Reviewer 2: Comments and Suggestions

The manuscript presents an interesting approach using AutoML for soil moisture prediction. However, the abstract lacks an introductory statement and would be clearer in one paragraph. The introduction should better review existing studies and explain how this work improves on previous methods. The use of only one year of data and black soil limits the study's generalisability, and the term "scalable" should be reconsidered without validation across multiple years and soil types. The formatting of subsections and capitalization consistency should be improved. Finally, the paper lacks references to related studies, which weakens its connection to existing literature. Addressing these points would strengthen the manuscript.

Authors' response: We sincerely thank the reviewer for the positive evaluation of our work and for recognising the novelty and potential of the proposed AutoML-SM framework for subsurface soil moisture estimation. We appreciate the constructive feedback and detailed suggestions, which have helped us improve the clarity and rigour of the manuscript. We aim to carefully address all the issues raised and provide detailed responses to each point below. We hope the planned revisions meet the reviewer's expectations and further strengthen the quality of the manuscript.

Comment 2.1

> The abstract lacks an introductory statement that introduces the importance of the research topic. It begins with the methodology. As per journal abstract guidelines, a brief, general introduction requires in abstract. Also, it will be better to have an abstract in single paragraph rather than two.

Authors' response: We thank the reviewer for this suggestion. As advised, we have revised the abstract to include a general introductory statement highlighting the significance of multi-depth soil moisture estimation in hydrological modelling, agricultural productivity, and climate prediction, while also acknowledging the challenges faced by existing methods. Furthermore, we have merged the abstract into a single paragraph, in accordance with the journal's guidelines.

The modified abstract is given below for the reviewer's reference. This will be added and refined further in the revised version.

"Understanding subsurface soil moisture dynamics is fundamental to hydrological modelling, water resource management, climate prediction, and agricultural productivity. Accurate multi-depth soil moisture estimation is particularly critical for drought and flood forecasting, as well as soil health monitoring. However, traditional methods and many machine learning models often struggle to capture its complexity. Moreover, investigating soil moisture responses to rainfall-driven events and their variability influenced by hydrometeorological factors is equally essential. This study proposes an integrated, event-based framework for quantifying soil moisture dynamics at multiple depths (10, 20, 30, and 40 cm) in response to rainfall events using an automated machine learning (AutoML) approach. At the observatory we record the hydrometeorological and soil moisture data at different depth below the ground surface at every 10-minute intervals. We use these datasets to capture both rapid single-peak and gradual multiple-peak soil moisture responses during diverse rainfall events. Recognising that manual model selection and hyperparameter tuning are labour intensive and may not fully capture the complex, non-linear interactions among hydrometeorological variables, here we propose an AutoML framework that leverages Bayesian optimisation to predict subsurface soil moisture at different depths. The model was evaluated under four temporal scenarios: S1 (March-May), S2 (March-June), S3 (March-July), and S4 (March-August), for the full dataset and rainfall-only instances, separately. This automatic selection and tuning of various regression models result in superior predictive performance as compared to benchmark algorithms. The coefficients of determination ranges from 0.88 to 0.98 and minimal root mean squared errors (1.6%–3.4%). Further, the global sensitivity analysis indicates that the atmospheric humidity and dew point strongly influence near-surface moisture. The solar radiance and evaporation drive moisture depletion, and soil temperature gradients play a critical role in the vertical profile of the soil column. These findings highlight the value of integrating advanced AutoML techniques with event-based hydrological analysis to enhance our understanding of soil moisture variability, which has significant implications for water resource management, agricultural planning, and hazard mitigation in variable climatic regimes."

Comment 2.2

> The introduction could benefit from a clearer review of existing studies to highlight the gaps your research is addressing. It would also be helpful to improve the flow of ideas by better connecting traditional methods, machine learning, and your method approach. Finally, emphasize more clearly why your study is needed and what unique contributions it makes. Line 135: The introduction mentions using an AutoML framework for soil moisture prediction at multiple depths but fails to discuss existing studies that have applied machine learning or deep learning for similar tasks. It would be helpful to clearly state how this study differs from or improves upon these approaches to highlight its contribution.

Authors' response: We sincerely thank the reviewer for their valuable feedback. We agree with the reviewer and have accordingly structured the review of existing studies to highlight the specific research gaps our study aims to address, as well as the unique contribution our proposed framework offers to this field. Given below are the related works which we will incorporate into the Introduction to strengthen it.

