measurements alongside sap flow and soil water content (SWC) monitoring. This experimental setup allows them to evaluate subsurface dynamics during non precipitation periods and contribute valuable data to the existing literature. Based on the information presented in the manuscript, the following points are brought forward for discussion:

4. The authors demonstrate a strong correlation between the measured SWC and the ERT-derived SWC at depths of 1.0 m and 2.0 m using Pearson’s r. However, the reported values call into question whether Pearson’s r is the most appropriate statistical measure for this data. Specifically, subplot d shows a severe deviation between the measured SWC and ERT-derived SWC after June 13, yet it still yields a deceptively high Pearson’s r of 0.74. In contrast, subplot c visually displays a much closer fit and better representation of the trend, but yields a lower Pearson’s r of 0.649. Because Pearson’s r evaluates linear trends rather than absolute differences, it may be masking systematic offsets or phase shifts in subplot d. The authors should consider reporting some other statistical metrics that capture absolute agreement.

5. In Figure 4, the data in subplots c and d are based on the SWC derived from ERT measurements and SWC recorded by the sensors. Although the exact derivation steps are not explicitly shown, it is reasonable to expect the same downward trend over time across both methods. Discrepancies here would otherwise imply instrumental or methodological errors, given that the measurements originate from the same location. However, a critical point requires clarification: the ERT values represent an integrated depth interval of 0.75–1.25 m, whereas the point-sensor SWC is measured strictly at 1.0 m. Should we expect these values to align perfectly, or is a higher degree of variance expected from the ERT data due to its volume-averaging nature over the 0.75–1.25 m interval compared to the discrete 1.0 m SWC sensor?

6. In section 3.1, the authors note that soil moisture was monitored at depths of 0.15 m, 0.3 m, 0.5 m, 1m, and 2m. However, the subsequent data analysis, figures, and comparisons are strictly limited to the 1.0 m and 2.0 m, leaving the shallower details completely unaddressed or masked. The authors need to provide a clear justification for excluding these data points. Incorporating the shallow-depth profiles is highly critical, as it would provide a complete picture and help clarify the anomalous lag-time behaviors observed deeper in the soil profile.

7. As indicated in Lines 175–178, the instrumentation deployed varies by depth: an FDR Wet150 sensor was used at 1.0 m, while a TDT SMT100 sensor was used at 2.0 m. Mixing entirely different measurement technologies (FDR vs. TDT) introduces distinct variations in

the operations. Therefore, the authors must address whether this discrepancy in sensor instrumentation influenced the monitored data outcomes, particularly the contrasting trends, sharp variations, and anomalous behaviors reported between the 1.0 m and 2.0 m depths.

8. Comparing subplot d with the precipitation data in Figure 3 (plot a) raises a critical question: what physical mechanism caused the soil moisture content at 2.0 m to suddenly spike to approximately 3.2 around 9:00 PM on June 13? This sudden increase contradicts expected drainage and drying behaviors. In fact, the moisture levels abruptly rebounded to match the peak baseline seen on June 11. When cross-referenced with sap flow measurements, this spike seems to point toward an unaccounted-for hydrological impact or artifact.

Notably, this phenomenon occurs exclusively at the 2.0 m depth and is completely absent at the 1.0 m depth. Is it possible that this delayed spike was triggered by the precipitation event on June 10? That specific rain event appears to have been cleanly captured by the 1.0 m sensor as a sharp spike on June 11, where moisture levels climbed well above their original baseline. Could preferential flow paths, perched water tables, or a delayed groundwater response explain why this wetting front bypassed or cleared the 1.0 m sensor but heavily saturated the 2.0 m sensor three days later?

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PROFESSIONAL SUMMARY

Computational Hydrologist, Systems Architect, and Environmental Modeler with a proven track record of engineering high-velocity software and mathematical solutions to complex catchment anomalies. Expert in continental-scale hydrological datasets, Physics-Informed Machine Learning, and high-resolution gridded watershed frameworks. Core contributions include solo-engineering the foundational spatial integration of the multi-million-element USGS NHDPlus dataset into the United States national grid using Soil and Water Assessment Tool (SWAT), and serving as the principal technical architect behind the 3D mathematical physics modeling for Singapore's sovereign urban stormwater initiatives.

CORE TECHNICAL COMPETENCIES

Hydroinformatics Frameworks: Expert in orchestrating multi-scale water frameworks and hydroinformatics pipelines using engines like SWAT.
Geospatial Engineering: Full-stack development across ESRI enterprise ecosystems and advanced open-source spatial stacks.
Intelligent Modeling: Design and deployment of Physics-Informed Machine Learning models.
Advanced Analytics: Production-grade integration of spatio-temporal statistical pipelines, custom APIs, and advanced clustering matrices.

CONCISE CAREER TRAJECTORY & IMPACT

- **One Tool Any Country (OTAC) Global Framework (Ongoing):** Conceptualized and independently developing a multi-year global Python framework fusing surface/groundwater, water quality, and climate science with GCMs, satellite imagery, and advanced ML pipelines.
- **Continental-Scale Big Data Integration:** Executed the integration of the multi-million-element **USGS NHDPlus** watershed dataset into the United States national grid using the **SWAT.**
- **Enterprise Software Engineering Support:** Engineered custom codebase workarounds for enterprise clients directly at **ESRI Headquarters (Redlands, CA).**
- **Sovereign Infrastructure Modeling:** Modeled 3D rain garden physics at the **National University of Singapore (NUS)**, directly defining Singapore's National Bioretention Guidelines.
- **Academic Instruction:** Delivered advanced undergraduate engineering curriculum covering core disciplines in hydrology, hydraulics, and fluid mechanics.

SCIENTIFIC SERVICE & GOVERNANCE

- **Interactive Scientific Peer Review:** Contribute analytical commentaries within the interactive open-access review platforms of **Hydrology and Earth System Sciences (HESS / European Geosciences Union)**, driving technical accountability in climate and hydrological literature (e.g., *hess-2023-275*).
- **Selected Peer-Reviewed Publication:** Mylevaganam, S., Srinivasan, R., & Singh, V. (2015). Ecohydrologically Driven Catchment Evaluation and Prioritization. *Open Journal of Applied Sciences*, 5, 325-334.

EDUCATION & CREDENTIALS

M.S. in Spatial Science (Hydrology) | Texas A&M University, USA

- MS GPA: 4.0/4.0 | Doctoral Coursework GPA: 3.78/4.0

M.Eng. in Water Engineering and Management | Asian Institute of Technology, Thailand

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B.Sc. Eng. in Civil Engineering | University of Moratuwa, Sri Lanka
- GPA: 3.86/4.0 | First Class Honors