

We sincerely thank both reviewers for their thorough review and insightful comments, which have greatly helped us improve the quality and clarity of our manuscript. We have carefully considered all comments and suggestions and have revised the manuscript accordingly.

In this point-by-point response, we provide detailed responses to the reviewers' comments and describe the corresponding revisions made in the manuscript. We have added detailed descriptions of the image assimilation method and further discussed the limitations and future development of the proposed framework.

Accordingly, in the revised manuscript, we have:

- Further detailed the image assimilation method, including the construction of the background and observation error covariance matrices, and added a new flowchart to improve the clarity of the assimilation framework.
- Added discussions to acknowledge the absence of a direct comparison with conventional point-based assimilation methods, clarify the potential complementarity between image assimilation and point-based assimilation and possible implementation pathways, and discuss the influence of interpolation on result evaluation.

Below, the reviewers' original comments are shown in blue, followed by our responses in black. The corresponding revised or newly added manuscript text is shown in red. All line, section, table, and figure references refer to the revised version of the manuscript.

## **Referee #1**

### **Overall evaluation:**

This study presents a novel EnKF-like image assimilation system that integrates curvelet transform into the Common Land Model (CoLM) to improve the spatial structure of soil moisture analyses. By shifting the assimilation process from point-based magnitude corrections to multi-scale structural adjustments in the spectral domain, the proposed method addresses a critical limitation of conventional land data assimilation systems. The experimental design is sound, the use of GLDAS and in-situ observations for validation is appropriate, and the results clearly demonstrate the advantages of the approach in enhancing spatial correlation and reducing errors across different soil layers and vegetation types. The manuscript is well-written and the scientific contribution is significant. I recommend publication after major revisions.

Response:

We thank you for the positive and encouraging assessment of our manuscript. We sincerely appreciate your careful reading, constructive comments, and positive feedback on the overall study design, validation strategy, and scientific contribution of this work.

Below, we provide point-by-point responses to your comments. All corresponding revisions have been marked in blue and red in the revised manuscript, with blue indicating added text and red indicating deleted text.

### **Major Comments:**

#### **1. Methodological Clarifications**

1.1 Flowchart/Schematic (Section 3): Section 3 would benefit from the inclusion of a flowchart or schematic diagram illustrating the overall structure of the EnKF-like image assimilation system. Such a visual aid would help readers better understand the integration of curvelet transform, ensemble-based error estimation, and the Kalman filter update within the spectral space. It would also clarify the sequential flow of data from observation space to image space and back.

Response:

Thanks for your comments. Following your suggestions, we have added a schematic flowchart as Figure 2 in the revised manuscript to Section 3.3, “EnKF-like image assimilation”, to illustrate the overall structure of the curvelet-transform-based EnKF-like image assimilation system. As shown in Figure R1, the flowchart presents the complete assimilation cycle, including ensemble perturbation generation in physical space, forward curvelet transformation, ensemble-based estimation of background and observation error covariances in spectral space, Kalman filter update of the curvelet coefficients, and inverse curvelet transformation back to physical space. We also added corresponding explanatory text in the manuscript to clarify the sequential data flow from physical space to spectral space and back. We have added the relevant description in the revised manuscript (Lines 274–286).

