Dear Editors and Reviewers,

Thank you for the constructive feedback. These comments greatly improved our manuscript. Below we provide detailed, point-by-point responses to all comments. The Editor's and the reviewers' comments are highlighted in boldface and italic. Our responses are in dark blue, while blue texts are the revisions. Please note that line numbers refer to that in the cleaned manuscript.

Sincerely,
Han Fu (on behalf of all authors)

Editor comments:
From the second review round we received contrasting feedbacks from Referees. To improve the scientific consistency of the mansucript, I invite the authors to include additional virtual tests which will allow to perform a sensitivity analysis and to better reflect the complexity of the interactions between land and atmosphere.

We sincerely thank you for the constructive guidance and for providing the opportunity for another round of revision.

Following your recommendation, we have conducted additional virtual experiments and sensitivity analyses to further evaluate the robustness of the ISONEVA framework and to better represent the complexity of land-atmosphere interactions. Specifically, we expanded the virtual tests from a single simulation scenario to two contrasting hydrological regimes: an arid regime (characterized by |E/P| > 1) and a humid regime (characterized by |E/P| < 1). In addition, the atmospheric boundary conditions in the virtual experiments now include diurnal variations in temperature and relative humidity.

Based on these updated simulations, we performed a series of sensitivity analyses to examine the response of ISONEVA to key environmental and methodological factors, including (i) hydrological regime (arid vs. humid conditions), (ii) the thickness of the topsoil control volume, and (iii) the prescribed atmospheric vapor isotopic composition.

These additional analyses are presented in Section 3.1 and also reported below. The results show that the performance of ISONEVA works well across various environmental conditions. We believe that these expanded virtual experiments substantially strengthen the methodological evaluation of the framework and improve the representation of land-atmosphere interactions in the manuscript.

"3.1 Comparison of estimated E/P and Q/P ratios between SS, NSS, and ISONEVA from virtual dataset.

3.1.1 Arid regime (|E/P| > 1)

The true E/P values derived from MOIST simulations (black circles in Figure 3) are consistently smaller than -1, indicating an evaporation-dominated water balance throughout the simulation period (arid regime). For E/P backward estimation, both SS and NSS show substantial deviations from the simulated values, with MAE values of 2.07, 1.73, and 1.38 for SS and 2.49, 2.08, and 1.76 for NSS under Δz = 0.2, 0.1, and 0.05 m, respectively (Figures 3a-3c). These discrepancies arise from the structural assumptions of the two approaches. The SS formulation assumes negligible changes in topsoil water storage, while NSS accounts for storage dynamics but neglects non-evaporative fluxes such as infiltration and percolation. Both assumptions are inconsistent with the simulated conditions, where topsoil water balance is simultaneously influenced by evaporation, precipitation, and vertical water exchange.

By contrast, ISONEVA produces E/P estimates that closely follow the simulated values across most time windows and spatial resolutions. Although noticeable deviations and relatively large uncertainty ranges occur during the earliest evaluation periods, the estimates rapidly converge toward the true values as the temporal window increases (Figures 3a-3c). Compared with SS and NSS, the estimation accuracy of ISONEVA improves by 49.8%-58.3%, 74.7%-79.0%, and 65.4%-72.9% under Δz = 0.2, 0.1, and 0.05 m, respectively. This improved performance arises because ISONEVA explicitly resolves both evaporative and non-evaporative fluxes while simultaneously enforcing dynamic water storage constraints in the topsoil layer.

