This manuscript presents the GloSVeT dataset, a global 0.05° monthly soil and vegetation component temperature product derived using the FuSVeT framework (Liu et al., 2025). The study addresses an important gap in separating apparent LST into more physically meaningful components and provides a potentially valuable dataset for land–atmosphere interaction studies. Overall, this is an interesting study.

However, I have several major concerns regarding the **physical definition of the retrieved variables, the consistency of the validation framework, and the interpretation of the results**. In addition, some claims are overstated or insufficiently supported, and parts of the methodology lack transparency or justification. I recommend **major revision** before the manuscript can be considered for publication.

Dear Dr. Jia,

We sincerely appreciate the time and effort you devoted to reviewing our manuscript. Your professional, insightful, and constructive comments and suggestions have been highly valuable in improving the quality of this work. We have carefully considered each of your comments and made substantial revisions to the manuscript. The revisions are summarized as follows:

1. We clarified the physical meaning and applicability boundaries of the retrieved component temperatures, particularly under dense canopy, snow-covered, and urban conditions (Q1, Q2, and Q20).
2. We added a discussion of the influence of clear-sky MODIS observations on the intended all-weather monthly mean component temperatures and the associated validation uncertainty (Q3).
3. We revised inappropriate or insufficiently supported interpretations, especially those related to lagged soil temperature–moisture relationships, vegetation temperature–SIF correlations, and positive soil temperature–moisture correlations in dryland regions (Q4, Q5, and Q11).
4. We updated the dataset combinations used in the triple collocation analysis to improve the independence and robustness of the validation framework (Q6).
5. We added necessary explanations to reduce ambiguity and avoid overinterpretation in the methodological description and result interpretation (Q7, Q10, Q24, and Q25).
6. We added two important analyses that were missing in the original manuscript: an internal closure check of the decomposition–reconstruction process (Q8) and a sensitivity analysis of the fixed emissivity assumption (Q9).

7. We supplemented methodological and product details, including data sources, validation procedures, seasonal evaluation, representative soil temperature products, trend uncertainty, and temporal consistency checks (Q12, Q13, Q14, Q15, Q19, Q21, Q22, and Q23).
8. We corrected or removed inappropriate, overstated, or unclear statements to improve the accuracy and clarity of the manuscript (Q16, Q17, Q18, Q26, and Q27).

We hope that these revisions have adequately addressed your concerns and improved the clarity, methodological rigor, and overall quality of the manuscript. Detailed point-by-point responses to your comments are provided below. For ease of review, all revisions in the revised manuscript are highlighted in red.

Major Comments

Q1. The physical definition of "soil temperature" is currently not sufficiently rigorous and may be misleading: The manuscript treats the land surface as a horizontally combined two-component radiative mixture of "soil" and "vegetation", whereas in reality land surfaces are strongly three-dimensional, especially in forested or shaded canopies. The "soil temperature" here is essentially the radiative temperature of the visible background, **not including the actual soil thermal state under canopy shading**. In other words, this is not always a physically complete "soil temperature" in the ecological or hydrological sense. This conceptual limitation needs to be handled much more carefully throughout the paper, especially in the Introduction, Results, and Discussion.

Reply:

We appreciate this important and technically insightful comment. We fully agree that the soil temperature retrieved through TIR component separation has a specific radiometric meaning and should not be interpreted as a physically complete soil thermal state under all land surface conditions. In particular, it represents the radiative temperature of the visible soil or background surface within the sensor field of view, rather than the actual soil temperature beneath dense canopies, shaded surfaces, or snow cover. We have therefore carefully revised the manuscript to clarify the distinction between remotely sensed component temperatures and soil or canopy temperatures in the conventional ecological and hydrological sense, and to define the physical meaning and applicability of GloSVeT more rigorously.

First, in the Introduction, we added an explicit definition of component temperature in the context of TIR remote sensing: "In the context of thermal infrared (TIR) remote sensing, component temperature separation enables the decomposition of the LST of a mixed pixel into the temperatures of its constituent land surface components (Zhan et al., 2013). These component temperatures have a specific radiometric meaning: they represent the thermal states of the visible vegetation and soil/background surfaces within the sensor field of view. Because real land surfaces have complex three dimensional structures, these radiometric temperatures are not necessarily equivalent to the thermal state of shaded soil beneath canopies or to that of the entire canopy. Nevertheless, they provide an effective and physically interpretable way for constructing a dataset that simultaneously characterizes the thermal behavior of soil and vegetation components." (Lines 65-71)

Second, we revised the interpretation of the TC results to distinguish the physical quantities represented by GloSVeT and the reanalysis soil temperature products. The revised text reads: "This may occur because JRA-3Q and GLDAS represent layer-averaged subsurface soil temperatures, whereas GloSVeT soil temperature represents the radiometric temperature of the visible surface and is more sensitive to snow cover and radiative inversions." (Lines 400-402)

Third, we restructured the manuscript by adding a dedicated Discussion section and, within it, Section 5.3, "Limitations," to explicitly clarify the physical meaning and applicability boundaries of GloSVeT: "Despite the broad application potential of GloSVeT, its physical meaning and applicability need to be clearly defined. First, the soil and vegetation temperatures in GloSVeT are separated from TIR LST, and represent the radiative thermal states of the visible surfaces within the sensor field of view. Therefore, under dense canopy or seasonal snow cover conditions, the retrieved soil temperature does not necessarily correspond to the actual soil temperature beneath the canopy or snowpack. Second, the current two component framework approximates the land surface as a combination of vegetation and soil components. However, over complex surfaces such as urban or mountainous regions, the so-called soil component temperature may include impervious surfaces, exposed rocks, or other non-vegetation materials, and should therefore be interpreted as a non-vegetation background component temperature in these areas. This simplification also does not explicitly distinguish between sunlit and shaded fractions, although their temperature differences can be substantial, especially for the soil component (Ermida et al., 2014). Finally, TIR observations correspond to the thermal state of a very shallow layer, typically on the order of 1–100 μm (Li et al., 2023), rather than the soil thermal state at a certain depth or the complete three dimensional thermal state inside the canopy. Consequently, GloSVeT is more suitable for characterizing the surface radiative thermal states of visible soil/background and vegetation components. For applications involving under-canopy soil temperature, sub-snow soil temperature, urban background thermal states, or vertical heat transfer processes, GloSVeT should be interpreted cautiously in combination with land cover, snow cover, topographic, or canopy structural information. Future developments could further integrate more detailed surface component structure information, soil heat diffusion models, and canopy energy transfer models to extend GloSVeT surface component temperatures toward more explicit vertical soil and canopy thermal states (Cao et al., 2023; Lundquist et al., 2018)." (Lines 650-667)

These revisions clarify that the term "soil temperature" in GloSVeT refers to the radiative temperature of the visible soil/background component and explicitly define the conditions under which it may differ from the actual soil thermal state. We believe that these changes substantially improve the conceptual rigor of the manuscript and address the concern regarding the physical interpretation and applicability of the dataset.

Q2. Snow-covered conditions create a serious physical inconsistency in the definition of "soil temperature": Related to the point above, under snow-covered conditions the retrieved "soil temperature" is effectively much closer to **surface snow temperature** than actual soil temperature. This issue is already visible in the high-latitude performance patterns and is indirectly acknowledged in the context, but it is not treated as a core limitation. The manuscript only masks permanent snow/ice based on MCD12C1 land cover, but does not account for dynamic seasonal snow cover during retrieval or evaluation. Why not involve snow fraction products to improve the product as this issue is already found in Liu et al. 2025.

Reply:

Thank you for this important comment. As noted in our response to Q1, we fully agree that seasonal snow cover can substantially alter the physical meaning of the GloSVeT soil component. Under snow-covered conditions, the retrieved soil component may be closer to the radiative temperature of the visible snow surface than to the actual soil temperature beneath the snowpack. We therefore agree that this issue should be treated as a core limitation, particularly in high-latitude region. We also agree that dynamic snow fraction products are valuable for identifying snow-affected pixels. However, incorporating snow fraction alone would not fully resolve the physical inconsistency. For partially snow-covered pixels, the observed TIR signal may consist of vegetation, exposed soil, and snow surface contributions. Accurately resolving these contributions would therefore require extending the current two-component framework to a three-component radiative model, which would substantially increase retrieval complexity. However, even such an extension would still retrieve the snow surface radiative temperature rather than the soil temperature beneath the snowpack.