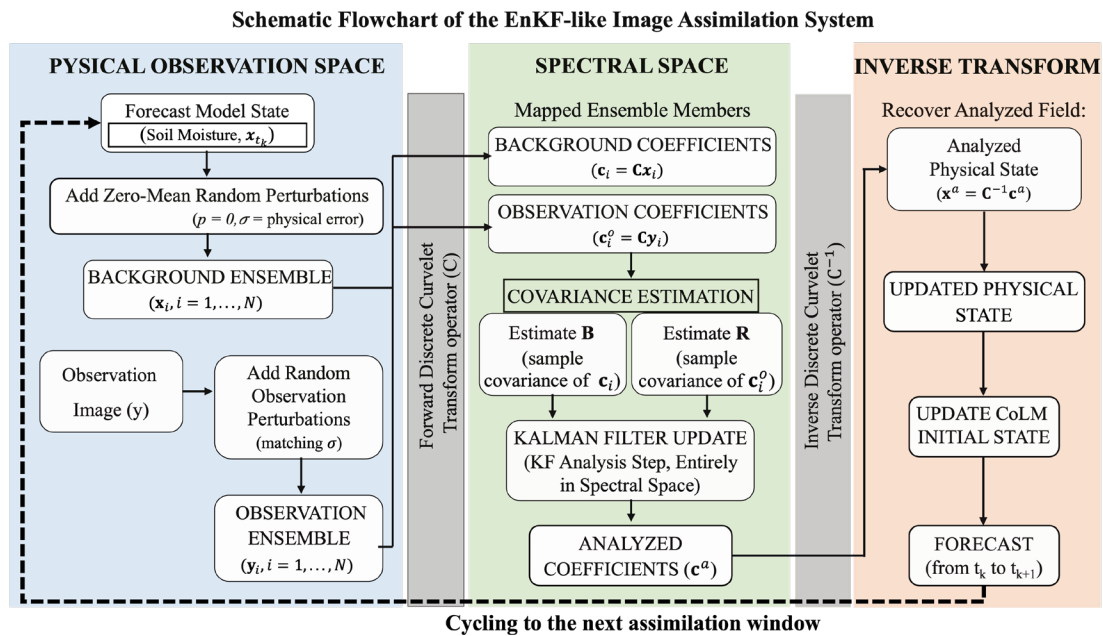


Figure R1: Schematic Flowchart of the EnKF-like Image Assimilation System.

1.2 Curvelet mode interpretation (Lines 170–175): The description of reconstruction using different modes is informative but somewhat abstract. It would be helpful to briefly explain what is meant by "first mode," "first two modes," etc., in terms of spatial scale (e.g., largest scale features correspond to low-frequency modes). This would improve accessibility for readers unfamiliar with curvelet decomposition.

Response:

Thank you for the comments. To help readers better interpret the reconstruction results based on different curvelet modes, we have added a short explanatory paragraph at the beginning of this section. The corresponding revision can be found in the revised manuscript, **Lines 179–188**. The added text is as follows:

Similar to the PCA method commonly used in meteorological studies, curvelet analysis can also decompose the variable into several components with different spatial characteristics. PCA usually extracts leading modes according to the magnitude of variance contribution in time series, and these modes reflect the dominant spatial structures of the variable. In contrast, curvelet analysis uses predefined basis functions at different scales and orientations and projects the variable field at a given time onto these basis functions, thereby obtaining components with different scales and orientations. A single mode in curvelet decomposition can be interpreted as a spatial fluctuation feature within a certain orientation and scale range, and can therefore represent soil moisture variations at a specific spatial scale. In general, lower-order modes correspond to low-frequency signals and mainly reflect large-scale spatial distribution features, whereas higher-order modes correspond to higher-frequency components and describe smaller-scale spatial details. As subsequent modes are gradually introduced, curvelet analysis can resolve increasingly finer spatial structures.

1.3 Error covariance transformation (Lines 210–215): The explanation of how background and observation error covariances are transformed from observation space to spectral space is critical but brief. A more explicit description—perhaps with a step-by-step outline or a mathematical summary—would help readers understand how ensemble perturbations are propagated through the curvelet transform.

Response:

Thank you for your comments. To present the covariance transformation procedure more explicitly, we have provided a step-by-step description of how perturbed ensemble members are generated, how the curvelet transform operator is applied, and how the covariance matrices are estimated in spectral space. In the revised manuscript, we have added the following text in **Lines 249–270**:

Leveraging the mathematical exactness of curvelet analysis, we can transform not only the structure of variables in physical space into spectral coefficients, but also the corresponding errors into coefficients in spectral space. In this EnKF-like assimilation framework, following the error estimation strategy of the EnKF, we first estimate the background error of soil moisture at each grid point in physical space, random perturbations with zero mean and a standard deviation corresponding to the physical-space error are added to the background soil moisture field, thereby generating an ensemble of perturbed members. Let the  $i$ -th ensemble member in physical space be denoted as  $\mathbf{x}_i$  ( $i = 1, 2, \dots, N$ ), where  $N$  is the ensemble size. In this study, the ensemble size is set to  $N = 50$ . By applying the curvelet transform operator  $C$ , these members are mapped one by one into spectral space, yielding the corresponding curvelet coefficients with errors:

$$\mathbf{c}_i = C(\mathbf{x}_i) \quad (7)$$

The background error covariance matrix  $\mathbf{B}$  in spectral space is dynamically estimated directly from the ensemble samples in spectral space:

$$\mathbf{B} = \frac{1}{N-1} \sum_{i=1}^N (\mathbf{c}_i - \bar{\mathbf{c}})(\mathbf{c}_i - \bar{\mathbf{c}})^T \quad (8)$$

where  $\bar{\mathbf{c}}$  denotes the ensemble mean of the curvelet coefficients, and the superscript T indicates matrix transpose. The observation error covariance matrix  $\mathbf{R}$  is transformed in a similar manner. The standard deviations of the random perturbations are prescribed as  $0.15 \text{ m}^3/\text{m}^3$  for the background soil moisture field and  $0.1 \text{ m}^3/\text{m}^3$  for the observation field. In fact, owing to the orthogonality of different basis functions, the background error covariance  $\mathbf{B}$  and observation error covariance  $\mathbf{R}$  are diagonal in the spectral space. Thus, the unrealistic divergence of error impacts can be avoided, making the error localization and inflation procedure unnecessary.