"Traditional methods such as the gravimetric technique, while accurate and low-cost, are destructive, time-consuming, and spatially limited. Indirect in-situ methods, especially Time-Domain Reflectometry (TDR), are widely used due to their precision and ease of deployment, though spatial coverage remains a constraint. Ground Penetrating Radar (GPR) offers broader spatial coverage but is less feasible due to its high cost and complexity [1]. To overcome these limitations, machine learning (ML) models emerged as powerful tools for estimating soil moisture. A comprehensive review by [2] showed that ML models like Random Forest, Neural Networks, and SVM are the most frequently applied for SM estimation, often using satellite-derived inputs. In a large-scale study using data from 1,722 ISMN stations, ensemble models such as KNR, RFR, XB achieved high predictive accuracy and outperformed individual models across climate zones [3]. However, these studies primarily focus on surface SM, with limited exploration of subsurface layers.

To estimate subsurface soil moisture (SSM), recent efforts have integrated remote sensing data with ML techniques. For example, [4] used RGB-thermal imagery and canopy characteristics to estimate SM at 10-40 cm depths in corn fields. While shallow depth predictions showed moderate accuracy ($R^2 = 0.79$), the performance declined at deeper layers ($R^2 = 0.69$). Similarly, [5] demonstrated that combining thermal and microwave retrievals in a data assimilation framework significantly improved root-zone SM estimates (R^2 increased from 0.51 to 0.73), though the approach relied on high-quality but often sparse inputs. Emerging deep learning models have further improved multi-depth SM estimation. [6] applied ANN and LSTM to predict subsurface soil moisture, achieving R^2 values of 0.80–0.98 depending on depth and model, though they used only daily-resolution data. [7] developed a dual-branch deep learning model (ALFSMP-DBCM) for alfalfa fields using half-hourly data, showing improved performance but the model is crop-specific and may not generalise well across other regions.

While these deep learning methods show promise, most models require manual tuning and are not automated, which limits their usability for broader applications. Addressing this, a recent study proposed an AutoML framework combining multi-source remote sensing, reanalysis, and field data to estimate SM at every 20 cm from 0-60 cm depth [8]. The model demonstrated moderate accuracy ($R = 0.81$–0.68) and still lacked performance at greater depths. In summary, although substantial progress is made using traditional, remote sensing, machine learning, and deep learning methods for soil moisture estimation, several challenges remain. These include reliance on manually designed workflows that are time-consuming, heuristic-based feature selection and hyperparameter tuning that may limit model robustness, and a narrow focus on specific crop types or short temporal datasets that fail to capture seasonal or event-driven soil moisture variability. Moreover, rainfall event-based modelling of subsurface soil moisture remains largely underexplored."

An automated machine learning (AutoML) approach, capable of integrating multiple input features and automating model selection and tuning, offers significant potential to overcome these limitations. By minimising manual effort and enhancing generalisability across soil depths, AutoML enables robust, high-resolution soil moisture predictions. Our manuscript clearly outlines how this approach stands apart from existing methods and addresses various research gaps.

Comment 2.3

> In Section 3.1.1, it would be clearer to use "a)", "b)", etc., instead of the hyphen ("-") when starting subsections for better readability and consistency.

Authors' response: Thank you for pointing this out. We will do as suggested.

Comment 2.4

> The study focuses on black soil, which has unique characteristics that may not apply to other soil types, but this is not addressed when discussing infiltration dynamics (line : 175). The influence of black soil's physical properties, such as clay content, on infiltration and moisture retention should be considered, as these factors are crucial for understanding the results and assessing their generalisability.

Authors' response: This was also pointed by the reviewer 1. We agree that the unique physical characteristics of black soil, particularly its high clay content play an importat role in governing infiltration dynamics and subsurface moisture behaviour. This demands a clearer explanation.

Black soils exhibit high water retention capacity but low permeability, resulting in reduced infiltration rates compared to coarser-textured soils like sandy loam. Their shrink–swell behaviour under wetting and drying cycles often leads to deep and wide cracks, which can influence preferential flow pathways and soil moisture redistribution following rainfall events. Moreover, their high bulk density and fine texture further contribute to delayed and prolonged moisture responses, particularly under intense or prolonged rainfall conditions.

In the revised manuscript, we will expand subsection 3.1.1 (Rainfall event analysis) to explicitly discuss how these physical properties influence the observed single-peak and multiple-peak soil moisture responses. We will correlate event-based infiltration behaviour with known characteristics of black soils, highlighting how soil structure, texture, and moisture retention capacity govern subsurface moisture variations under different rainfall regimes.