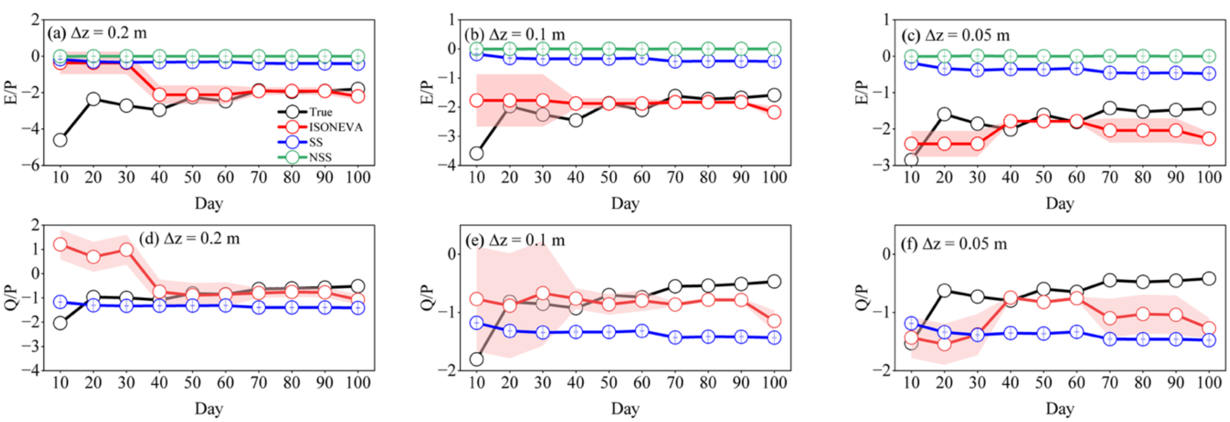

Figure 3. Performance of SS, NSS, and ISONEVA in estimating E/P and Q/P ratios under the arid regime (|E/P| > 1). Panels (a-c) show the estimated E/P ratios for three topsoil thicknesses (Δz = 0.2, 0.1, and 0.05 m), while panels (d-f) show the corresponding Q/P ratios. Black circles represent the true values derived from MOIST simulations, blue circles represent the SS method, green circles represent the NSS method, and red circles represent the ISONEVA estimates. Shaded areas indicate the uncertainty ranges derived from Monte Carlo simulations accounting for $\delta^{18}O$ measurement uncertainty (±0.7‰).

For Q/P estimation (Figures 3d-f), NSS cannot provide estimates because non-evaporative fluxes are not included in its formulation. Under arid conditions, the simulated Q/P values are negative, indicating an upward compensating flux from deeper soil layers. SS provides relatively better approximations of Q/P than E/P. This behaviour likely results from error compensation associated with the steady-state assumption, where biases in E/P estimation partially propagate into the derived Q/P ratio. Nevertheless, ISONEVA still improves the accuracy of Q/P estimation compared with SS, with MAE reductions of 24.2%, 30.7%, and 65.0% under Δz = 0.2, 0.1, and 0.05 m, respectively.

Uncertainty in ISONEVA estimates of E/P and Q/P ratios is relatively large during early evaluation windows but decreases as the temporal window expands. By contrast, SS and NSS show much narrower uncertainty ranges (Figure 3). Although identical Monte Carlo perturbations (±0.7‰ for $\delta^{18}O$ in soil water) are applied to all methods, the SS and NSS formulations rely on closed-form ratio expressions in which isotope values appear in both the numerator and denominator. As a result, small perturbations in isotope measurements tend to partially cancel, leading to limited propagation of measurement uncertainty. By contrast, ISONEVA estimates flux ratios through a nonlinear inversion that combines isotope mass balance with dynamic soil water storage constraints. Under short evaluation windows, changes in soil water storage and isotope composition are small, resulting in limited information content for constraining the inversion. In this situation, ISONEVA can result large uncertainties from small soil water isotopic perturbations. As the temporal window increases, the inversion becomes progressively better constrained, and the associated uncertainty correspondingly decreases.

3.1.2 Humid regime (|E/P| < 1)

Under humid conditions, the true E/P values derived from the MOIST simulations (black circles) remain between -1 and 0 throughout the simulation period, indicating a precipitation-dominated hydrological regime. Compared with the arid regime, SS produces relatively reasonable E/P estimates, with MAE values of 0.41, 0.42, and 0.33 under Δz = 0.2, 0.1, and 0.05 m, respectively. Nevertheless, these errors remain larger than those obtained from ISONEVA (0.24, 0.15, and 0.10). Additionally, NSS continues to exhibit the largest deviations (MAE = 0.86, 0.84, and 0.78) in E/P estimates across all spatial resolutions.

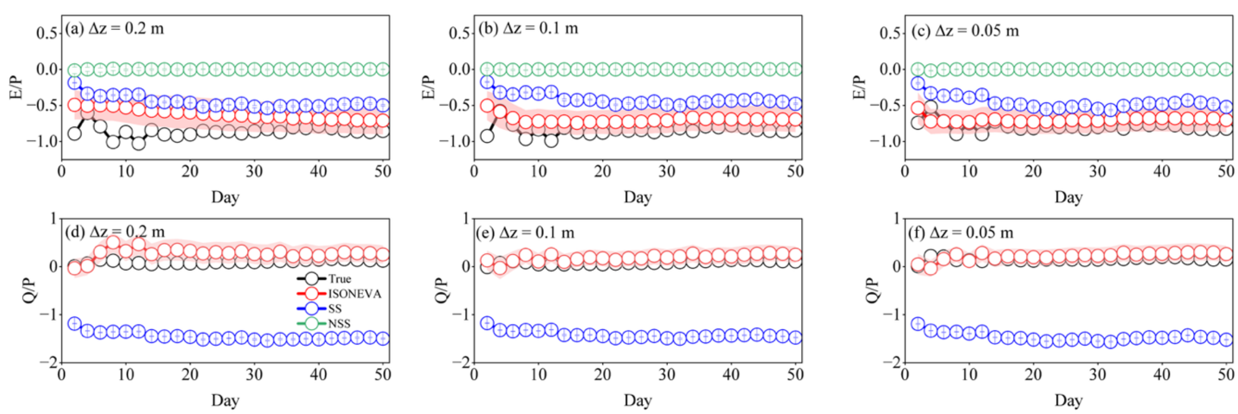

Figure 4. Comparison of estimated E/P and Q/P ratios from SS, NSS, and ISONEVA under the humid regime (|E/P| < 1) using the virtual dataset generated by the MOIST model. Panels (a-c) show the estimated E/P ratios, while panels (d-f) present the corresponding Q/P ratios. The black circles represent the true values derived directly from the simulated evaporation, precipitation, and percolation fluxes. Red circles denote estimates from ISONEVA, blue circles from SS, and green circles from NSS. Results are shown for three topsoil thicknesses (Δz = 0.2 m, 0.1 m, and 0.05 m). The shaded regions indicate the uncertainty ranges derived from Monte Carlo simulations accounting for $\delta^{18}O$ measurement uncertainty (±0.7‰).