After  $\mathbf{B}$  and  $\mathbf{R}$  are constructed, the assimilation system performs the EnKF analysis step in spectral space to compute the updated curvelet coefficients  $\mathbf{c}^a$ . Finally, the inverse curvelet transform operator  $C^{-1}$  is applied to map the updated curvelet coefficients back to physical space, thereby obtaining the final analyzed field:

$$\mathbf{x}^a = C^{-1}(\mathbf{c}^a) \quad (9)$$

1.4 Sensitivity to GLDAS biases (Section 3.4): The decision to omit bias correction to preserve spatial structure is reasonable given the study's focus. However, the potential sensitivity of results to systematic biases in GLDAS is not addressed. A brief discussion or a sensitivity test (even in a supplement) would strengthen the robustness of the conclusions.

Response:

Thank you for your comments. To strengthen the robustness of our conclusions, we have included an additional discussion on the potential influence of interpolation in the Discussion section of the revised manuscript. The added text is as follows, and can be found in **Lines 590–596**:

Bias correction represents another source of uncertainty. A spatially uniform bias may have a limited impact on image-based assimilation because it does not substantially alter spatial patterns. Conversely, regionally varying systematic biases in observations can be incorrectly incorporated as spatial structures during assimilation, thus degrade assimilation performance. But because estimating such regional bias characteristics requires long-term observational records, and because this study focuses on evaluating the ability of image assimilation to capture and reconstruct spatial structures, systematic bias correction is not considered here. Future work will assess the impact of bias correction using long-term observational datasets.

## 2. Data and Validation

2.1 Interpolation effects (Lines 100–105): Bilinear interpolation of GLDAS data from  $0.25^\circ$  to  $1.4^\circ$  is mentioned, but the potential impact of this resampling on spatial structure—especially in heterogeneous regions—is not discussed. A short comment on how this might affect the comparison would be valuable.

Response:

Thanks for your suggestions. We have included additional discussion of the potential impact of bilinear interpolation on the spatial structure of the GLDAS data. The revised text clarifies that resampling the  $0.25^\circ$  GLDAS data to the  $1.4^\circ$  model grid may introduce a smoothing effect, especially in heterogeneous regions, where local soil

moisture extremes and small-scale spatial gradients may be weakened. We also explain that this preprocessing step is necessary to ensure spatial-scale consistency between the observation field and the model background field, and that the smoothing effect is expected to be reduced in future applications with higher-resolution land surface models. The corresponding discussion has been added to the revised manuscript from **Lines 99 to 104**.

2.2 Scale mismatch in in-situ validation (Lines 380–385): The independent validation using in-situ data is a strong point. However, station density in some regions (e.g., western China) is low, and the representativeness of point-scale measurements for grid-scale ( $1.4^\circ$ ) soil moisture is not addressed. A brief note on this scale mismatch and its implications for interpreting correlation and ubRMSE values would improve transparency.

Response:

Thank you for the comments. To provide additional context for the interpretation of these metrics, we have added a brief discussion of this issue in the Discussion section. The added discussion can be found in the revised manuscript from **Lines 584 to 589**. The added text is provided below:

It should be noted that the in-situ validation is affected by a point-to-grid scale mismatch. A single station may not fully represent the mean soil moisture condition of a  $1.4^\circ$  grid cell, particularly in heterogeneous or sparsely instrumented regions such as western China. Therefore, the correlation and ubRMSE values should be interpreted as indicators of temporal consistency with independent observations rather than exact point-scale accuracy. In particular, ubRMSE may include both retrieval/model errors and representativeness errors associated with spatial scaling.

### 3. Figures and Visual Presentation

Figure 2 caption (Line 225): As noted in the initial review, the caption should be corrected to read: "Figure 2: (a) Soil moisture background field and (b) difference

between the background field and the reconstructed field after adding background error perturbations and applying first-mode curvelet inverse transformation."