For these reasons, permanent snow and ice pixels were excluded in the current version of GloSVeT, while seasonal snow cover was explicitly added as a major limitation in Section 5.3. The revised text reads: "Therefore, under dense canopy or seasonal snow cover conditions, the retrieved soil temperature does not necessarily correspond to the actual soil temperature beneath the canopy or snowpack…For applications involving under-canopy soil temperature, sub-snow soil temperature, urban background thermal states, or vertical heat transfer processes, GloSVeT should be interpreted cautiously in combination with land cover, snow cover, topographic, or canopy structural information. Future developments could further integrate more detailed surface component structure information, soil heat diffusion models, and canopy energy transfer models to extend GloSVeT surface component temperatures toward more explicit vertical soil and canopy thermal states (Cao et al., 2023; Lundquist et al., 2018)." (Lines 650-667)

Q3. There is a major inconsistency between the source observations and the validation framework: The FuSVeT/GloSVeT product is driven primarily by monthly MODIS LST observations, which are fundamentally **clear-sky constrained**. However, the ERA5-Land monthly diurnal cycle used in the model, as well as the flux-tower reference, are constructed by averaging all available instantaneous longwave-derived LST observations regardless of sky conditions. This mismatch is not trivial. It may be less severe for vegetation temperature, but for soil temperature with low heat capacity, which responds much more strongly to radiative forcing and sky conditions, this can introduce systematic inconsistency.

Reply:

We sincerely appreciate this valuable comment. We agree that the MODIS LST observations used in GloSVeT are clear-sky constrained, whereas ERA5-Land and the flux-tower references represent all-sky conditions. This difference can introduce representativeness uncertainty, especially for the soil component, which has lower heat capacity and responds more directly to radiative forcing and sky conditions.

However, the objective of this study is not to generate clear-sky monthly mean component temperatures, but to estimate monthly mean soil and vegetation component temperatures that are as close as possible to the all-weather monthly mean thermal state. Although MODIS LST is fundamentally constrained by clear-sky observations, using satellite LST observations together with a diurnal temperature cycle model to derive monthly mean temperature is a commonly used temporal upscaling strategy. In the GloSVeT framework, ERA5-Land hourly data provide continuous all-sky diurnal cycle information and help constrain the monthly mean diurnal cycle parameters, thereby partly reducing the temporal sampling limitation and clear-sky sampling effect associated with MODIS observations. Therefore, ERA5-Land is used as an auxiliary constraint to approach the intended all-weather monthly mean temperature target, rather than as a source of conceptual inconsistency. For the same reason, using all-sky flux-tower monthly mean LST as a validation reference is consistent with the target variable of GloSVeT, although we agree that the mismatch between clear-sky satellite constraints and all-sky monthly reference data may still contribute to uncertainty, particularly for soil temperature.

In revised manuscript, we added a reference to support the temporal averaging procedure used to derive monthly mean component temperatures: "Finally, using this calibrated model, 24 hourly temperature steps were simulated to derive instantaneous soil and vegetation temperatures, which were then averaged temporally to obtain the final monthly mean component temperatures (Hong et al., 2022). (Line 268)" We also explicitly discussed the influence of clear-sky sampling and possible pathways for future improvement in Section 5.3:"A second limitation arises from the clear-sky nature of TIR satellite observations and uncertainties in related input data. The MODIS LST observations used in GloSVeT are available only under clear-sky conditions, whereas the intended monthly mean component temperatures are expected to represent the average thermal state under all-weather conditions within each month. Although ERA5-Land provides continuous all-sky diurnal thermal information and helps constrain the monthly mean diurnal cycle, the retrieved component temperatures are still ultimately constrained by clear-sky TIR observations. This mismatch between clear-sky observation and the all-weather monthly mean target may introduce sampling biases, especially in persistently cloudy regions or during periods when cloudy-sky and clear-sky surface thermal conditions differ systematically. Such uncertainty could be reduced by incorporating cloud-contaminated LST reconstruction algorithms (Jia et al., 2024; Du et al., 2025) or by directly using advanced all-weather LST products. For example, GHA-LST (Jia et al., 2023), a global, hourly, 5 km, and all-weather LST dataset, provides a promising data source for improving the temporal completeness and all-weather representativeness of component temperature retrievals." (Lines 668-678)

Q4. Lagged soil temperature–moisture analysis is not convincing: I do not find the lag interpretation in Figure 7 sufficiently credible, especially the implied **1–2 month delayed response** of soil temperature to soil moisture in dry regions. In water-limited bare systems, the thermal response of the upper soil surface to changes in soil moisture is usually rapid. Possible lag may occur due to soil watter saturation, whihc may occur over **days** following rainfall, rather than over one to two months. The explanations currently provided are too speculative and are not well supported by either the figure itself or the cited literature.

Reply:

We have taken this comment very seriously. We fully agree that the thermal response of the upper soil surface to changes in soil moisture in water-limited bare systems is generally rapid, and that our previous interpretation could misleadingly imply a 1–2 month delayed physical response. We apologize for this insufficiently cautious interpretation.

In the revised manuscript, we have substantially revised both the methodological description and the interpretation of Figure 7 in the original manuscript, now Figure 8 in the revised manuscript. First, we clarified the scope of the lagged correlation analysis in the Methods section, stating that these lagged correlations were used to identify the monthly window in which soil temperature and soil moisture anomalies showed the strongest association, rather than to estimate an exact physical response time. Second, we rewrote the interpretation of correlation strength and lag dependence. The revised text now emphasizes that 0-month lags are the dominant pattern in most biomes, including arid ecosystems, indicating that synchronous monthly coupling is the primary feature. The interpretation of nonzero lags has been reframed as biome-dependent temporal ordering rather than delayed physical responses. Specifically, moisture-leading associations are more evident in tropical and wetland-related ecosystems, whereas temperature-leading associations are more evident in temperate and high-latitude regions. Third, we added a discussion of the limitation of monthly products, acknowledging that monthly data cannot resolve day-scale responses following rainfall or soil water saturation events. The relevant revisions are provided below.

**Clarification in the Methods section (Lines 310-319)**

For the soil component, correlations were calculated between soil temperature anomalies and soil moisture anomalies for seven monthly lag conditions, namely −3, −2, −1, 0, +1, +2, and +3 months. Positive lags were defined as soil temperature anomalies preceding soil moisture anomalies, whereas negative lags indicate the opposite temporal ordering. These lagged correlations were used to identify the monthly window in which the two variables showed the strongest association, rather than to estimate an exact physical response time. For each valid pixel, only lagged correlations passing the significance test ($p < 0.05$) were retained as candidates. If only one candidate lag was identified, it was selected directly. If multiple candidate lags were identified, the lag with the largest absolute correlation coefficient was selected as the best lag only when its absolute correlation exceeded the second largest absolute correlation by at least 0.05. The retained best lag and its corresponding correlation coefficient were then used in the subsequent analyses."

