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 1

This research presents a new set of global land surface parameters with a resolution of 1 km for multiple years from 2003 to 2020. This manuscript is well-structured. The figures are well produced. The English is good. The results are clearly presented. However, major issues should be addressed before this manuscript may be reconsidered for publication in the esteemed ESSD.

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

For a majority of data description papers in ESSD, a solid verification of the new data based on ground truth data and the comparison between the new data set and the existing mainstreaming data set are necessary and always included. Without such information, readers cannot fully understand whether the new data set is reliable and how much this data set has been improved compared with existing data sets. Consequently, the significance of this research cannot be highlighted. Therefore, I strongly recommend the authors to present a quantitative comparison between the new data set and mainstream data sets (e.g. CLM5 and K2012 datasets) based on already existing reference data or manually collected reference data.

Thank you for your suggestions regarding the two aspects of quantitative comparison: first with existing reference and benchmark data, and second with mainstream datasets such as K2012 and ELM2/CLM5 default.

1. On the first point, it is important to note that the 1k parameters are derived from datasets that have been rigorously validated and described in the literature. Consequently, we have chosen not to duplicate the evaluation of these source datasets. Instead, we have expanded our manuscript to include details about the validation undertaken for each data source.

- LULC parameters in L147–155.
  In this study, the MODIS MCD12Q1 version 6 (Friedl et al., 2022) was employed to ascertain the Plant Functional Types (PFT) as well as other non-vegetative land categories at a spatial resolution of 1 km spanning the years 2001 to 2020. The integrity of the MODIS land cover product has been established through a 10-fold cross-validation accuracy assessment using the Terrestrial Ecosystem Parameterization database (Sulla-Menashe et al., 2019). This land

cover product offers richer and more flexible land cover data with higher accuracy and substantially less year-to-year stochastic variation in classification results (Sulla-Menashe et al., 2019). Being the sole operational global land cover product available with annual intervals, it addresses a significant gap in the realm of global change research.

- LAI parameters in L196–201.

  BNU_LAI, an enhanced version of the MODIS LAI product, has been subjected to thorough quality control, incorporating multiple algorithms for improved accuracy (Yuan et al., 2011). Its validation involved an extensive array of LAI reference maps and employed the bottom-up approach advocated by the CEOS Land Product Validation sub-group (Morisette et al., 2006). Compared to the original MODIS LAI, the BNU_LAI dataset exhibits superior performance, along with enhanced spatiotemporal continuity and consistency.

- Canopy height parameters in L210–L217.

  We leveraged a global vegetation canopy height dataset sourced from Lang et al. (2023). This dataset, derived using a probabilistic deep learning model, fuses Sentinel-2 images with the Global Ecosystem Dynamics Investigation (GEDI) to retrieve canopy height. It stands out as the inaugural global canopy height dataset offering consistent, wall-to-wall coverage at a 10 m spatial resolution across all vegetation types. Assessments using hold-out GEDI reference data and comparisons with independent airborne LiDAR data demonstrate that the approach outlined by Lang et al. (2023) produces a meticulously quality-controlled, state-of-the-art global map product, accompanied by quantitative uncertainty estimates.

- Soil-related parameters in L224–227.

  The soil product underwent rigorous quantitative evaluation using a cross-validation method, which ensures alignment with established pedo-landscape features and provides spatial uncertainty to guide product users (Poggio et al., 2021).

- Topography-related parameters in L239–244.

  We employed the digital elevation from the Multi-Error-Removed Improved-Terrain DEM (MERIT DEM, Yamazaki et al., 2019) to obtain topography-related parameters. The MERIT

DEM provides globally consistent elevation data at 90 m resolution, distinguished by its exceptional vertical accuracy. This accuracy was rigorously validated against ICESat's lowest elevations in both forested and non-forested regions and was further benchmarked using the UK's premium airborne LiDAR DEM (Yamazaki et al., 2019).

2. Regarding the comparison with existing mainstream datasets, we have included a comprehensive comparison between our new 1k parameters and the K2012 and ELM2/CLM5 default parameters. This comparison has been elaborated in the methods, results, discussion, and supplementary sections of our manuscript. Considering that K2012 encompasses only LULC and LAI/SAI parameters, we focused our comparison on these aspects, contrasting LULC and LAI among the new 1k, CLM5, and K2012 datasets. For other parameters, including those related to soil and topography, we conducted comparisons between the new 1k and ELM2/CLM5 default parameters. We excluded the comparison of SAI, owing to limited data availability in K2012, and vegetation canopy height (top and bottom parameters) because the ELM2/CLM5 default parameters from the CESM input data repository only provide tabulated values for each PFT. Below are the detailed modifications included.