Response:

Thank you for your comments. We have revised the caption accordingly. Because a new flowchart has been added to the revised manuscript, the original Figure 2 has been renumbered as Figure 3. The revised caption is as follows:

**Figure 3: (a) Soil moisture background field and (b) difference between the background field and the reconstructed field after adding background error perturbations and applying first-mode curvelet inverse transformation.**

#### 4. Terminology and Consistency

uRMSE vs. ubRMSE (Line 370): The term "uRMSE" appears here, while "ubRMSE" is used elsewhere. Please ensure consistent terminology throughout (preferably "ubRMSE" as defined earlier).

Response:

Thank you for your comments. We have checked all references to this metric throughout the manuscript and ensured that the abbreviation is consistently written as "ubRMSE", following its earlier definition.

#### 5. Interpretation and Discussion

5.1 Vertical propagation mechanisms (Lines 325–335): The discussion of how assimilation increments propagate under different vegetation types is insightful. It could be strengthened by linking these patterns to known hydrological processes (e.g., root water uptake, preferential flow) and noting whether the model's parameterizations are capable of representing such processes.

Response:

Thank you for your suggestions. We have revised this paragraph to strengthen the physical linkage between the vegetation-dependent vertical propagation patterns and relevant hydrological processes. The revised text has been added in the revised manuscript (**Lines 414–424**) as follows:

The more rapid propagation at the Non-arctic Grass and Corn sites is likely related to the shallower effective rooting depth of low-stature vegetation. In a Richards-equation-based matrix-flow framework, positive surface increments raise soil moisture and local hydraulic conductivity, favoring downward redistribution and percolation. After the anomaly moves below the main root zone, the constraint from root water uptake becomes weaker, and the signal can continue downward through gravity drainage and matric-potential gradients (Zeng, 2001). At the NET Temperate site, the slower but more persistent deep-layer response is consistent with the deeper rooting profile of forest ecosystems and the longer memory of soil moisture in the deeper root zone. Deep roots interact with a broader soil column through sustained water uptake, which can slow the downward transfer of assimilation increments while maintaining their influence at depth. The current CoLM2014 configuration, however, does not explicitly represent macropore preferential flow. Simulated downward propagation, particularly in forested or structurally heterogeneous soils, may therefore be smoother and slower than actual field responses when preferential flow is active (Beven and Germann, 2013; Fatichi et al., 2020).

The following references have been added to the reference part of the revised manuscript:

Beven, K. and Germann, P.: Macropores and water flow in soils revisited, *Water Resour. Res.*, 49, 3071–3092, <https://doi.org/10.1002/wrcr.20156>, 2013.

Fatichi, S., Or, D., Walko, R., Vereecken, H., Young, M. H., Ghezzehei, T. A., Hengl, T., Kollet, S., Agam, N., and Avissar, R.: Soil structure is an important omission in Earth system models, *Nat. Commun.*, 11, 522, <https://doi.org/10.1038/s41467-020-14411-z>, 2020.

Zeng, X.: Global vegetation root distribution for land modeling, *J. Hydrometeorol.*, 2, 525–530, [https://doi.org/10.1175/1525-7541\(2001\)002<0525:GVRDFL>2.0.CO;2](https://doi.org/10.1175/1525-7541(2001)002<0525:GVRDFL>2.0.CO;2), 2001.

5.2 Hybrid assimilation outlook (Lines 475–490): The conclusion states that image assimilation and point-based assimilation are complementary. This is an important point, but the manuscript does not explore how such a hybrid system might be implemented. A brief outlook on potential hybrid approaches (e.g., scale-dependent assimilation weights) would add value.

Response:

Thank you for the comment. We have added a brief discussion on the potential technical pathway for developing a hybrid system in the Discussion section. The added text can be found in the revised manuscript (**Lines 615–620**), as follows:

For example, one potential implementation would be to use image assimilation to efficiently adjust the spatial structure of soil moisture in the background field, while also identifying regions with coherent change patterns. Conventional high-accuracy point-based assimilation could then be applied within these specific regions. This strategy would allow observational data to precisely constrain local states and anomalies without disrupting the large-scale structural continuity maintained by image assimilation, and may therefore provide a promising pathway for future hybrid assimilation.

5.3 Acknowledgement of ChatGPT: The acknowledgment of ChatGPT for language polishing (Lines 490–495) is appreciated. However, it might be more appropriate to place this in the Acknowledgements section rather than the main text.

