Responses to comments <essd-2023-242>

Dear Editor and referees,

We greatly appreciate your insightful comments and suggestions, and your time in reviewing our manuscript, which have helped us improve our manuscript. In response to your comments, we have made several significant changes in the revised manuscript, which are summarized below:

- In response to Reviewer 1's feedback, we have enriched the manuscript with more detailed descriptions of the validation of each data source used in our dataset development. Additionally, we have conducted a comprehensive comparison between our newly developed 1k parameters and the K2012 and ELM2/CLM5 default parameters, with corresponding updates made to the methods, results, discussion, and conclusions sections.
- In response to Reviewer 2's feedback, we have added two new paragraphs in the discussion section 4. These additions focus on the challenges and considerations related to parameter aggregation and the evaluation of k-scale simulations, providing a more thorough exploration of these critical aspects.

The point-by-point responses to the specific comments are provided below in blue. All line numbers listed below correspond to those in the clean version of the revised manuscript. We hope that our modifications have addressed all the concerns raised, and we appreciate your consideration of our revised manuscript.

Sincerely,

Lingcheng Li and co-authors

Referee 2

This manuscript highlights the importance of developing new global land surface parameters with a resolution of 1 km for Earth system models (ESMs) running at the kilometer scale. The study demonstrates that these parameters significantly impact the spatial heterogeneity and information loss in ESM simulations, particularly in relation to soil moisture, latent heat, emitted longwave radiation, and absorbed shortwave radiation. The use of eXplainable Machine Learning methods helps identify the influential factors driving this variability and information loss. The new land surface parameters have implications for advancing our understanding of water, carbon, and energy cycles under global change. The paper is well written and has significant value for high resolution LSM modeling. However, I have several concerns as shown in the following comments for the authors to be considered.

Thank you for your encouraging comments and suggestions for improving our manuscript. We provide a response for each comment as detailed below.

Major comments:

The aggregation order problem should be addressed when upscaling the secondary derived parameters including DEM-derived variables, PTF-dervived (Pedotransfer functions) soil parameters such as saturated water content. Previous studies have proved that this order has significant effect on the derived parameters and thus the modeling results. For example, the aggregation after method has been recommended by Shangguan et al. (2014) and (Dai et al., 2019). That is, you should first calculate the derived parameters at the high resolution and then aggregate them into low resolution. This is majorly due to the nonlinear relationship between the original parameters and derived ones.

However, the authors chose the aggregate first way according to the description in line 219~222, which is not a good way. At least, you should compare these two methods yourself, evaluate them and choose the better way.

Thank you for your insightful comments and recommendations regarding the aggregation order of secondary derived parameters, particularly in the context of soil parameters derived from DEM and PFTs. The studies by Shangguan et al. (2014) and Dai et al. (2019) effectively underscore the importance of the correct aggregation approach. For instance, in soil properties, the basic parameters (e.g., percent sand) are often utilized to derive secondary parameters (e.g., saturated water content). This aggregation procedure, whether performs before or after deriving secondary parameters—known as 'aggregating first' and 'aggregating after'—is influenced by the non-linear relationships between basic and derived parameters, with the latter method generally preferred (Shangguan et al., 2014; Dai et al., 2019).

In our initial approach when upscaling soil and topography-related parameters, we adopted an 'aggregate first' methodology, such as for the parameters related to soil and topography. We acknowledge that this method might not optimally preserve the accuracy of derived parameters. This choice was primarily influenced by the structure of current models like ELM2 and CLM5, where first-order parameters are inputs, and secondary derived parameters are computed within the model, precluding the 'aggregating after' approach for developing secondary derived parameters. We recognize this might not be the ideal method and suggest that future developments of these models should consider incorporating secondary parameters directly as inputs to mitigate potential inaccuracies.

In contrast, models such as CoLM (Dai, et al., 2014) and Noah-MP (He et al., 2023; Niu et al., 2011; Yang et al., 2011) use secondary derived parameters directly as inputs, facilitating the 'aggregating after' method. These models can utilize secondary derived parameters, like saturated water content, sourced from databases such as the Global Soil Dataset for Earth System Models (GSDE, Shangguan et al., 2014) and SoilGrids (Hengl et al., 2017). This approach highlights a crucial direction for future model development, advocating a shift towards using secondary derived parameters as direct inputs to enhance modeling accuracy and reliability.