**Revised interpretation in the Results section (Lines 490-520)**

Regarding correlation strength and lag dependence, Figure 8 reveals a clear hierarchy in the soil temperature and soil moisture association. The dominant pattern is the prevalence of 0 month lags. In several mid and low latitude biomes, such as tropical seasonal forests and savannas, montane grasslands, Mediterranean shrublands, and arid ecosystems (Figures 8c, d, h, k, m, n), 0 month lags account for approximately 40–60% of the pixels. A weaker but still evident 0 month dominance is also found in humid tropical forests, temperate forests and grasslands, and flooded grasslands (Figures 8b, e, f, i, j), where the 0 month lag remains the largest category but accounts for about 20–30% of the pixels. These patterns indicate that the strongest monthly association between soil temperature and soil moisture anomalies most commonly occurs within the same month. Together with the generally negative median correlations and relatively compact spreads, this synchronous dominance is consistent with contemporaneous energy and water partitioning between soil moisture and surface thermal conditions. Beyond this overall synchronous pattern, nonzero lags reveal biome dependent differences in temporal ordering. In tropical and wetland related ecosystems, including tropical broadleaf forests, tropical savannas, and flooded grasslands (Figures 8b, c, h, j), negative lags are relatively more frequent than positive lags of the same length. This pattern indicates that soil moisture anomalies tend to precede soil temperature anomalies in part of these regions, suggesting that antecedent moisture conditions may remain linked to the subsequent monthly soil thermal state through soil water memory and rainfall driven drying and rewetting dynamics (Manzoni et al., 2020). In contrast, temperate and high latitude biomes, including temperate forests and grasslands, boreal forests, and tundra (Figures 8e, f, g, i, l), show relatively higher proportions of positive lags, indicating that soil temperature anomalies more often precede soil moisture anomalies. This temperature leading association may be related to cold season thermal transitions, during which seasonal snow cover and snow insulation strongly modulate ground surface temperature and complicate its monthly relationship with soil moisture (Cao et al., 2023). Collectively, these biome specific patterns suggest that GloSVeT soil temperature anomalies are linked to independent soil moisture anomalies through a physically interpretable temporal structure, characterized by dominant synchronous coupling, more evident moisture leading associations in tropical and wetland related ecosystems, and more evident temperature leading associations in temperate and high latitude regions. These results further support the physical consistency of GloSVeT in representing soil hydrothermal variability across diverse climatic regimes.

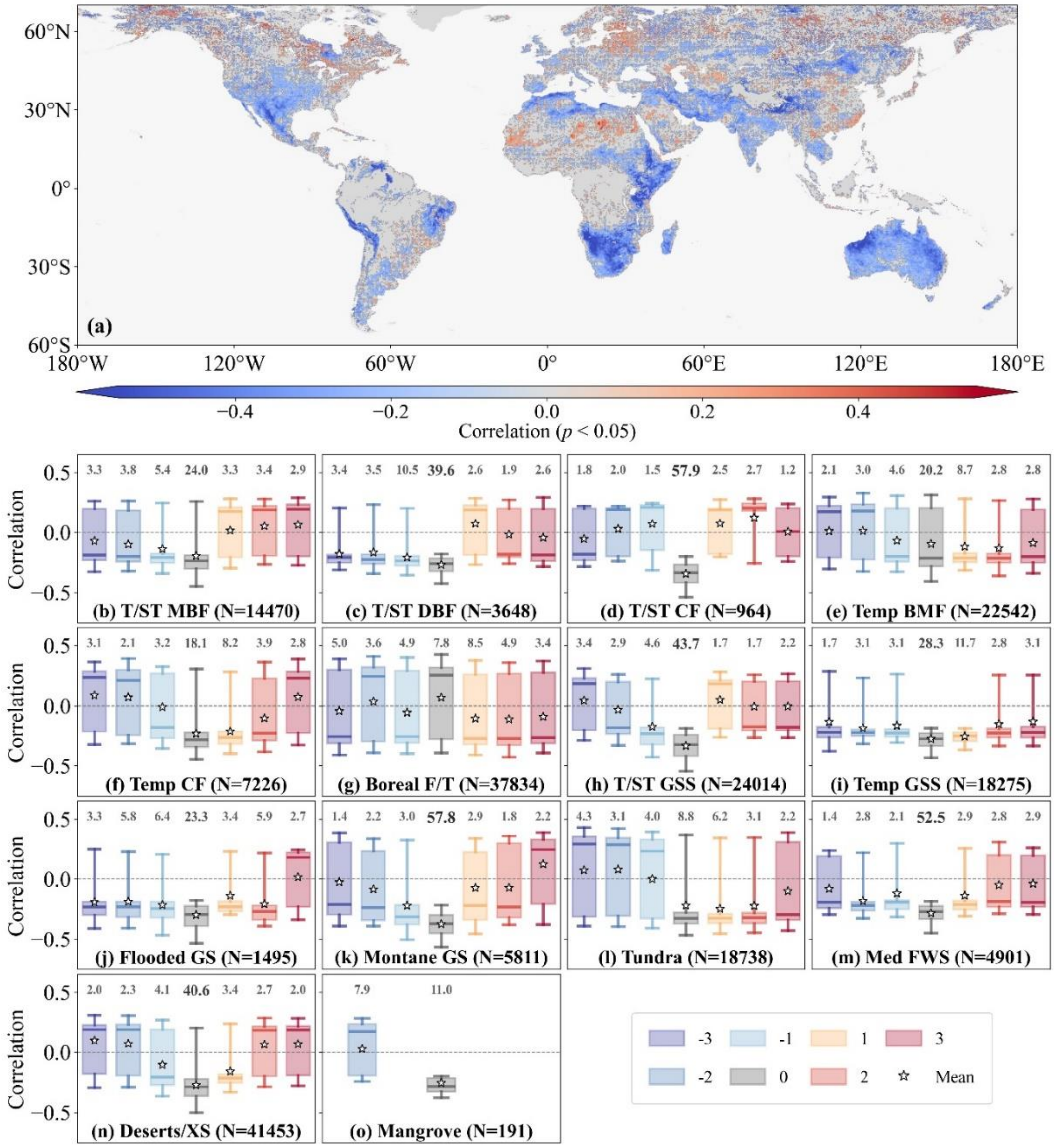


**Figure 8: Correlation between GloSVeT soil temperature anomalies and ESA CCI soil moisture anomalies for the best lag. Panel (a) shows the spatial distribution of correlations for pixels with an identified best lag, where red and blue indicate positive and negative relationships, respectively. Panels (b–o) present the distributions of these correlations across 14 major biomes. Boxplots with different colors denote the identified lag months from −3 to +3. The numbers above each box indicate the percentage of pixels assigned to each identified lag month within the corresponding biome, with darker colors and larger font sizes representing higher proportions. N denotes the total number of pixels in each biome category.**

**Discussion of the limitation of monthly resolution (Lines 701–705)**

In addition, GloSVeT currently produced at a monthly temporal resolution and reports monthly mean surface component temperatures. This design reflects a balance among input data availability, computational efficiency, and the intended use of the dataset for climate scale analyses. However, monthly data cannot resolve short term thermal responses to rainfall, irrigation, soil water saturation, heatwaves, or rapid vegetation stress events.

Q5. Vegetation temperature–SIF correlations: The manuscript attributes positive correlations mainly to "reduced radiative or aerodynamic constraints". I do not think this is the most convincing interpretation. This relationship is more naturally discussed in terms of **photosynthetic thermal optimum** and growing-season physiological activation, which vary strongly by vegetation type. At present, the manuscript mainly shows **latitudinal correlation** contrasts, but does not actually demonstrate the physiological mechanism it claims.

Reply:

We sincerely appreciate this professional suggestion. We agree that attributing the positive vegetation temperature and SIF correlations mainly to reduced radiative or aerodynamic constraints was not sufficiently convincing. In the revised manuscript, we have reinterpreted these positive correlations in terms of photosynthetic thermal optimum and growing season physiological activation. Specifically, positive correlations in energy limited high latitude regions are now described as indicating that warmer growing season canopy conditions may bring vegetation closer to its photosynthetic thermal optimum and coincide with stronger physiological activity (Lines 525–526).

We also revised the biome level interpretation to avoid an overly mechanistic explanation. For example, the original wording that canopy warming "stimulates photosynthesis" or that negative correlations are "driven by water stress and stomatal closure" has been softened to indicate associations between warmer vegetation conditions, SIF, and possible thermal or water constraints (Lines 530–542). These revisions better reflect the correlation based nature of the analysis while retaining the main conclusion that GloSVeT captures a biome dependent continuum between canopy thermal dynamics and photosynthetic activity.

Q6. Figure 3: the claim that "GloSVeT performs best in tropical rainforest regions" is not clearly demonstrated as shown close to the equatorial belt at Figure 3d; More broadly, Figure 3 seems to show that **ERA5-Land generally has higher correlation**, especially for soil temperature, which weakens the central narrative of GloSVeT superiority. Why ERA-land is still compared considering it is used in soil temperature modeling. Why not use other reanalysis or soil temperature datasets mentioned in the introduction.