Response:

Thank you for your suggestions. We have moved this content to the Acknowledgements section of the revised manuscript.

### **Minor Comments:**

#### 1. Minor Technical Issues

Reference formatting: Line 625: The reference for Shen et al. (2023) is listed as "Numerical methods," which appears incomplete. Please update with the full journal or conference name.

Response:

Thank you for your comments. We have updated the incomplete reference to the final published version of Shen et al. (2024), and revised the corresponding in-text citation from “Shen et al., 2023” to “Shen et al., 2024” in **Line 317** of the revised manuscript.

## Referee #2

### Overall evaluation:

This study develops an EnKF-like image assimilation system for the Common Land Model and validate the assimilation results. It is a well-motivated work with good novelty.

Response:

We sincerely thank you for your valuable time and positive assessment of our manuscript. We appreciate your careful reading and encouraging feedback on the motivation and novelty of this study.

Below, we provide point-by-point responses to your comments. All corresponding revisions have been marked in blue and red in the revised manuscript, with blue indicating added text and red indicating deleted text.

### Minor Comments:

1. The content of section 3 includes the model description, but the title does not correspond. It is recommended to modify it.

Response:

Thanks for your suggestions. We revised the title of Section 3 to “Methodology and experimental design” to cover the model description, assimilation system construction, and experimental design more concisely.

2. Line 160, coarsest-scale spatial features, Line 165, large-scale, Line 170, continental-scale. In this section, the author provides various descriptions of the scale names. A brief explanation of the basis for this classification is needed.

Response:

Thank you for your comments. Following the commonly used scale classification in meteorology, we have revised these descriptions and now describe the spatial features extracted by the curvelet multiscale decomposition as planetary-scale, large-scale, and mesoscale features from coarse to fine levels. We also added a brief

explanation of the basis for this classification in the revised manuscript (**Lines 189–191**), as follows:

The curvelet-derived spatial features are grouped according to the meteorological scale convention, from planetary-scale to large-scale and mesoscale features. These categories correspond respectively to broad background patterns, regional structures, and finer variations associated with local heterogeneity.

3. Line 210. Is  $X^f$  stand for the variable or spectral coefficients after curvelet transformation? Please explicitly state it.

Response:

Thank you for your comments. We rewrote the relevant section using more explicit notation, with  $x$  representing variables in physical space and  $c$  representing curvelet coefficients in spectral space. We also provided additional details on the generation of perturbed ensemble members, the application of the curvelet transform, and the estimation of covariance matrices in spectral space. Furthermore, a new schematic flowchart has been added as Figure 2 to clearly illustrate the overall structure and workflow of the EnKF-like image assimilation system. The revised manuscript now includes the following text in **Lines 249–286**:

Leveraging the mathematical exactness of curvelet analysis, we can transform not only the structure of variables in physical space into spectral coefficients, but also the corresponding errors into coefficients in spectral space. In this EnKF-like assimilation framework, following the error estimation strategy of the EnKF, we first estimate the background error of soil moisture at each grid point in physical space, random perturbations with zero mean and a standard deviation corresponding to the physical-space error are added to the background soil moisture field, thereby generating an ensemble of perturbed members. Let the  $i$ -th ensemble member in physical space be denoted as  $x_i$  ( $i = 1, 2, \dots, N$ ), where  $N$  is the ensemble size. In this study, the ensemble size is set to  $N = 50$ . By applying the curvelet transform operator  $C$ , these members are mapped one by one into spectral space, yielding the corresponding curvelet coefficients with errors:

$$\mathbf{c}_i = C(\mathbf{x}_i) \quad (7)$$

The background error covariance matrix  $\mathbf{B}$  in spectral space is dynamically estimated directly from the ensemble samples in spectral space:

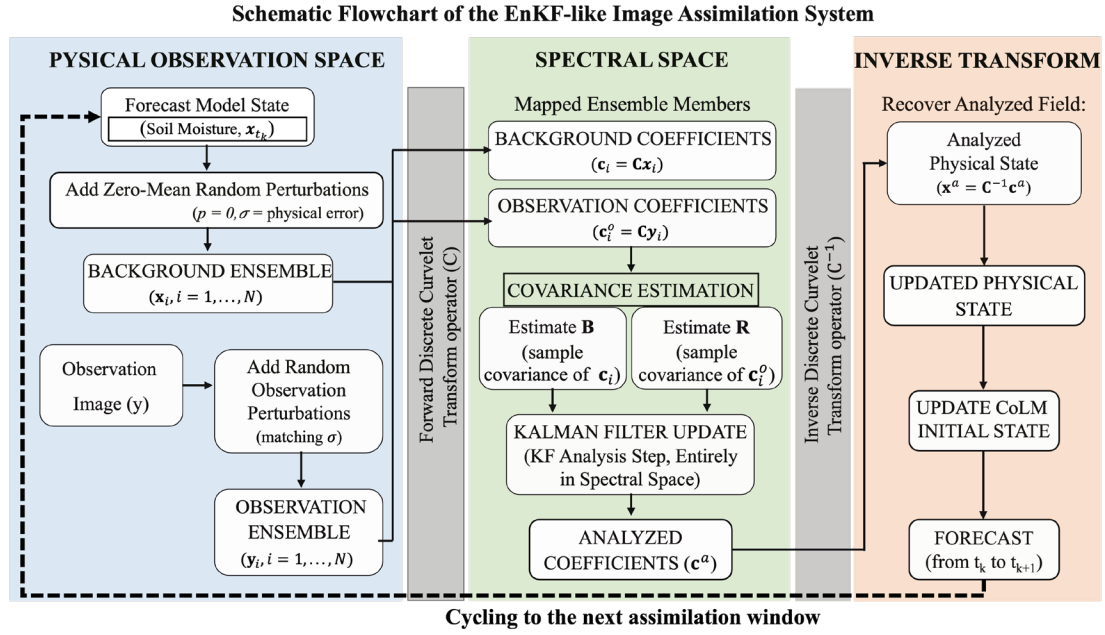
$$\mathbf{B} = \frac{1}{N-1} \sum_{i=1}^N (\mathbf{c}_i - \bar{\mathbf{c}})(\mathbf{c}_i - \bar{\mathbf{c}})^T \quad (8)$$

where  $\bar{\mathbf{c}}$  denotes the ensemble mean of the curvelet coefficients, and the superscript T indicates matrix transpose. The observation error covariance matrix  $\mathbf{R}$  is transformed in a similar manner. The standard deviations of the random perturbations are prescribed as  $0.15 \text{ m}^3/\text{m}^3$  for the background soil moisture field and  $0.1 \text{ m}^3/\text{m}^3$  for the observation field. In fact, owing to the orthogonality of different basis functions, the background error covariance  $\mathbf{B}$  and observation error covariance  $\mathbf{R}$  are diagonal in the spectral space. Thus, the unrealistic divergence of error impacts can be avoided, making the error localization and inflation procedure unnecessary.

After  $\mathbf{B}$  and  $\mathbf{R}$  are constructed, the assimilation system performs the EnKF analysis step in spectral space to compute the updated curvelet coefficients  $\mathbf{c}^a$ . Finally, the inverse curvelet transform operator  $C^{-1}$  is applied to map the updated curvelet coefficients back to physical space, thereby obtaining the final analyzed field:

$$\mathbf{x}^a = C^{-1}(\mathbf{c}^a) \quad (9)$$

To provide a clearer illustration of the overall architecture of the curvelet-transform-based EnKF-like image assimilation system, we present a schematic flowchart in Figure 2. As shown in Figure 2, one assimilation cycle of the framework consists mainly of four key steps. First, in the physical space, the initial ensemble is generated by adding random perturbations to both the background field and the observation field. Second, the forward curvelet transform operator is applied to map the ensemble members from physical space to spectral space. Third, in spectral space, the background and observation error covariances are dynamically estimated from the ensemble samples, and the Kalman filter update is performed to obtain the analysis field of curvelet coefficients. Finally, the inverse curvelet transform is applied to convert the updated curvelet coefficients back to the physical space, thereby optimizing the spatial structure of the model state variables as a whole.



**Figure 2: Schematic Flowchart of the EnKF-like Image Assimilation System.**

4. The proposed image-based method is reasonable for land assimilation. However, the authors do not show the comparison with point-based method. It is recommended to conduct a simple comparative analysis, or to address the limitations in the conclusion.

Response:

Thank you for your comments. Following your suggestions, we have added a discussion in the revised manuscript to acknowledge that a direct comparison with point-based assimilation methods was not included in this study and to clarify this limitation. The corresponding revision has been made in **Lines 607–615**. The added text is as follows:

Although the above analysis demonstrates the potential advantages of image assimilation in preserving spatial structures, a direct comparison with point-based assimilation methods would further clarify its relative strengths and limitations. However, a mature point-based assimilation system specifically applicable to CoLM is not yet available, making it difficult to objectively compare the performance differences between image-based and point-based assimilation at this stage. From a methodological perspective, the two are highly complementary. Image assimilation offers clear advantages in capturing spatial patterns and maintaining structural continuity, whereas

point-based assimilation is more effective for assimilating high-accuracy in-situ observations and handling localized extreme anomalies. Therefore, future work will focus on developing hybrid assimilation strategies that apply scale-appropriate techniques at different spatial scales, fully leveraging the strengths of each method.