Your feedback has been invaluable in highlighting this significant aspect of modeling methodology, and we will certainly consider this in our future research endeavors.

We added relevant content in the discussion:

In L697–712.

The strategic aggregation of high-resolution parameters to coarser resolutions are crucial to maintain accuracy and effectiveness in modeling applications. For instance, in soil properties, the basic parameters (e.g., percent sand) are often utilized to derive secondary parameters (e.g., saturated water content). This aggregation procedure, whether performs before or after deriving secondary parameters—known as 'aggregating first' and 'aggregating after'—is influenced by the non-linear relationships between basic and derived parameters, with the latter method generally preferred (Shangguan et al., 2014; Dai et al., 2019). Our study's initial approach in upscaling soil-related parameters follows the 'aggregate first' approach, aligning with the structure of models like ELM2 and CLM5. Conversely, models such as Common Land Model (CoLM, Dai et al., 2003) and community Noah with multi-parameterization options (Noah-MP, He et al., 2023; Niu et al., 2011; Yang et al., 2011) integrate secondary derived soil related parameters directly as inputs, effectively demonstrating the advantages of the 'aggregating after' approach. By leveraging secondary derived parameters from comprehensive databases such as SoilGrids (Hengl et al., 2017) and GSDE (Shangguan et al., 2014), these models provide a valuable framework for future development of models like ELM2 and CLM5.

References:

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2. This manuscript only shows how the coarse resolution simulation may lead to spatial information loss but not the improvement in modeling accuracy leading by incorporating the high-resolution parameters. You need to evaluate the results to prove that how much gain in the high-resolution simulation compared to low resolution using some benchmark data such as high-resolution SM observations from remote sensing.

Thank you for the constructive comments. We recognize the importance of demonstrating the use of the 1 km input parameters for k-scale simulations and evaluating the accuracy of such simulations. Our current study focuses on the development of 1 km datasets so the ELMv2 simulations showcased here are only intended to illustrate the capabilities enabled by these new parameters. In this context, we have not engaged in direct comparisons of the simulation results with reference datasets like soil moisture. An evaluation of k-scale simulations is currently underway and will be detailed in a forthcoming publication. Therefore, recognizing the crucial need for precise evaluation of k-scale simulations, we have included pertinent discussions in the discussion section of our manuscript.

In L656–L679,

Evaluation of k-scale simulations, while essential, faces significant challenges as merely updating the land surface input data to the new 1k parameters for k-scale simulations doesn't guarantee improved model performance, which depends on both input data as well as model parameters and structures. First, LSMs and ESMs that have been adapted for simulations at coarser resolutions commensurate with the resolutions of previous land surface data require recalibration for effective high-resolution modeling. This necessity for recalibration is echoed by Ruiz-Vásquez et al., (2023), who noted that updating the ECMWF system with new land surface data did not inherently improve performance, but improvements were seen after recalibrating key soil and vegetation-related parameters. Second, high-resolution modeling requires the incorporation of new physical processes crucial at finer scales. For example, hillslope-scale processes like lateral flow and topography-radiation interactions are key to water and energy fluxes at high resolution (Han et al., 2023; Hao et al., 2021). With increased heterogeneity at higher resolutions, larger differences in land surface properties such as vegetation water use strategies requires more attention to plant hydraulics besides the traditional focus on soil hydraulics for a more accurate depiction of plant water use, as highlighted by Li et al., (2021). Third, the lack of high-resolution benchmarks for large-scale applications, like k-scale atmospheric forcing data, remains a challenge, despite the availability of relative coarse resolution global datasets such as ERA5_Land (Muñoz-Sabater et al., 2021) and MSWX (Beck et al., 2021). Additionally, using soil moisture as an example, multiple high-resolution datasets exhibit significantly different performance when compared to in-situ measurements (Beck et al., 2021). Lastly, when evaluating simulations against benchmarks, it is crucial not only to assess absolute differences using metrics like bias and root mean square error but also to examine other metrics, such as the relationships between physical variables (e.g., rainfall vs. runoff; soil moisture vs. evapotranspiration), information loss, and the tail quantiles of the probability distribution functions for simulations (e.g., extreme events).