Additionally, to address the generalisability of our model both temporally and spatially, we will extend the analysis on two additional field sites in Africa (Kalipululira and Chipata). These sites have different soil type and climatic conditions. This will allow us to conduct a comparative assessment of model performance and soil moisture responses across these sites, providing a better evaluation of our framework's adaptability beyond black soils.

Comment 2.5

> The writing style of the subsections and sections should be consistent throughout the manuscript. If capitalizing section and subsection titles, it is important to maintain this style consistently across all sections. (Section 3.1.2)

Authors' response: We will ensure to be consistent throughout in the revised manuscript.

Comment 2.6

> Results and Discussion: The study uses data from only one year (March to August 2024) to train and validate the model. This limits the model's ability to generalize and capture the variability in soil moisture dynamics that could arise in different years, especially under varying climatic conditions such as extreme weather events such as droughts or unusually heavy rains. It needs to be mentioned.

Authors' response: We acknowledge that our current study utilises data collected over a limited time period (March to August 2024). This limitation stems from the availability of data at the time of analysis. However, we would like to clarify that data collection at our observatory is ongoing, and we plan to extend the study using at least 1.5 years of continuous data. This will allow us to capture two monsoonal cycles and evaluate soil moisture dynamics over a wider temporal scale, including seasonal transitions and potential rainfall events of varying magnitude and intensities.

In addition to this, we also have access to high-resolution (10-minute interval) time-series data from two other sites located in Africa- Kalipululira and Chipata. The dataset is accessible to us from Zambia metrological department. These sites differ from our study area in terms of soil type and climatic conditions. For the reviewer's reference, Figure 1 show the time series of soil moisture measurement recorded at multiple depths (10, 20, 30, and 40 cm) at the observatory in Chipata.

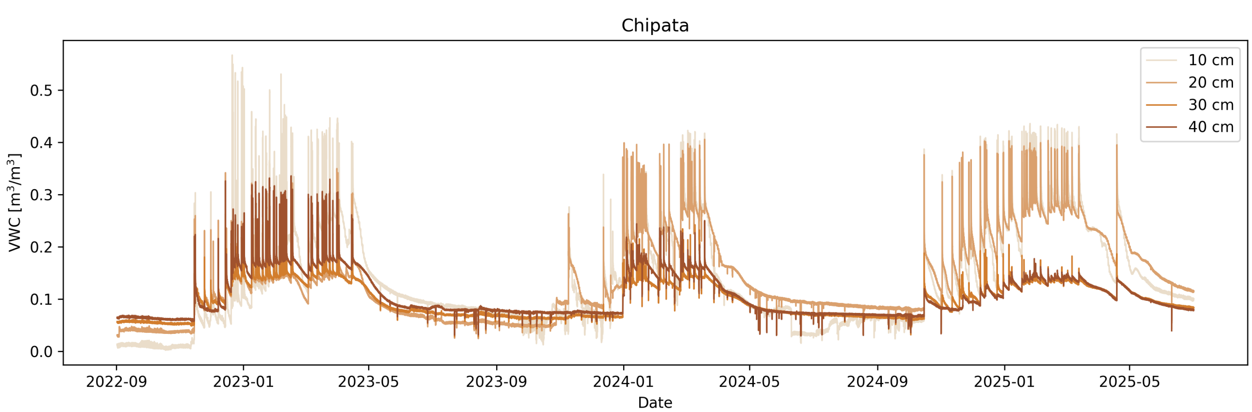

Figure 1: Time-series showing soil moisture variation across multiple soil depths (10, 20, 30,

and 40 cm) at Chipata in Africa.

Preliminary results show that our model achieves reasonable performance at these additional sites, demonstrating its potential to generalise across diverse environmental settings. In the revised manuscript, we will include these additional datasets and our model performances in the discussion to address the limitations associated with the initial one-season analysis.

Comment 2.7

> The study focuses exclusively on black soil, which has unique characteristics, including high moisture retention capacity and shrinkage behaviour in alternate wetting and drying cycles. However, this is not adequately discussed when analysing infiltration or moisture dynamics.

Authors' response: We thank the reviewer for reiterating this important point. We kindly refer the reviewer to Comment 2.4 for the detailed response and planned revisions.

Comment 2.8

> While the study mentions the impact of small perturbations in input variables on soil moisture predictions, it lacks a detailed discussion or analysis of how these small variations affect the model's accuracy.