## **Community Referee #1**

### **Overall evaluation:**

The manuscript has a clear methodological motivation: standard land DA is often column-wise and does not directly improve the spatial organization of soil-moisture anomalies, which matters for land–atmosphere coupling. The curvelet-based framework is also conceptually well aligned with multiscale spatial structure, and the manuscript explains this reasonably clearly with the reconstruction examples in Figure 1 and the spectral-space assimilation formulation. The paper also includes both global diagnostics and independent station-based checks, which is important. Overall, the study is interesting, potentially useful, and relevant to hydrological modeling and land data assimilation and worth publishing GMD.

Response:

We sincerely thank you for your valuable time and professional guidance. We appreciate your positive assessment of the methodological motivation and the curvelet-based framework for improving the multiscale spatial representation of soil-moisture anomalies.

Below, we provide point-by-point responses to your comments. All corresponding revisions have been marked in blue and red in the revised manuscript, with blue indicating added text and red indicating deleted text.

### **Minor Comments:**

1. Please define more explicitly what makes the method “EnKF-like” rather than a standard EnKF. At present, the wording may confuse readers expecting a full ensemble state update in model space.

Response:

Thank you for your comments. We clarify that the framework is termed “EnKF-like” because it adopts the ensemble-based error covariance estimation strategy of the EnKF, while differing from the standard EnKF in the update space and ensemble treatment. Specifically, ensemble members are mapped into curvelet spectral space, where the covariance of spectral coefficients is estimated from the ensemble samples.

The analysis is then performed in this space using the standard Kalman filter equation. For computational simplicity, the framework does not include a full ensemble update after the analysis step.

This clarification has been added to the revised manuscript in **Lines 229–235**.

2. The description of the ensemble perturbation strategy for estimating BB and RR is too brief. Please state the ensemble size, perturbation distributions, and whether any localization or inflation is used.

Response:

Thank you for your comments. Following your suggestions, we have expanded the method description to specify how the ensemble members are generated by adding random perturbations, how the curvelet transform operator is applied, and how the covariance matrices are estimated in spectral space.

The ensemble size is now explicitly stated as 50 in **Line 255** of the revised manuscript. The perturbations are generated from zero-mean random distributions, with standard deviations prescribed according to the corresponding background and observation errors in physical space. These perturbed ensemble members are then mapped into spectral space using the curvelet transform, and the spectral-space ensemble samples are used to estimate BB and RR.

Regarding localization and inflation, the proposed image assimilation system does not apply either procedure. In fact, owing to the orthogonality of different basis functions, the background error covariance BB and observation error covariance RR are diagonal in the spectral space. As a result, the unrealistic spreading of error impacts can be avoided, making conventional error localization and inflation unnecessary in this study. These clarifications have been added to the revised manuscript in **Lines 264–266**.

3. Figures 3–5 are informative, but the captions could better state which fields are instantaneous and which are accumulated or averaged, to avoid ambiguity.

Response:

Thank you for your comments. We have revised the captions of Figures 3–5 by adding “instantaneous” to clarify that the soil moisture fields and GLDAS reanalysis data shown in these figures are instantaneous values rather than time-averaged quantities.

4. Please report the number of U.S. ISMN stations actually used after screening, as this is less explicit than for the CMA dataset.

Response:

Thank you for your comments. We have added the information on the ISMN stations actually used in this study in **Lines 119–121** of the revised manuscript. The added text is provided below:

In this study, we select 10 cm soil moisture observations from the ISMN network located in the United States for the period from June to August 2022, including 148 stations used for validation.

5. The manuscript should discuss whether the method is expected to remain effective at higher spatial resolution, where fine-scale heterogeneity and representativeness errors become more important.