The performance patterns differ for Q/P estimation. Under humid conditions, SS shows substantial bias in estimating Q/P with MAE values are 1.55 (Δz = 0.2 m), 1.50 (Δz = 0.1 m), 1.61 (Δz = 0.05 m), whereas ISONEVA continues to reproduce the simulated Q/P values with higher accuracy (Figure 4d-4f) and respective MAE are 0.18, 0.11, 0.09. This discrepancy arises because the SS formulation neglects temporal changes in soil water storage and therefore cannot correctly partition precipitation inputs between evaporation and non-evaporative fluxes. Under humid conditions, frequent precipitation events induce substantial changes in soil water storage, violating the steady-state assumption underlying SS. By contrast, ISONEVA provides more physically consistent estimates of Q/P by explicitly accounting for both storage dynamics and non-evaporative fluxes.

3.1.3 Sensitivity analysis

Sensitivity of ISONEVA to regime and topsoil thickness

To synthesize the sensitivity of the inversion performance to hydrological regime and sampling configuration, Table 2 summarizes the mean absolute error (MAE) and the mean standard deviation (SD) of E/P estimates from ISONEVA under different topsoil thicknesses and associated multi-window settings.

Under arid conditions, estimation errors of E/P remain relatively large across all sampling depths, with MAE values of 1.04, 0.44, and 0.47 for Δz = 0.2, 0.1, and 0.05 m, respectively. In this regime, the inversion frequently relies on the multi-window strategy (up to three expanding windows) to obtain stable solutions. This behavior reflects the limited information content of individual evaluation windows under arid conditions. Because rainfall events occur infrequently, precipitation introduces weak perturbations to topsoil water storage and isotopic composition within each window. Consequently, the isotope signal from a single window often provides insufficient constraints for resolving E/P, requiring the use of multiple expanding windows and resulting in larger estimation errors. Consistent with this pattern, the mean uncertainty is also higher under arid conditions, with SD values ranging from 0.21 to 0.42.

Table 2. ISONEVA inversion performance to hydrological regime and topsoil thickness. Mean absolute error (MAE) of estimated E/P ratios is reported for different sampling depths under arid and humid regimes. The "multi-window number" denotes the number of expanding windows used in the inversion to obtain a stable solution when single-window information is insufficient.

	Thickness of topsoil layer	Multi-Window numbers	MAE of estimated E/P	Mean SD of estimated E/P
Arid regime	0.2 m	3	1.04	0.42
	0.1 m	3	0.44	0.35
	0.05 m	3	0.47	0.21
Humid regime	0.2 m	1	0.24	0.21
	0.1 m	1	0.15	0.18
	0.05 m	1	0.12	0.18

By contrast, under humid conditions the inversion becomes substantially more stable. The MAE values decrease to 0.24, 0.15, and 0.12 for Δz = 0.2, 0.1, and 0.05 m, respectively, and the optimal solutions are typically obtained using a single window. This improvement reflects the stronger storage signals and more frequent precipitation inputs in humid regimes, which increase the information content available for ISONEVA to estimate E/P. Correspondingly, the associated uncertainties are smaller and remain relatively consistent across sampling depths (SD ≈ 0.18-0.21). As a result, ISONEVA achieves higher accuracy and stability under humid than arid conditions.

Sampling depth also influences estimation performance. Under arid conditions, MAE decreases markedly by about 58% when the topsoil thickness is reduced from 0.2 m to 0.1 m (from 1.04 to 0.44), whereas slightly increased 7% from 0.1 m to 0.05 m. A similar pattern is observed under humid conditions, where MAE decreases by about 38% from 0.2 m to 0.1 m (0.24 to 0.15), but 20% from 0.1 m to 0.05 m (0.15 to 0.12). This pattern reflects a trade-off between signal smoothing and measurement sensitivity. Thicker topsoil (0.2 m) tends to smooth isotope signals and reduce sensitivity to short-term flux dynamics, whereas thinner topsoil (0.05 m) may amplify short-term variability and become more sensitive to measurement noise. Overall, these results demonstrate that the identifiability of E/P using ISONEVA is strongly controlled by the information content of isotope and storage signals, which in turn depends on hydrological regime and topsoil thickness.

Sensitivity of ISONEVA to atmospheric isotopic composition

To evaluate the sensitivity of ISONEVA to the atmospheric isotopic composition, we repeated the inversion using four prescribed values of atmospheric $\delta^{18}O$ (-10‰, -14‰, -20‰, and -30‰), where -14‰ corresponds to the value used in the MOIST simulations (also corresponds to the results reported in Figures 3 and 4). The resulting MAE values of E/P estimates under different hydrological regimes and sampling depths are summarized in Table 3.