Authors' response: We greatly appreciate the reviewer's observation. As noted rightly, we have analysed the impact of small perturbations ($\pm 5\%$ and $\pm 10\%$) on the input variables on soil moisture predictions. We acknowledge this analysis lacks a sufficiently detailed explanation of how these variations influence the model's internal mechanism and predictive accuracy.

In this analysis, we introduced small disturbances to each input variable by adding white Gaussian noise; a commonly used technique to simulate purely random and uncorrelated fluctuations in input data. White Gaussian noise is characterized by a normal distribution with zero mean and specified variance, which allows us to realistically model the kind of uncertainty often encountered in environmental measurements. By applying this noise to input variables, we can simulate this uncertainty and observe how it propagates through the model and affects the predicted soil moisture values across different depths.

We will revise the subsection 4.3 (Uncertainty analysis) to elaborate more about this process. While the resultant deviations in model predictions due to induced input perturbations as well as the quantification of model sensitivity are already shown in Figure 16, we believe that adding this information will not only clarify the purpose and methodology of this analysis but also offer readers a deeper understanding of the model's resilience to input variability.

Comment 2.9

> The model demonstrates high performance with high-intensity rainfall events, but may face challenges with lower-intensity, long-duration events. The discrepancy in prediction accuracy between these events suggests the model may be overfitting to extreme rainfall events.

Authors' response: We thank the reviewer for this critical observation. Our proposed model exhibits relatively lower performance during medium- and low-intensity rainfall events, particularly at deeper soil layers. As noted, occasional signs of overfitting are observed under these conditions, which may be attributed to model's tendency to learn patterns more effectively from high-intensity rainfall events that present distinct soil moisture peaks.

To address this issue, we plan to incorporate k-Fold Cross-Validation (with $k = 5$) technique. This technique systematically partitions the dataset into k equal subsets (folds), training the model on k-1 folds and validating it on the remaining fold. This process is repeated k times, with each fold used once for validation. The results are then averaged to obtain a more reliable estimate of model performance. By adopting this technique, we aim to reduce overfitting and enhance its prediction accuracy, especially under less pronounced rainfall conditions. The k-fold cross-validation will ensure that the model is exposed to a wider variety of rainfall scenarios during training and validation, helping it to learn more balanced and robust patterns across different rainfall intensities and soil depths.

We believe incorporating this additional technique will enhance the model's performance under diverse hydrological conditions, and reporting these revised results will further strengthen the manuscript.

Comment 2.10

> The manuscript lacks adequate reference of related studies in the introduction, methodology, and discussion sections. It introduces concepts such as the AutoML-SM framework for soil moisture prediction without contextualizing them within existing literature. This makes it challenging for readers to understand how the proposed approach aligns with or diverges from previous research in the field.

Authors' response: We will add the relevant references in the revision. We request the reviewer to refer to our response to Comment 2.1 for the detailed explanation of these improvements, where we have elaborated on how we plan to revise the Introduction to better contextualize the AutoML-SM framework within the existing body of literature.

Comment 2.11

> Line 555: The study uses data from only one year and one soil type (black soil). Given this limited scope, it may not be entirely appropriate to refer to the approach as a "scalable" one. For a more accurate claim of scalability, it would be beneficial to include validation across multiple years, soil types, and diverse environmental conditions to ensure the model's broader applicability.

Authors' response:

We acknowledge the limitations associated with using data from a single year and soil type in the current version of the study. As outlined in our response to the previous comment (Comment 2.6), we plan to address this by incorporating extended datasets from our observatory covering at least 1.5 years, as well as additional time-series data from two geographically and climatically distinct sites in Africa. These additions will allow us to more rigorously evaluate the model's scalability and applicability. We will include these results and a more detailed discussion in the revised manuscript.

For further details, we kindly refer the reviewer to our earlier response addressing this point in detail.

References

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[5] Fuqin Li, Wade T Crow, and William P Kustas. Towards the estimation root-zone soil moisture via the simultaneous assimilation of thermal and microwave soil moisture retrievals. *Advances in Water Resources*, 33(2):201–214, 2010.

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[7] Rui Liu, Lifeng Lu, Yongqi Ge, Liguo Dong, and Juan Zhou. An approach for multi-depth soil moisture prediction in alfalfa based on a dual-branch combined model. *Computers and Electronics in Agriculture*, 222:109038, 2024.

[8] Shenglin Li, Yang Han, Caixia Li, and Jinglei Wang. A novel framework for multi-layer soil moisture estimation with high spatio-temporal resolution based on data fusion and automated machine learning. *Agricultural Water Management*, 306:109173, 2024.