Reply:

We thank the reviewer for this valuable comment. We agree that the previous statement that "GloSVeT performs best in tropical rainforest regions" was too strong and was not sufficiently supported by the latitudinal profile in Fig. 3d. We also agree that the use of ERA5-Land in the TC analysis may introduce a potential dependence issue. Although ERA5-Land skin temperature and ERA5-Land soil temperature are different variables, they are generated within the same land surface modelling and forcing framework. Therefore, their errors may not be fully independent, which could affect the TC-based comparison.

To address this concern, we redesigned the TC triplet and replaced ERA5-Land with JRA-3Q in the revised analysis. JRA-3Q was selected because it provides globally continuous land-surface analysis variables, including near-surface soil/air temperature, over the study period, and is produced by an independent reanalysis system that was not used in the generation of GloSVeT. In addition, because GLDAS was already included in the TC triplet and is a NASA land data assimilation product, we preferred JRA-3Q rather than introducing another NASA reanalysis product such as MERRA-2. This choice helps maximize the independence among the three datasets in terms of data source, modelling system, and institutional origin. Therefore, the revised TC analysis was based on GloSVeT, JRA-3Q, and GLDAS, thereby reducing the potential dependence associated with ERA5-Land.

We have updated Figures 3–6 (Figures 4-7 in the new manuscript) and revised the corresponding text accordingly. Overall, the revised TC triplet produces broadly consistent large-scale spatial patterns compared with the previous analysis, but we have modified the interpretation to be more cautious and objective. Specifically, we removed the overstrong statement that "GloSVeT performs best in tropical rainforest regions" and replaced it with a more accurate description that GloSVeT shows locally higher or comparable TC-based correlations in humid tropical and subtropical regions. We also removed overly emphatic wording, such as notably, and revised the conclusion to clarify that reanalysis products perform better in high-latitude regions, whereas GloSVeT shows relatively more balanced performance across latitudes and retains certain advantages in humid tropical regions. Accordingly, we further clarified that an important value of

GloSVeT is to provide complementary satellite-constrained soil and vegetation component temperature information to conventional reanalysis products for large-scale applications.

The revised text has been highlighted in red in the manuscript (Please see Lines 390–410). For clarity, the main revised sentences are also listed below:

Figure 4 shows the results of the TC-based correlation (R) for soil temperature. In general, the three products exhibit largely consistent spatial patterns (Figures 4a–c) and latitudinal variation (Figure 4d). High correlations (R > 0.7) are found mainly in the Northern Hemisphere high latitudes and the humid tropics, whereas low correlations (R < 0.5) appear in many mid-latitude transitional regions. This spatial coherence across independent datasets indicates that the major large-scale thermal variations are consistently captured among the different data sources, and further supports the physical plausibility of the GloSVeT retrievals.

Although their patterns are broadly similar, some differences can be observed among the three datasets. Overall, the inter-product differences are more evident in the Northern Hemisphere than in the Southern Hemisphere (Figure 4d). JRA-3Q shows the highest correlations over regions north of 30 °N, but shows the weakest performance across much of the remaining areas, particularly in tropical regions between 10 °N and 30 °N (Figure 4d). Its distribution contains a larger share of both very high (R > 0.8) and very low (R < 0.4) correlations (Figures 4e, f), reflecting spatial heterogeneity and less stable behaviour at global scale. In contrast, GLDAS and GloSVeT achieve more equivalent performance (Figures 4e, f). GLDAS shows a distribution concentrated around moderate-to-high R values (R between 0.6 and 0.8), whereas GloSVeT presents a smoother distribution and maintains more concentrated distribution toward higher R values (Figure 4a, e). In particular, GloSVeT shows locally higher or comparable R values in humid tropical and subtropical regions, such as southern China, the Amazon and the Congo Basin, underscoring its advantage in these environmentally sensitive and data-scarce areas. By contrast, its correlations are lower at high latitudes. This may occur because JRA-3Q and GLDAS represent layer-averaged subsurface soil temperatures, whereas GloSVeT soil temperature represents the radiometric temperature of the visible surface and is more sensitive to snow cover and radiative inversions (Cao et al., 2023; Liu et al., 2025). Taken together, the TC-based evaluation suggests that reanalyses perform better in high latitude regions, whereas GloSVeT shows a relatively more balanced performance across latitudes and retains certain advantages in humid tropical regions. These results indicate that

GloSVeT provides reliable surface soil temperature estimates and serves as a useful complement to conventional reanalysis soil temperature products for large-scale applications.

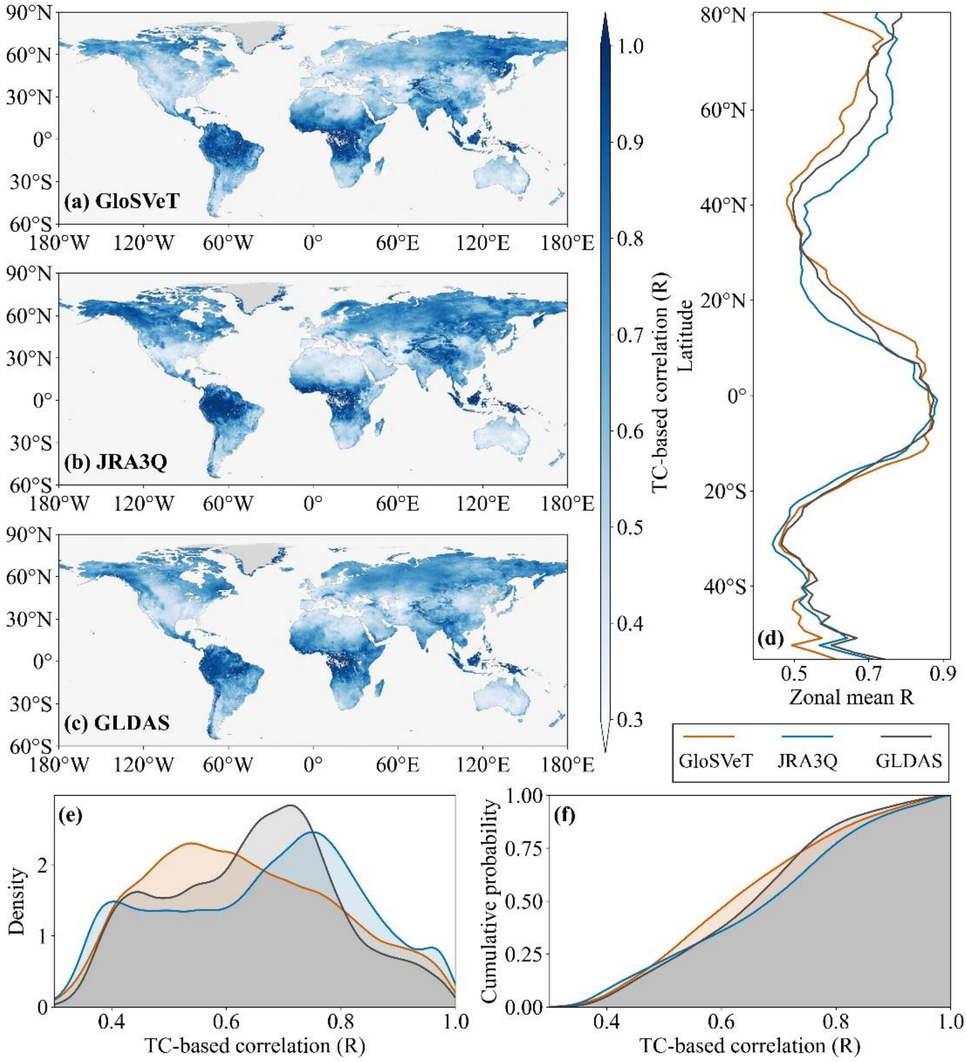


**Figure 4: TC-based correlation (R) for soil temperature. Panels (a–c) illustrate the spatial distributions for GloSVeT, JRA-3Q, and GLDAS, respectively, with light gray and medium gray indicating the ocean and land backgrounds; (d) shows the zonal-mean R as a function of latitude; and panels (e) and (f) present the probability density and cumulative distribution functions, respectively.**

Q7. Figure 4: Some biome-level patterns are difficult to reconcile physically. For example, the very low or inconsistent correlations in Mediterranean and arid systems deserve much more scrutiny, although the soil temperature there should be easier to model.