The performance of ISONEVA shows limited sensitivity to the prescribed atmospheric $\delta^{18}O$ values. Across the tested range (-10‰ to -30‰), MAE values vary only moderately. Under arid conditions, MAE differences across atmospheric $\delta^{18}O$ scenarios remain within approximately 0.08-0.12, depending on sampling depth. The coefficient of variation (CV) of MAE further indicates that the sensitivity of ISONEVA to atmospheric $\delta^{18}O$ decreases with increasing topsoil thickness, with thicker topsoil layers exhibiting smaller CV values (Table 3).

A similar but even weaker sensitivity is observed under humid conditions. In this regime, the variation of MAE across atmospheric $\delta^{18}O$ scenarios is considerably smaller, typically within 0.01-0.02 (Table 3). The corresponding CV values also show a decreasing trend with increasing topsoil thickness, indicating that E/P estimates from thicker topsoil is less sensitive to atmospheric isotopic compositions than the thinner one.

Table 3. Sensitivity of ISONEVA performance to the prescribed atmospheric $\delta^{18}O$. Mean absolute error (MAE) of E/P estimates under arid and humid regimes is shown for different topsoil thicknesses. The reference atmospheric isotope composition (-14‰) corresponds to the value used in forward and backward simulations in this study, while -10‰, -20‰, and -30‰ represent alternative plausible atmospheric vapor isotope conditions used to evaluate ISONEVA sensitivity.

	Topsoil thickness	-10‰	-14‰ (reference)	-20‰	-30‰	CV
Arid	0.2 m	1.04	1.04	1.14	1.14	0.05

regime	0.1 m	0.37	0.44	0.47	0.49	0.10
	0.05 m	0.47	0.47	0.39	0.39	0.09
Humid regime	0.2 m	0.23	0.24	0.24	0.25	0.03
	0.1 m	0.13	0.15	0.14	0.14	0.06
	0.05 m	0.11	0.12	0.09	0.10	0.10

Overall, the relationship between model performance and topsoil thickness is not strictly monotonic. As shown in Tables 2 and 3, thicker topsoil layers tend to smooth short-term isotope fluctuations and reduce sensitivity to uncertainties in atmospheric $\delta^{18}O$, but excessive thickness (e.g., 0.2 m) can dilute isotope signals and lead to larger estimation errors (especially under arid regime). Conversely, very thin topsoil (e.g., 0.05 m) preserves stronger isotope signals and can improve estimation accuracy, but is also become more sensitive to external parameters such as atmospheric isotope composition (especially under the humid regime). This trade-off also interacts with hydrological regime, as precipitation frequency and storage dynamics influence the information content available for constraining the inversion. As a result, a topsoil of 0.1 m would provide the balance between estimation accuracy and sensitivity. ”

Reviewer #1
No comments

Reviewer #2
General comments
The authors have revised the manuscript and introduced the ISONEVA framework to estimate soil evaporation by incorporating non-evaporative fluxes. While the objective of addressing dynamic soil water storage and non-evaporative processes (e.g., infiltration and root water uptake) is commendable, the revised manuscript remains scientifically insufficient for publication in HESS. The core issues raised in the previous review—specifically methodological rigor, physical consistency, and validation depth—have not been resolved. The framework relies on problematic mathematical constraints and lacks the mechanistic evidence required to prove its reliability in real-world, non-idealized conditions.

Thank you for the thoughtful comments and for highlighting the importance of methodological rigor, physical consistency, and validation.

In this revision, we have substantially revised the formulation of the ISONEVA framework to address these concerns. In particular, the current version of the manuscript no longer relies on a Genetic Algorithm to optimize two parameters. Instead, we introduce an explicit physical constraint derived from the soil water balance, which establishes a relationship between the two unknown variables ($\Delta V/P = 1 + E/P - Q/P$, x = E/P and y = Q/P). This constraint reduces the feasible solutions from a two-dimensional parameter space to a one-dimensional constraint line in the E/P-Q/P space. Consequently, the inversion becomes a single-parameter optimization problem along the physically admissible water-balance line, rather than a free two-parameter search.

Moreover, to better evaluate the reliability of the framework under realistic environmental conditions, we expanded the virtual experiments following the Editor's suggestion. The revised simulations now include two contrasting hydrological regimes: an arid regime ($|E/P| > 1$) and a humid regime ($|E/P| < 1$). In addition, the atmospheric forcing in the virtual tests now includes diurnal variations in air temperature and relative humidity, rather than fixed values as used in the previous version.

Based on these expanded simulations, we performed sensitivity analyses to evaluate the performance of ISONEVA in estimating E/P (and Q/P) under varying environmental and methodological conditions. These analyses include the effects of hydrological regime, topsoil control volume thickness, and atmospheric vapor isotope composition. Details of these additional tests and results are presented in Section 3.1.

Through these revisions, we aim to improve the physical consistency of the framework and provide a more comprehensive evaluation of its performance.