References:

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Minor comments:

Table 1: the LAI data is updated for 2000-2021, see the link: http://globalchange.bnu.edu.cn/research/laiv061

Thank you for highlighting this. We worked on the 1k datasets and manuscript before the extended LAI source data was published. Consequently, the current 1k data version doesn't incorporate these extended datasets, but we plan to include them in a future version.

Line 255: γ? You should explain it here.

We have revised the text in L312–L315.

A more negative β indicates a larger dependency of data spatial variability on spatial scales, resulting in a higher information loss, denoted as $\gamma_{scale} = (1 - \sigma_{scale}/\sigma_{1\,km}) \times 100\%$. In this study, we focus on information loss at a 12 km scale, denoted as $\gamma_{12\,km}$. For simplicity in subsequent discussion, $\gamma_{12\,km}$ will be referred to as γ in the results section.

Figure 4: why choose these four locations as they are located in the arid and semi-sarid regions? It is recommended to choose locations with a representation of various climate zones or PFT.

The four locations we selected serve solely for demonstration in the spatial scaling analysis. As the complete spatial scaling analysis for each CONUS grid, encompassing spatial variability and information loss, is depicted in Figures 8 and 9, we refrain from displaying additional grid demonstrations across different climate zones.

Line 340~341: the effect of soil texture is very likely amplified by the PTF-derived soil parameters especially soil hydraulic conductivity. Try to investigate this issue. In addition, try to answer questions like is the value of beta related to the clay content itself or other factors like soil heterology?

We acknowledge the potential impact of using Pedotransfer Function (PTF)-derived soil parameters on ELM2 simulations, which may have a more pronounced effect than soil texture. Due to the structural design of the model, soil texture serves as an input and PTF-derived parameters such as soil hydraulic conductivity are calculated internally within ELM2, and thus we have not performed analysis using PTF-derived soil hydraulic parameters. However, we emphasize the importance of considering secondary derived parameters as direct inputs, rather than relying solely on soil texture, for future model developments. This aspect is elaborated in the last paragraph of the discussion section, specifically at L688.

Regarding the slope of the linear regression line, β, it serves as a measure of the strength of the negative relationship between spatial scale and spatial variability. A more negative β value indicates higher spatial-scale dependency, leading to increased information loss at coarser spatial scales. Thus, β is utilized to quantify the extent of standard deviation reduction across different scales. For a detailed explanation and visual representation, please refer to Figure 5 and its accompanying caption.

Figure 6: it shows that L1 has a lower standard deviation of clay, but a more negative beta than L2. This indicate that lower soil heterology does not lead to lower spatial-scale dependence. So, how to explain this? Also, the information loss is higher when the standard deviation is lower. How can it be? Same thing happened in Figure 7.

The definition of information loss is designed to quantify the relative changes in standard deviation as scaling from high to coarse resolution (see L316). Therefore, the information loss is associated with the rate of change in standard deviation across scales, rather than being directly tied to the absolute value of the standard deviation itself.

Figure 8 and 9: what is the link between these two figures? You may discuss this.

Figures 11 and 12 (previously Figures 8 and 9) are employed to highlight the impact of using the new 1k data on the spatial heterogeneity observed in water and energy simulations over CONUS. Figure 11 illustrates the spatial heterogeneity (i.e., the standard deviation) within each 0.5-degree grid cell, whereas Figure 12 demonstrates how this spatial heterogeneity diminishes when the 1 km simulations are upscaled to a coarser 12 km resolution (i.e., information loss). Essentially, the information loss depicted in Figure 12 serves as a secondary metric derived from the standard deviation presented in Figure 11. Figures 11 and 12 also elucidate the primary drivers influencing both the standard deviation and the information loss in our simulations.

The related discussion is elaborated in the second paragraph of the discussion section (L589–L597), where we have included specific references to these figures for enhanced clarity.

Upscaling 1 km to a coarser 12 km resolution, we observe significant spatial information loss, with SM experiencing an average loss of 31%, and LH, ELR, and ASR experiencing around 50% information loss on average (Figure 12). This conclusion is in line with the results of Vergopolan et al. (2022), which showed a substantial loss of spatial information in soil moisture when upscaling from 30 m to 1 km resolution, with an average loss of approximately 48% and up to 80% over the CONUS region. The XML analysis reveals that the spatial variability and information loss of ELM2 simulations are influenced by the spatial variability and information loss of the different variables of land surface parameters, as well as the mean precipitation and temperature (Figures 11 and 12).