Reply:

Thank you for this insightful comment. We agree that the relatively low and inconsistent TC-based correlations in Mediterranean and arid systems should be interpreted carefully. To further examine this issue, we additionally calculated the TC-based RMSE across biome types (Figure R1). The results show that the lower R values in Mediterranean forests, woodlands and scrub and deserts/xeric shrublands are not necessarily accompanied by larger RMSEs. This indicates that low TC-based R values in these biomes should not be interpreted simply as evidence of poorer absolute accuracy or as evidence that soil temperature is intrinsically more difficult to estimate there. Instead, the biome-level R values mainly reflect the relative temporal consistency among the three products with respect to the unknown soil-temperature signal within the TC framework. In this sense, Figure 4 is intended to compare the relative consistency and product ranking within each biome, rather than to diagnose the absolute accuracy or physical modelling difficulty of soil temperature across biome types. The additional RMSE analysis supports this interpretation: although the absolute magnitude of R varies among biomes, the relative ranking among products within the same biome is generally consistent between TC-based R and RMSE.

We have revised the manuscript to clarify the interpretation of TC-based correlation coefficients and to avoid overinterpreting low biome-level R values as direct evidence of low absolute accuracy. Specifically, we added the following statement in the TC method section: "It should be noted that these TC-based correlation coefficients are not direct measures of absolute accuracy against a known ground truth, but rather indicators of where GloSVeT shows stronger or weaker agreement with independent datasets under the TC assumptions" (Lines 306-308).

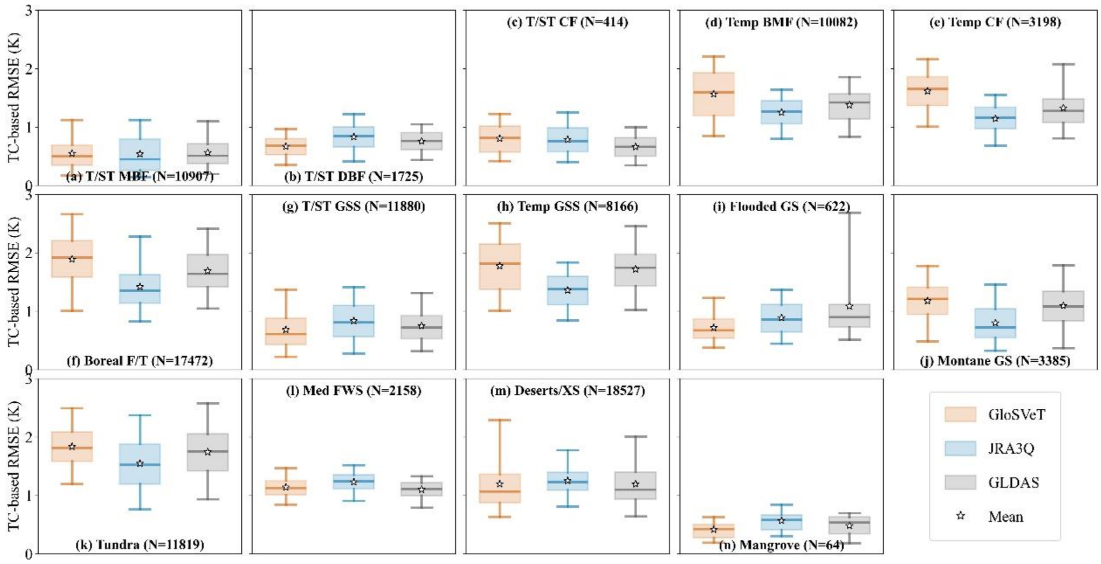


**Figure R1: TC-based RMSE (K) for soil temperature across 14 major biomes. Boxplots show the distributions of RMSE for GloSVeT (orange), JRA3Q (blue), and GLDAS (dark gray). Stars denote the mean values. T/ST, MBF, DBF, CF, Temp, BMF, F/T, GSS, GS, Med, FWS, and XS, are the abbreviations of**

**'Tropical/subtropical', 'moist broadleaf forests', 'dry broadleaf forests', 'coniferous forests', 'Temperate', 'broadleaf and mixed forests', 'forests/taiga', 'grasslands, savannas and shrublands', 'grasslands and savannas', 'Mediterranean', 'forests, woodlands and scrub or sclerophyll forests', and 'xeric shrublands', respectively.**

Q8. Consistency test: A key missing analysis is to recombine the soil and vegetation temperatures back into a synthetic mixed surface temperature and compare that reconstructed LST against the original MODIS LST. This is a basic closure check for any decomposition framework. Without it, it is difficult to know how much error or structural bias is introduced during the separation process.

Reply:

We sincerely appreciate your valuable comment. In the revised manuscript, we have added this key consistency check by recombining the retrieved soil and vegetation component temperatures into synthetic mixed-pixel LSTs at the four MODIS overpass times and comparing them with the corresponding original MODIS LSTs. The results suggest that GloSVeT can largely reproduce the original MODIS mixed-pixel LST signal, while systematic overpass-dependent residuals remain. Specifically, the monthly global RMSEs generally ranged from approximately 1.2 to 2.0 K, and the Bias values were mostly within about ±1 K during 2003–2023. These results support the internal consistency of the decomposition–reconstruction process and help quantify the potential residual errors introduced during component separation.

For clarity, the major revisions are listed below.

**Method description in Section 3.3 (Lines 289-295)**

To examine whether GloSVeT preserves the original mixed-pixel LST signal and to quantify potential structural residuals introduced during the separation process, an internal closure check was first performed. Specifically, based on Equation (7), the calibrated MDC model was used to reconstruct mixed-pixel LSTs at the four MODIS overpass times. The closure residual was defined as the difference between the reconstructed LST and the corresponding original MODIS LST. For each month and each MODIS overpass time during 2003–2023, global RMSE and bias were calculated using all valid pixels. The resulting monthly global RMSE and bias statistics were used to evaluate the long-term internal closure of the decomposition–reconstruction process, as well as its dependence on MODIS overpass time.

**Results in Section 4.1 (Lines 325-350)**

## 4.1 Internal closure check

Figure 2 summarizes the internal closure check for GloSVeT. Overall, the reconstructed mixed-pixel LSTs were reasonably consistent with the original MODIS LST values at the four overpass times. The monthly global RMSEs generally ranged from approximately 1.2 to 2.0 K, while the bias values mostly remained within about ±1 K. The relatively compact boxplots further suggest that the closure errors were temporally stable during 2003–2023, with RMSE variations generally within about 0.2–0.5 K and bias variations within about 0.4–0.6 K.

The closure residuals also exhibited clear overpass-time dependence. In terms of RMSE, MYD11C3_Nighttime (i.e., 01:30 nominal local time) yielded the smallest closure error, with a median RMSE of about 1.24 K, whereas MOD11C3_Daytime (i.e., 10:30 nominal local time) had the largest error, with a median RMSE close to 1.94 K. MYD11C3_Daytime (i.e., 13:30 nominal local time) and MOD11C3_Nighttime (i.e., 22:30 nominal local time) had intermediate RMSEs, both around 1.61 K. The bias statistics revealed a broadly consistent overpass-dependent pattern. MOD11C3_Daytime and MYD11C3_Nighttime had negative median biases of -1.04 and -0.64 K, respectively, whereas MYD11C3_Daytime and MOD11C3_Nighttime had positive median biases of 0.92 and 0.56 K, respectively. Although the biases were not uniformly negative, the negative residuals were slightly larger in magnitude than the positive residuals, suggesting a weak overall negative tendency in the closure residuals. This overpass-dependent behavior may be partly related to the uneven temporal distribution of MODIS sampling times (Liu et al., 2025). In particular, the long interval between the MYD11C3_Nighttime and MOD11C3_Daytime overpasses spans the nocturnal minimum, sunrise transition, and morning warming period, but this key transition phase is not directly constrained by MODIS. As a result, the fitted MDC curve may still contain residual uncertainties in phase and morning warming dynamics, which can lead to overpass-dependent closure biases. Overall, the closure check suggests that GloSVeT can largely reproduce the original MODIS mixed-pixel LST signal, while systematic overpass-dependent residuals remain.