Major Scientific Deficiencies

1. Fundamental Indeterminacy and Numerical Manipulation

The ISONEVA framework remains an underdetermined problem with one equation but two unknowns (x for E/P and y for Q/P). The use of a Genetic Algorithm (GA) embedded in a Monte Carlo framework does not resolve the mathematical non-uniqueness of the solution; it merely provides a stochastic average of an unconstrained space. The introduction of a penalty term in Eq.25 to avoid "optimization traps" appears to be a mathematical convenience to force convergence rather than a physically justified constraint. The authors admit that and provide redundant information in their setup, yet they fail to utilize the dual-isotope space (e.g., d-excess or lc-excess) to provide the necessary additional constraints that would justify a two-unknown model.

Thank you for raising this important point regarding the determinacy of the inversion problem. As we replied to general comments, the formulation of the ISONEVA framework in the revised manuscsirpt has been modified to address this concern. We explicitly introduce the water-balance constraint, $\Delta V/P = 1 + E/P - Q/P$, which is derived from Eq. 7.

This relationship establishes a deterministic link between the two unknown variables (*E/P* and *Q/P*). Consequently, the inversion becomes a single-parameter optimization along this physically constrained line rather than a free two-parameter search.

This revised formulation substantially reduces the structural indeterminacy. The role of the optimization is no longer to explore an unconstrained parameter space, but simply to identify the minimum of the objective function along the physically admissible water-balance relationship.

Consistent with this reformulation, the revised manuscript no longer relies on a Genetic Algorithm. The inversion is now implemented as a constrained search along the water-balance line, which removes the possibility of stochastic convergence artifacts associated with GA-based optimization. The corresponding equations and descriptions have been revised in Section 2.2:
"E/P ratio evaluation
The forward simulation of these two scenarios are conducted by MOIST model under various spatial resolution (Δz = 0.2 m, 0.1 m, and 0.05 m) within a one-meter depth column, whose capability to accurately simulate isotope transport in soil has been demonstrated previously (Fu et al., 2025). MOIST output daily soil water content and soil isotope profiles. Additionally, the true E/P ratio (and Q/P) can be calculated directly from the simulated evaporation (percolation) and precipitation fluxes provided by MOIST. These outputs from MOIST are used to evaluate backward calculaton of E/P from SS (Eq. 11), NSS (Eq. 19), and ISONEVA (Eq. 23) method. Note that in the humid regime, precipitation events are prescribed every 2 days, resulting in a much denser sequence of wetting-drying cycles than in the arid regime (every 10 days). Therefore, a shorter simulation period (50 days) is sufficient to generate a comparable (and larger) number of rainfall events and evaluation windows for method assessment, while keeping the numerical experiment computationally tractable. By contrast, the arid regime requires a longer simulation (100 days) to include an adequate number of rainfall events and to span multiple multi-day aggregation windows under infrequent forcing. Consequently, the two regimes are configured with different simulation lengths to ensure comparable information content (event count and window samples) rather than identical duration.

To ensure consistency with typical field sampling practice, we evaluate multiple temporal windows (every 5 days in humid regime and every 2 days in arid regime) and three representative topsoil thicknesses (Δz = 0.05, 0.10, and 0.20 m), reflecting common sampling depths and frequencies (Dubbert et al., 2013; Shokri et al., 2008). Each temporal window is defined such that at least one rainfall event occurs within the interval. For a given temporal window, the initial and final soil water content and isotopic composition of the defined topsoil layer are extracted from MOIST outputs and used to estimate E/P over that period. For example, in a 5-day window, soil water content and isotopic composition on Day 1 and Day 5 are used to estimate the cumulative E/P for those five days. This procedure is repeated across all spatial resolutions to assess the sensitivity of SS, NSS, and ISONEVA to topsoil thickness and temporal aggregation.

Note that δ^2H and $\delta^{18}O$ in soil water can be strongly linearly correlated, resulting in near collinearity in isotope space. Consequently, they provide largely redundant rather than independent constraints on the unknown flux ratios and cannot be jointly used to uniquely constrain both x and y. In addition, $\delta^{18}O$ generally exhibits smaller analytical uncertainty compared to δ^2H, which reduces noise propagation during the inversion and improves numerical stability. Therefore, $\delta^{18}O$ is selected as the representative tracer in this study.

Since SS and NSS contain only one unknown, which can be solved directly using output data from MOIST. By contrast, ISONEVA originally involves two unknowns, x = E/P and y = Q/P, but only one isotope-based equation, which makes the problem underdetermined if treated purely as a two-unknown inversion. To improve identifiability and enforce mass conservation more rigorously, we a water-balance constraint derived from the observed change in topsoil water storage over the evaluation window (derived from Eq. 7):

$$\frac{\Delta V}{P} = 1 + x - y \tag{24}$$

where ΔV is the change in water storage of the topsoil layer and P is cumulative precipitation over the same interval. This constraint allows y to be eliminated in Eq.(23) and reduces the inversion to a one-dimensional optimization problem in x. By explicitly enforcing mass conservation, this reformulation removes the structural non-uniqueness associated with unconstrained (x, y) search.