Response:

Thanks for your comments. Following your suggestions, we have added a discussion in **Lines 597–605** of the revised manuscript to clarify the potential applicability of image assimilation in high-resolution land surface modeling. The added text is provided below:

Recent studies have increasingly demonstrated the potential of satellite data assimilation to improve high-resolution land surface and hydrological modeling by better constraining soil moisture, vegetation dynamics, and surface–groundwater interactions (Pinnington et al., 2021; Montaldo et al., 2022; Zafarmomen et al., 2024). Image assimilation may offer greater advantages in high-resolution land surface modeling applications. Owing to the exactness of the curvelet transform, the small-scale spatial heterogeneity associated with high-resolution modeling can be represented

by curvelet modes. The ensemble-based error estimation approach can also translate representativeness errors into uncertainties of curvelet coefficients at the corresponding scales. Therefore, through the curvelet transform, image assimilation can identify and extract dominant physical signals in spectral space and apply targeted assimilation adjustments, thereby helping to preserve the accuracy of small-scale soil moisture features in high-resolution analysis fields.

The following references have been added to the reference part of the revised manuscript:

Montaldo, N., Gaspa, A., and Corona, R.: Multiscale Assimilation of Sentinel and Landsat Data for Soil Moisture and Leaf Area Index Predictions Using an Ensemble-Kalman-Filter-Based Assimilation Approach in a Heterogeneous Ecosystem, *Remote Sens.*, 14, 3458, <https://doi.org/10.3390/rs14143458>, 2022.

Pinnington, E., Amezcuca, J., Cooper, E., Dadson, S., Ellis, R., Peng, J., Robinson, E., Morrison, R., Osborne, S., and Quaife, T.: Improving soil moisture prediction of a high-resolution land surface model by parameterising pedotransfer functions through assimilation of SMAP satellite data, *Hydrol. Earth Syst. Sci.*, 25, 1617–1641, <https://doi.org/10.5194/hess-25-1617-2021>, 2021.

Zafarmomen, N., Alizadeh, H., Bayat, M., Ehtiat, M., & Moradkhani, H.: Assimilation of sentinel-based leaf area index for modeling surface-ground water interactions in irrigation districts, *Water Resour. Res.*, 60, e2023WR036080, <https://doi.org/10.1029/2023WR036080>.

6. Some language needs polishing for grammar and precision. For example, there are occasional awkward phrases such as “he assimilation experiment” and repeated wording around “spatial structure.”

Response:

Thank you for your comments. We have carefully checked and polished the manuscript for grammar, spelling, and wording. In the revised manuscript, “he assimilation experiment” has been revised to “the assimilation experiment” in **Line 378**. We also checked the use of articles and pronouns throughout the manuscript. In addition, repeated wording related to “spatial structure” has been revised using more context-specific expressions, such as “spatial pattern”, “spatial feature”, “structural continuity”, and “spatial heterogeneity”.

7. I strongly recommend that the authors cite the following relevant study, which appears closely related to the manuscript's topic of data assimilation for hydrologic and land-surface interactions: "Assimilation of Sentinel-Based Leaf Area Index for Modeling Surface-Ground Water Interactions in Irrigation Districts."

Response:

Thank you for your comment. We have added a brief discussion on recent progress in satellite data assimilation for high-resolution land surface and hydrological modeling in **Lines 597–599** of the revised manuscript. The added text is provided below:

Recent studies have increasingly demonstrated the potential of satellite data assimilation to improve high-resolution land surface and hydrological modeling by better constraining soil moisture, vegetation dynamics, and surface-groundwater interactions (Pinnington et al., 2021; Montaldo et al., 2022; Zafarmomen et al., 2024).

The following references have been added to the reference part of the revised manuscript:

Montaldo, N., Gaspa, A., and Corona, R.: Multiscale Assimilation of Sentinel and Landsat Data for Soil Moisture and Leaf Area Index Predictions Using an Ensemble-Kalman-Filter-Based Assimilation Approach in a Heterogeneous Ecosystem, *Remote Sens.*, 14, 3458, <https://doi.org/10.3390/rs14143458>, 2022.

Pinnington, E., Amezcua, J., Cooper, E., Dadson, S., Ellis, R., Peng, J., Robinson, E., Morrison, R., Osborne, S., and Quaife, T.: Improving soil moisture prediction of a high-resolution land surface model by parameterising pedotransfer functions through assimilation of SMAP satellite data, *Hydrol. Earth Syst. Sci.*, 25, 1617–1641, <https://doi.org/10.5194/hess-25-1617-2021>, 2021.

Zafarmomen, N., Alizadeh, H., Bayat, M., Ehtiat, M., & Moradkhani, H.: Assimilation of sentinel-based leaf area index for modeling surface-ground water interactions in irrigation districts, *Water Resour. Res.*, 60, e2023WR036080, <https://doi.org/10.1029/2023WR036080>.