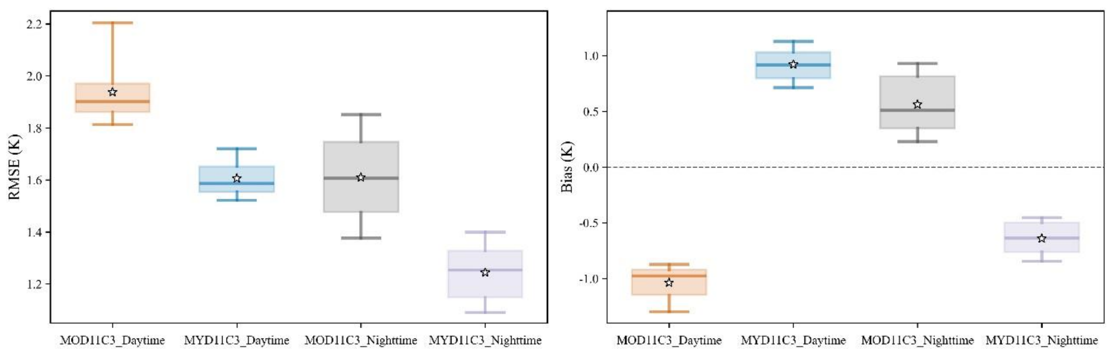


**Figure 2: Internal closure check of GloSVeT. Boxplots show the distributions of monthly global (a) RMSE and (b) Bias between reconstructed mixed-pixel LST and the corresponding original MODIS LST during 2003–2023 at the four MODIS overpass times. Stars denote the mean values, and the dashed line in panel (b) indicates zero Bias.**

Q9. fixed soil emissivity assumption: The manuscript fixes broadband emissivity to 0.98 for vegetation and 0.95 for soil. This may be acceptable as a simplifying assumption in algorithm development, but for a global product covering deserts, bright soils, drylands, and diverse mineral backgrounds, it becomes a non-trivial source of uncertainty. This assumption deserves much more discussion.

Reply:

This comment is taken seriously. We agree that using fixed broadband emissivities for soil and vegetation is a simplifying assumption and can introduce non-negligible uncertainty for a global product, especially over deserts, bright soils, drylands, and heterogeneous soil backgrounds.

To address this concern, we added a new discussion subsection entitled “Influence of fixed emissivity” and conducted an emissivity sensitivity analysis. Specifically, nine soil–vegetation emissivity combinations were tested, with soil emissivity set to 0.90, 0.93, and 0.95, and vegetation emissivity set to 0.97, 0.98, and 0.99. Based on the 2023 monthly datasets, global valid pixels were stratified into FVC bins at an interval of 0.1, and 1000 valid samples were randomly selected from each FVC bin for each month. The component temperatures retrieved under the other eight emissivity perturbation scenarios were then compared with the baseline setting used in GloSVeT ($\varepsilon_s$ = 0.95 and $\varepsilon_v$ = 0.98), and the resulting MAE was quantified.

The results indicate that the fixed-emissivity assumption has a clear FVC-dependent influence. Without separating FVC conditions, the median MAEs of soil and vegetation component temperatures were 1.16 K and 1.26 K, respectively, suggesting that the overall influence remains within a relatively limited range. More importantly, the sensitivity analysis shows that emissivity uncertainty has a smaller impact on the dominant component within a mixed pixel. When FVC is below 0.5, the soil component dominates the mixed-pixel thermal signal, and the MAE of soil temperature is generally below 1 K. Conversely, when FVC exceeds 0.5, the vegetation component is more strongly constrained, and the MAE of vegetation temperature is generally below 1 K. Larger uncertainties mainly occur for the weakly represented component under very low or very high FVC conditions, where the MAE can approach or exceed 2 K. We therefore clarified that the fixed-emissivity assumption does not substantially weaken the overall ability of GloSVeT to represent the dominant component temperature, but the non-dominant component temperature under extreme FVC conditions should be interpreted with caution.

For clarity, the major revision is as follows (Lines 603-629).

5.1 Influence of fixed emissivity

In GloSVeT, the broadband emissivities of soil and vegetation were uniformly set to 0.95 and 0.98, respectively. For a global product, such fixed emissivity assumptions inevitably introduce uncertainty, particularly for soil component (García-Santos et al., 2015). Therefore, we conducted an emissivity sensitivity analysis to evaluate the potential influence of this assumption on the retrieved soil and vegetation component temperatures. Specifically, nine soil–vegetation emissivity combinations were tested, with soil emissivity set to 0.90, 0.93, and 0.95, and vegetation emissivity set to 0.97, 0.98, and 0.99. Based on the 12 monthly datasets in 2023, the global valid pixels were stratified into FVC bins at an interval of 0.1, and 1000 valid samples were randomly selected from each FVC bin for each month. Soil and vegetation component temperatures were then recalculated under each emissivity combination. Taking the baseline setting used in GloSVeT ($\varepsilon_s$ = 0.95 and $\varepsilon_v$ = 0.98) as the reference, the mean absolute error (MAE) induced by the other eight emissivity perturbation scenarios was calculated.

Figure 13 presents the distribution of MAE across FVC bins, where each boxplot contains 96 MAE statistics derived from 12 months and 8 emissivity perturbation scenarios. The results reveal that sensitivity to emissivity assumptions is strongly dependent on FVC: as FVC increases, the emissivity sensitivity of soil component temperature gradually increases, whereas that of vegetation component temperature decreases. Without separating FVC conditions, the median MAEs of $T_s$ and

$T_v$ are 1.16 K and 1.26 K, respectively, suggesting that the overall influence of the fixed emissivity assumption remains within a relatively limited range. A more detailed FVC-dependent analysis further indicates that emissivity uncertainty has a smaller impact on the dominant component within a mixed pixel. When FVC is below 0.5, the soil component dominates the mixed-pixel thermal signal, and the MAE of $T_s$ is generally below 1 K. Conversely, when FVC exceeds 0.5, the vegetation component is more strongly constrained, and the MAE of $T_v$ is typically below 1 K. In contrast, under very low or very high FVC conditions, the weakly represented component contributes less to the mixed-pixel thermal signal and therefore becomes more sensitive to emissivity perturbations. Therefore, the fixed emissivity assumption does not substantially weaken the overall ability of GloSVeT to represent the dominant component temperature, but the non-dominant component temperature under extreme FVC conditions should be interpreted with caution.

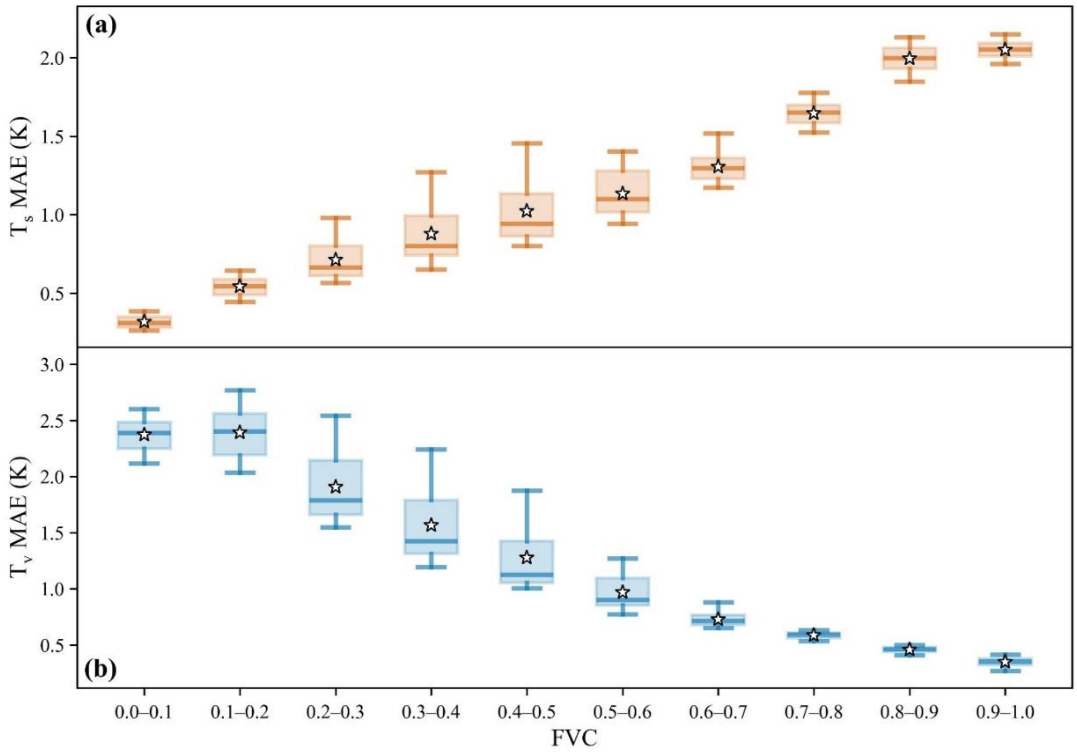


**Figure 13: Sensitivity of GloSVeT to emissivity perturbations across FVC gradients for soil temperature (a) and vegetation temperature (b). Boxplots summarize the MAE distributions derived from 12 monthly datasets in 2023 and eight emissivity perturbation scenarios relative to the baseline emissivity setting used in GloSVeT.**

Q10. The purpose and logic of the second "model calibration" step are not sufficiently clear.