Despite dimensionality reduction, the objective function remains highly nonlinear in x (Eq. 23) due to its ratio structure and exponential dependence, which may cause numerical instability under certain hydrological states. As a result, the objective function (Eq. 23) may exhibit strong curvature or local flat regions under certain hydrological states, potentially affecting numerical convergence and solution stability. We adopt the following optimization strategy to solve x:

- *Single-window inversion (default):*

  For each evaluation window, x is estimated by minimizing the isotope residual objective with y analytically eliminated using the storage constraint (Eq. 24). The optimization is performed using a bounded one-dimensional search (fminbnd function in MATLAB), which ensures deterministic and reproducible solutions within physically meaningful limits.

- *Multi-window coupled inversion (fallback):*

  When a single evaluation window provides insufficient information content (e.g., weak storage change, near-steady-state conditions, boundary convergence, or numerical degeneracy), we implement a multi-window coupled inversion strategy. In this approach, x is assumed to remain constant within a short predefined block (up to three consecutive windows), and isotope mass balance constraints from these windows are jointly used to estimate a single value of x. For instance, if the inversion over an initial 5-day window does not yield a stable interior solution, subsequent consecutive windows (e.g., Days 1-10 and/or Days 1-15) are incorporated, and a common x is estimated using the combined constraints. By aggregating multiple end-point isotope and storage-change signals, this strategy increases effective information content while maintaining a physically interpretable assumption of quasi-constant flux partitioning over short time scales.

  Although assuming constant x within a block may introduce limited approximation error if flux partitioning varies temporally, it represents a controlled bias-variance tradeoff that substantially enhances parameter identifiability under weak-signal conditions and prevents spurious boundary-constrained solutions. In practice, the block length is deliberately restricted to a maximum of three windows to minimize potential bias while improving numerical stability.

To quantify uncertainty and avoid reliance on stochastic optimizer variability, measurement uncertainties are propagated through the inversion using Monte Carlo simulation. Specifically, we perturb (i) topsoil $\delta^{18}O$ measurements and (ii) precipitation $\delta^{18}O$ data by adding Gaussian noise with a standard deviation of 0.7‰ (von Freyberg et al., 2020), recompute x for each perturbed realization (1000 simulations per window), and report uncertainty as the standard deviation of the resulting x. This approach explicitly links reported uncertainty to observational error, thereby providing a physically interpretable confidence estimate.”.

Lastly, we agree that utilising dual-isotope metrics (e.g., d-excess or lc-excess) may provide additional constraints in isotope-based hydrological analyses. However, the aim of ISONEVA is to derive evaporation and non-evaporative flux ratios by jointly exploiting soil-water isotope dynamics and storage changes. The revised formulation demonstrates that the inversion can be physically constrained using the water-balance relationship without introducing additional isotope-derived variables. Incorporating dual-isotope metrics could represent a useful extension of the framework, but it is not required for the determinacy of the present formulation. In the current study, we focus on $\delta^{18}O$ because oxygen isotopes are generally considered more stable and less sensitive to post-sampling exchange or analytical artifacts than hydrogen. We therefore used $\delta^{18}O$ as the representative tracer for this study. We agree that dual-isotope diagnostics (e.g., d-excess or lc-excess) could be explored as an extension in future applications.

2. Idealized and Non-Representative Virtual Validation
The virtual tests remain overly simplistic and do not reflect the complexity of land-atmosphere interactions. Boundary conditions are kept constant (e.g.,T=40°C , RH=0.2) , ignoring diurnal cycles and seasonal variability which are the primary drivers of non-steady-state conditions in nature. The "optimal" topsoil thickness of 0.08 m identified in the results is highly dependent on the specific soil type (Yolo light clay) and the artificial frequency of rainfall used in the MOIST model. The lack of sensitivity analysis regarding diverse soil textures and varying climatic regimes undermines the claim that ISONEVA is a robust or scalable tool.

Thank you for raising this important concern regarding the representativeness of the virtual validation. In the revised manuscript, the virtual experiments have been substantially expanded to better reflect the complexity of land-atmosphere interactions. In the previous version, atmospheric boundary conditions were prescribed as constant values (e.g., T = 40°C, RH = 0.2) in order to provide a controlled demonstration of the ISONEVA framework. Following the Editor’s recommendation and the reviewers’ comment, we have now introduced diurnal variations in air temperature and relative humidity in the virtual simulations. These revised boundary conditions allow the simulations to capture non-steady-state dynamics that more closely resemble natural soil-atmosphere systems.

Furthermore, the revised virtual experiments now include two contrasting hydrological regimes: an arid regime ($|E/P| > 1$) and a humid regime ($|E/P| < 1$). This allows us to evaluate the performance of ISONEVA under different precipitation frequencies and atmospheric forcing conditions.