Reply:

Thank you for this careful and helpful comment. In the revised manuscript, we clarified the purpose and logic of the second model calibration step. This step is not a repeated initialization, but is designed to further introduce MODIS LST constraints after the ERA5-Land based initialization, thereby improving the retrieval accuracy of soil and vegetation component temperatures.

The revised text is as follows: Then, model calibration was performed to further introduce satellite observation constraints and improve the retrieval accuracy of soil and vegetation component temperatures. Because only four MODIS LST retrievals at the overpass times are available for each month, directly solving all 11 parameters of the MDC model would lead to underdetermination and instability. Therefore, parameter reduction was applied by retaining the seven temperature independent parameters initialized from ERA5-Land, while only the four temperature dependent parameters were optimized using the 0.05° GLASS FVC and the MOD11C3/MYD11C3 monthly LST retrievals. The temperature difference constraint and the Bayesian optimization algorithm were also imposed during the calibration process. This step enables the resulting MDC model to retain the continuous diurnal cycle shape information provided by ERA5-Land as well as being directly constrained by MODIS LST in terms of temperature level."(Lines 258-266)

Q11. Figure 7: The manuscript interprets negative correlations between soil temperature and moisture as expected evaporative cooling, which is reasonable in many regions. However, the broad areas of positive correlations across parts of West Asia, Central Asia, the Sahara, and northwestern China are not trivial and should not be casually explained away.

Reply:

We sincerely appreciate this valuable comment. We agree that the broad positive correlations across parts of West Asia, Central Asia, the Sahara, and northwestern China are not trivial and should not be treated simply as minor exceptions to the dominant negative relationship. In the revised manuscript, we have rewritten the relevant text to provide a more cautious and region specific interpretation.

Specifically, we now describe these positive correlations as indicating that the relationship between soil temperature and soil moisture is not uniformly governed by evaporative cooling. We further discuss the possible explanations separately for cold regions, arid and semi-arid regions, including the dryland areas highlighted by the reviewer, and coastal and wetland environments. In this way, the revised text avoids casually explaining away the positive correlations and instead interprets them as part of the hydroclimatic heterogeneity of soil hydrothermal coupling.

For clarity, the main revision is provided below.

In contrast, positive correlations (22.4%; red shading) are also evident in several dryland regions, particularly across the Sahara, West and Central Asia, and northwestern China, as well as in parts of high latitude and coastal areas, indicating that the soil temperature and soil moisture relationship is not uniformly characterized by evaporative cooling. In cold regions, these positive associations may be related to snowmelt, freeze thaw transitions, and snow insulation effects, through which warmer ground conditions can coincide with increases in liquid soil moisture (Hu et al., 2006; Jiang et al., 2023). In arid and semi-arid regions, where persistent evaporative cooling is often constrained by limited water availability, positive correlations may reflect episodic rainfall, irrigation, or warm season wetting events (Kong and Huber, 2023; Manzoni et al., 2020). In coastal and wetland environments, hydrological regulation, inundation, and coupled water and energy dynamics may further complicate the soil temperature and soil moisture relationship (Yu et al., 2024). (Lines 470-479)

Other comments

Q12. Why does the dataset end at 2023 only?

Reply:

Thank you for this question. The current version of GloSVeT covers the period up to 2023 because the necessary ancillary datasets, including the MODIS land cover product and GLASS FVC data, were consistently available only up to 2023 at the time of dataset generation. Although the corresponding input data for 2024 have now become available, part of the current processing workflow still relies on a legacy Python 2 environment, which is difficult to reproduce on our current workstations. Therefore, extending routine production to more recent years requires a systematic migration of the workflow to a more stable and modern Python 3 environment.

To ensure the timely completion of this revision, we did not extend the temporal coverage of the current version beyond 2023. It should be noted that the emissivity sensitivity analysis conducted in this revision was a targeted experiment based on sampled data, whereas updating GloSVeT to a new year requires a full production scale run of the complete workflow. Under the remaining legacy computing environment, such full scale processing would be highly time consuming and impractical for this revision. Nevertheless, continuous updating remains an intended development direction for GloSVeT. After completing the workflow migration and validation, we would update the dataset to include more recent years.

Q13. In the abstract, I would write out FuSVeT in full rather than using only the acronym.

Reply:

Done.

Q14. The abstract should clearly state how many flux tower sites were used in the evaluation.

Reply:

Corrected. The abstract now states 'flux-tower validation at 72 representative sites'.

Q15. In abstract, the sentence reporting warming rates for the two components is not sufficiently clear. It should be clarified whether the warming trends refer to global land mean values, or only to pixels where both soil and vegetation temperatures are simultaneously available.

Reply:

Clarified. The sentence has been revised to specify that the warming trends were calculated 'Over pixels where soil and vegetation temperatures are simultaneously available'.

Q16. "version 6.1" should be written as Collection 6.1 where MODIS products are referenced.

Reply:

Done.

Q17. "one retrieved LST" is awkward wording. This should be revised to something like "a single retrieved apparent LST".

Reply:

Done.

Q18. The final part of the Introduction contains result-like wording ("these results demonstrate…"), which is not appropriate for an Introduction.

Reply:

Thanks for your suggestion. The result-like wording has been removed from the Introduction.

Q19. The Introduction would benefit from a more systematic overview of existing soil temperature products, related metadata, and accuracy, validation strategy, probably list them in the appendix.

Reply:

Thank you for this constructive suggestion. We have reorganized this part of the Introduction to more clearly summarize the strengths and limitations of existing soil temperature products, removed the previous overgeneralized statement, and added a new supplementary table, Table A1, which lists representative products together with their spatial and temporal coverage, resolution, target depth, methodology, and data access. We did not include a direct numerical accuracy comparison because validation strategies, study regions, target depths, and evaluation metrics differ substantially among products, and some products do not report directly comparable accuracy information. Listing these values together could therefore be misleading.

The revisions are listed below.