Regarding the model sensitivity, we conducted a series of sensitivity analyses examining the influence of several key factors, including (i) hydrological regime, (ii) topsoil control volume thickness, and (iii) atmospheric vapor isotope composition. These analyses are now presented in Section 3.1 (also available to our responses to Editor in this rebuttal letter) and demonstrate how the performance of the inversion depends on the information content of soil water storage and isotope signals. These newly added contents can be referred to in our response to Editor's comment.

Regarding the "optimal" topsoil thickness, we agree that the specific value reported in the previous version (0.08 m) may depend on the soil hydraulic properties used in the MOIST simulations (Yolo light clay). However, identifying a universally optimal sampling depth is not the objective of the virtual experiments. Rather, the purpose of these simulations is to illustrate the trade-off between signal smoothing and measurement sensitivity when defining the topsoil control volume for isotope-based evaporation estimation.

To clarify this point, we revised the analysis by evaluating three representative topsoil thicknesses (0.2 m, 0.1 m, and 0.05 m). The results consistently show the same pattern: thick topsoil layers (0.2 m) tend to smooth isotope signals and reduce the sensitivity of the inversion, whereas thin layers (0.05 m) amplify short-term variability and become more sensitive to measurement noise. An intermediate thickness (~ 0.1 m), therefore, provides more stable estimates. Importantly, this result reflects a general signal-detectability trade-off rather than a soil-specific optimal depth. Revisions are made to Line 592-602: "For spatial scale, virtual experiments showed that ISONEVA achieves the highest accuracy in estimating both E/P and Q/P when the topsoil layer thickness is approximately 0.1 m under humid conditions. This pattern is consistent with the field sampling campaign, where frequent precipitation and irrigation events resulted in $|E/P| < 1$, indicating a humid hydrological regime. The agreement between virtual and field results confirms that the performance of ISONEVA strongly depends on the information content of soil water storage and isotope signals within the control volume. For example, the spike experiment conducted in the field further enhanced the isotopic information in the topsoil. By introducing isotopically enriched water, the experiment amplified the isotopic signal within the soil profile, increasing the contrast between evaporative enrichment and incoming water signals. Such signal amplification has been widely recognized as an effective approach for improving the detectability of isotope-based hydrological processes (Beyer et al., 2020; Dubbert et al., 2022; Penna et al., 2018). Consequently, the strengthen ed isotopic gradients improved the identifiability of both evaporation and non-evaporative fluxes, even within a relatively thick control volume."

Overall, the expanded virtual experiments and additional sensitivity analyses provide a more comprehensive evaluation of the ISONEVA framework under a range of environmental conditions and better reflect the complexity of land-atmosphere interactions.

3. Weak Mechanistic Interpretation of Fluxes
The physical interpretation of Q (non-evaporative flux) as a proxy for transpiration (T) is logically flawed in its current form. The assumption that Q primarily represents root water uptake ignores other significant processes like capillary rise or lateral flows, which are not accounted for in the 1D mass balance. Providing only an "upper bound" for the ratio limits the practical utility of the method. Without independent validation (e.g., sap flow or eddy covariance), there is no way to verify if these limits are physically meaningful or simply artifacts of the mass balance residuals.

Thank you for this comment. We have revised the manuscript to clarify the physical interpretation of the non-evaporative flux Q in the ISONEVA framework in line 338-356 "In the ISONEVA framework, Q represents the total non-evaporative flux within the topsoil control volume and may include contributions from root water uptake, percolation, or other subsurface exchanges. The ratio derived from the ISONEVA framework is $\frac{\left|\frac{E}{P}\right|}{\left|\frac{E}{P}\right|+\left|\frac{Q}{P}\right|}=\frac{|E|}{|E|+|Q|}$, while the true ratio of E to ET is $\frac{|E|}{|E|+T_{total}}$. The relationship between these two quantities depends on the relative magnitude of Q and T_{total}, where T_{total} is the total transpiration within the estimating time window.

Within the time interval that ISONEVA is applied, if the non-evaporative flux within the topsoil does not exceed T_{total} ($Q \leq T_{total}$), then $\frac{|E|}{|E|+|Q|} \geq \frac{|E|}{|E|+T_{total}}$ and $\frac{|E|}{|E|+|Q|}$ from ISOENVA represents and upper bound of the true E/ET. By contrast, if additional subsurface fluxes within the topsoil become substantial (e.g., strong percolation or lateral flow), it is possible for Q to exceed total transpiration ($|Q|>T_{total}$). Then, the ratio $\frac{|E|}{|E|+|Q|}$ would underestimate the true value.

However, in the lysimeter validation used in this study, hydrometric observations (Benettin et al., 2021) provide evidence that the non-evaporative flux within the topsoil control volume is likely smaller than total plant transpiration during the experimental period. The lysimeter experiment is characterized by high evapotranspiration rates (5-20 mm d^{-1}) and mostly negligible bottom drainage. Tracer-based water balance analysis further showed that transpiration accounted for approximately 58% of the exported water, whereas bottom drainage contributed only about 10.4%. In addition, soil water observations from the lysimeter (Nehemy et al., 2021) indicate that no sustained downward drainage occurred during the experimental period. Together, these observations suggest that the non-evaporative flux is therefore likely smaller than total transpiration from the entire rooting zone ($|Q| \le T_{total}$). Consequently, the ratio derived from ISONEVA, $\frac{|E|}{|E|+|Q|}$, represents a conservative upper bound of the true evaporation fraction $\frac{E}{ET}$."