Over the past decades, considerable efforts have been made to estimate soil temperature at global and regional scales, resulting in two main types of products: reanalysis products and machine learning based datasets. Reanalysis products, such as ERA5-Land (Muñoz-Sabater et al., 2021) and GLDAS (Rodell et al., 2004), which rely on data assimilation techniques and land surface modelling, provide spatially continuous soil temperature information at multiple depths and temporal scales. Their main advantage lies in long-term continuity, global coverage, and physically consistent land surface modelling. However, these products are generally provided at relatively coarse spatial resolutions, typically ranging from 0.10° to 0.625°, and their performance can be affected by land surface model structure, parameterization schemes, and forcing uncertainties. With the recent advances in artificial intelligence and the expansion of in situ observational networks, several machine learning–based soil temperature datasets have been developed (Wang et al., 2026; Baumberger et al., 2024; Lembrechts et al., 2022). Compared with reanalysis products, these datasets can better exploit observational constraints and environmental covariates, and often achieve higher spatial resolutions, such as 1 km. Nevertheless, they are generally limited in regional coverage or representation of only climatological averages (Lembrechts et al., 2022; Wang et al., 2026), which constrains their broader applicability. A summary of representative soil temperature products, including their spatial and temporal coverage, resolution, target depth, methodology, and access information, is provided in Table A1. (Lines 45-58)

Appendix A: Supplementary tables and figures

**Table A1. Summary of representative soil temperature products**

| **Product** | **Spatial coverage** | **Temporal coverage** | **Spatial resolution** | **Temporal resolution** | **Depth** | **Methodology** | **Access** |
|---|---|---|---|---|---|---|---|
| GLDAS | Global | 1948–2014 (GLDAS-2.0); 2000–present (GLDAS-2.1) | 0.25 ° × 0.25 ° | 3-hourly | 0–10, 10–40, 40–100, 100–200 cm | Land surface modeling | https://ldas.gsfc.nasa.gov/gldas |
| ERA5-Land | Global | 1950–present | 0.1 ° × 0.1 ° | Hourly | 0–7, 7–28, 28–100, 100–289 cm | Reanalysis | https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land |
| MERRA-2 | Global | 1980–present | 0.5 ° × 0.625 ° | Hourly | 0–9.88, 9.88–19.52, 19.52–38.59, 38.59–76.26, 76.26–150.71, 150.71–1000 cm | Reanalysis | https://disc.gsfc.nasa.gov/datasets/M2T1NXLND_5.12.4/summary |
| JRA-3Q | Global | 1947–present | 0.375 ° × 0.375 ° | 6-hourly | 0–2, 2–7, 7–19, 19–49, 49–99, 99–199, 199–349 cm | Reanalysis | https://gdex.ucar.edu/datasets/d640000/dataaccess/ |
| Lembrechts et al. (2022) | Global | Climatology | 1 km × 1 km | Monthly climatology | 0–5, 5–15 cm | Machine learning | https://zenodo.org/record/4558732 |
| Wang et al. (2026) | China | 2010–2020 | 1 km × 1 km | Daily | 0, 5, 10, 15, 20, and 40 cm | Machine learning | https://doi.org/10.11888/Terre.tpdc.302333 |

Q20. MCD12: It is unclear how urban pixels are treated. Is it considered as soil? The physical definition may not be consistent again.

Reply:

Thank you for this question. Urban and built-up pixels were retained in GloSVeT, mainly for spatial completeness and because such pixels may still contain mixed vegetation and non-vegetation background signals at the 0.05 °scale. However, we agree that the physical interpretation of the soil component over urban areas is different from that over natural soil surfaces.

In the revised manuscript, we clarified the treatment of urban pixels in the section 2.1: By contrast, urban and built-up pixels (IGBP type = 13) were retained for spatial completeness, since such pixels may contain mixed vegetation and non-vegetation background signals at the 0.05 °scale. (Lines 154-156)

We also explicitly discussed this limitation in Section 5.3: However, over complex surfaces such as urban or mountainous regions, the so-called soil component temperature may include impervious surfaces, exposed rocks, or other non-vegetation materials, and should therefore be interpreted as a non-vegetation background component temperature in these areas … Consequently, GloSVeT is more suitable for characterizing the surface radiative thermal states of visible soil/background and vegetation components. For applications involving under-canopy soil temperature, sub-snow soil temperature, urban background thermal states, or vertical heat transfer processes, GloSVeT should be interpreted cautiously in combination with land cover, snow cover, topographic, or canopy structural information. (Lines 655-665)

Q21. In the Methods, it would help to explicitly distinguish temperature-independent and temperature-dependent parameters more clearly when they are first introduced.

Reply:

Thank you for this helpful suggestion. Following your comment, we have clarified the distinction between temperature independent and temperature dependent parameters when they are first introduced in the Methods section. Please see Lines 244–245.

Q22. It is not clear whether the “detrended monthly anomalies” used in the TC analysis is deseasonalized?

Reply:

Yes, the monthly anomalies used in the TC analysis were deseasonalized. In the revised manuscript, we have clarified this point as follows: "The analysis was conducted on a monthly basis from 2003 to 2023 using deseasonalized and detrended monthly anomalies for each dataset, obtained by removing the multi-year climatological mean for each calendar month and then the linear trend from each time series. This preprocessing minimized the influence of seasonal cycles and long-term trends, thereby emphasizing temporal co-variability among datasets" (Lines 301-305).

Q23. The flux-tower validation section should include a site distribution map.

Reply:

Thank you for this helpful comment. We have clarified that the flux tower sites used in this study were not newly selected by us, but were adopted from the representative site sets identified by He et al. (2025). The detailed site information and spatial distribution have already been provided in Table II and Figure 6 of He et al. (2025). In the revised manuscript, we have clarified this point and specified that this study used the union of these season-specific site sets, comprising 72 unique flux sites in total.

The revisions are listed below.

Using random forest modelling and Landsat LST data, He et al., (2025) systematically evaluated the spatial representativeness of 211 flux sites from five observation networks worldwide, and identified 46, 36, 49, and 62 sites with strong spatial representativeness across multiple scales (1 km, 3 km, 5 km, and 10 km) for spring, summer, autumn, and winter, respectively. Detailed information on the selected sites and their spatial distribution can be found in Table II and Figure 6 of He et al. (2025). Following their findings, this study adopted these season-specific site sets and collected available upward and downward longwave radiation records from 2003 to 2023 for the union of these sites, comprising 72 unique flux sites in total. (Lines 167-173)

Q24. Figure 2 is not fully intuitive. In particular, the seasonal amplitude and magnitude range of vegetation temperature appear unexpectedly unchanged.

Reply:

Thank you for this careful observation. After further checking the validation samples, we found that this pattern is mainly related to the latitude composition of the vegetation temperature records. Specifically, unlike the soil temperature records, which were almost entirely from mid-latitude sites in all seasons, the vegetation temperature records included a relatively high proportion of low-latitude samples. Because vegetation temperature in low-latitude regions generally has weaker seasonal variability and may remain relatively high even in winter, the less distinct seasonal amplitude and magnitude range of vegetation temperature are reasonable. Accordingly, we have added the following explanation to the revised manuscript.

In addition, it should be noted that the seasonal amplitude of vegetation temperature was less pronounced than that of soil temperature. Further examination shows that the soil temperature validation records were almost entirely from mid-latitude sites in all seasons, with 159/161, 66/66, 86/90, and 158/160 records in spring, summer, autumn, and winter, respectively. By contrast, the vegetation temperature validation records included a relatively high proportion of low-latitude samples, with 33/94, 37/121, 27/174, and 37/83 records in the four seasons, respectively. Because vegetation temperature in low-latitude regions generally has weaker seasonal variability and may remain relatively high even in winter, it is reasonable that the seasonal amplitude and magnitude range of vegetation temperature were less distinct than those of soil temperature in the validation samples. (Lines 371-379)

Q25. Why R in Figure 6c is weaker.

Reply:

Thanks for this comment. As clarified in our response to Q7 and in the revised TC method section, the TC-based R should be interpreted as a diagnostic of relative temporal consistency among products under the TC assumptions, rather than as a direct measure of absolute accuracy against a known ground truth. Therefore, the weaker R in Figure 6c indicates lower inter-product consistency in representing monthly vegetation-temperature anomalies in temperate broadleaf and mixed forests, rather than necessarily indicating poorer absolute accuracy of GloSVeT. A detailed attribution of the biome-specific low correlation is beyond the scope of this study, and we have revised the text to avoid overinterpreting the TC-based results: “It should be noted that these TC-based correlation coefficients are not direct measures of absolute accuracy against a known ground truth, but rather indicators of where GloSVeT shows stronger or weaker agreement with independent datasets under the TC assumptions" (Lines 306-308).

Q26. delete the space before the 2nd affiliation.

Reply:

Done.

Q27. The statement "neither reanalysis nor machine learning products can accurately characterize the spatial pattern of soil thermal conditions in the real world" is very strong and may need to be revised or add direct reference support.

Reply:

Thank you for this helpful comment. We agree that the original statement was too strong. In the revised manuscript, we have removed this overgeneralized wording and replaced it with a more balanced description of the limitations of existing reanalysis and machine learning based soil temperature products, mainly regarding spatial resolution, model and forcing uncertainties, regional coverage, temporal continuity, and climatological representation. Please see the reply to Q19.