Importantly, even when interpreted as an upper bound, the estimate remains informative. Because the evaporation fraction E/ET is inherently constrained between 0 and 1, determining an upper bound effectively reduces the feasible range of ET partitioning. This constraint, therefore, provides useful diagnostic information about the relative contributions of evaporation and transpiration, particularly in situations where direct transpiration measurements are unavailable or uncertain.

Finally, we acknowledge that the current validation remains limited. While the lysimeter experiment supports the theoretical feasibility of the ISONEVA framework, additional field observations (e.g., sap flow or eddy covariance measurements) would further help evaluate its performance under more complex natural conditions. We therefore highlight this as an important direction for future research. This is also discussed in the revised manuscript Line 646: "However, it should be noted that because Q/P is derived from water balance closure, its value may incorporate residual uncertainties in storage change and precipitation measurements. Independent flux measurements (e.g., sap flow or eddy covariance) would further constrain the physical interpretation of Q. In the present study, validation was conducted under controlled lysimeter conditions, where lateral flow is physically excluded and drainage is directly monitored. Moreover, the water balance of this experimental system has been independently verified in previous studies (Benettin et al., 2021), which increases confidence that the derived E/ET values are physically reasonable rather than artifacts of mass balance residuals. In natural field applications, additional processes such as deep percolation beyond the monitored layer, capillary rise, or spatial heterogeneity in root water uptake may introduce ambiguity in attributing Q solely to transpiration. Therefore, future studies should integrate independent transpiration measurements or multi-layer flux observations to further constrain the partitioning of non-evaporative fluxes and strengthen the physical interpretation of E/ET estimates derived from isotope-based inversion.".

4. Insufficient Field Validation and Data Quality
The field validation is restricted to a single 23-day period using a specific lysimeter experiment. The reliance on proxy atmospheric isotope values from a different geographic location (Vienna) introduces significant uncertainty that the provided sensitivity test does not fully mitigate. The use of artificial isotopic labeling in the field experiment creates unnaturally high isotopic gradients, which artificially enhances the model's performance compared to natural conditions where signals are often much more muted. A "Technical Note" in HESS requires a more rigorous demonstration of applicability across different sites or at least a multi-seasonal dataset to prove its "long-term assessment" capabilities.

Thank you for this comment. We agree that the field validation presented in this study is based on a relatively short observation period (24 days) from a controlled lysimeter experiment. The purpose of this dataset is to provide an initial empirical evaluation of the ISONEVA framework under well-constrained hydrological conditions rather than to demonstrate its long-term or multi-site applicability. Lysimeter experiments offer a particularly suitable environment for this type of validation because lateral flow is physically excluded and drainage can be directly monitored, allowing a well-constrained water balance for testing new methodological frameworks.

Regarding the atmospheric vapor isotope composition, we acknowledge that in situ measurements were not available at the experimental site. To address this uncertainty, we adopted representative values derived from cold-trap measurements conducted under comparable climatic conditions (Kurita et al., 2012). In addition, we explored a plausible range of isotopic compositions in atmospheric vapor around these reported values and propagated this uncertainty through the calculations. The reported profiles and associated uncertainties therefore account for both the measurement uncertainty of soil water isotopes and the uncertainty in atmospheric vapor isotope composition.

With respect to the use of isotopic labeling in the field experiment, we note that isotope spike experiments are widely used in ecohydrology and tracer hydrology to enhance signal detectability and evaluate process-based methods (Beyer et al., 2020; Dubbert et al., 2022; Penna et al., 2018). The labeling applied in this study provides a controlled perturbation that allows a clearer evaluation of the inversion performance. Such approaches are particularly useful during early-stage methodological development, where enhanced isotope contrasts help reveal the behavior of the inversion under well-defined conditions.

We also appreciate the comment regarding the expectations for Technical Notes in Hydrology and Earth System Sciences. According to the journal guidelines, Technical Notes are intended to report new developments, significant advances, and novel aspects of experimental or theoretical methods that are relevant for scientific investigations. In this study, our objective is to introduce a new isotope-based framework and demonstrate its feasibility through a combination of controlled lysimeter validation and virtual experiments under well-constrained hydrological conditions. While broader validation across multiple sites, soil types, or longer observation periods would certainly strengthen the assessment of the method, such analyses are beyond the scope of the present Technical Note and represent an important direction for future work, which is now discussed in the revised manuscript (Lines 646-655).

Overall, the aim of this study is to introduce and evaluate a new isotope-based inversion framework. The combination of controlled lysimeter validation and virtual experiments provides an initial assessment of the method’s behavior, while future studies should further test the

ISONEVA framework using longer-term datasets and additional field sites, potentially integrating independent measurements such as sap flow or eddy covariance.

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