- In L258–L287, a new method description "2.5 Comparison between new and existing land surface parameters" has been added.

In this study, since the data sources used to develop the 1k global land surface parameters have already undergone rigorous validation, we do not perform additional evaluations against reference datasets (e.g., observations). Instead, our focus is on comparing the newly developed 1k parameters with those from K2012 and the ELM2/CLM5 default parameters. The K2012 parameters, obtained through personal communication (refer to the data availability section for details). The ELM2/CLM5 default parameters were sourced from the CESM input data repository (https://svn-ccsm-inputdata.cgd.ucar.edu/trunk/inputdata/). Given the different resolutions of these datasets—our new parameters at 1km, K2012 at 0.05 degree, and ELM2/CLM5 defaults with varying resolutions—we adapt our comparison at different resolutions for different variables.

For PFT parameters, we aggregated both the 1k new parameters and the 0.05-degree K2012 data to the 0.5-degree resolution of the ELM2/CLM5 default. For non-vegetated land units (i.e., urban, glacier, and lake), we upscaled the 1k new parameters to a 0.05-degree resolution to align with the ELM2/CLM5 default. It is important to note that the urban parameter in K2012 is only available for the northern hemisphere, due to limitations in data acquisition.

When comparing LAI, we aggregated the 1k new and K2012 LAI to 0.5-degree resolution, matching the ELM2/CLM5 default LAI/SAI resolution. We excluded the comparison of SAI from our analysis due to the limited availability of the global K2012 dataset, from which we only acquired coverage for North America. We have not included a comparison of vegetation canopy height (top and bottom parameters) in our study. This is because the K2012 dataset does not contain these parameters, and the ELM2/CLM5 default parameters in the CESM input data repository provide only tabular values for each PFT, rather than spatially variable canopy heights for tree PFTs.

For soil and topography-related parameters, our comparison was limited to the 1k new parameters and the ELM2/CLM5 default, as K2012 does not include these parameters. Specifically, for soil comparisons, we aggregated the new 1k parameters to 0.083° resolution to match the ELM2/CLM5 default soil parameters. For topography, given that the ELM2/CLM5 default parameters is a combination of 1k and 10 arc-minute data sources, we simplify the comparison by aggregating both the new 1k parameters and ELM2/CLM5 default to 0.5-degree resolution, including elevation and slope.

- In L376–L443, the results section titled "3.2 comparison between new and existing land surface parameters" has been added.

The global distributions of different PFTs show varying degrees of difference when comparing the new parameters with the K2012 and ELM2/CLM5 default parameters (Figure 4 and Supplementary Figures S1 to S16). Predominant types such as bare soil, BET-Tropical tree, C3 and C4 grass, and crop are found consistently across all datasets. Notable differences include less bare soil in the new parameters and K2012 compared to ELM2/CLM5 default, especially in high-

latitude North America, western US, South Africa, Central Asia, and Central Australia (Figure S1). While the new NDT PFT shows larger coverage in Siberia than K2012 and ELM2/CLM5 (Figure S4), BET-Tropical PFT is more prevalent in the new parameters across Central and South America (Figure S5). BET-Temperate PFT has greater area coverage in southern China in the new parameters (Figure S6). For BDT-Tropical, BDT-Temperate, and BDT-Boreal PFTs, both the new and ELM2/CLM5 default parameters surpass K2012 data in coverage (Figures S7 to S9). The coverage of new BDS-Temperate PFT is smaller than K2012 but larger than ELM2/CLM5 default (Figure S11), and the new BDS-Boreal PFT is less extensive in the boreal northern hemisphere compared to both K2012 and ELM2/CLM5 defaults (Figure S12). The C3-Arctic PFT shows larger areas in the new parameters, particularly in northern Canada, with the new C4 grass PFT being similar to that of K2012 and larger than ELM2/CLM5 C4 grass. Crop PFT is less extensive in the new parameters, particularly in Southeastern China, Europe, South America, Africa, and Australia.

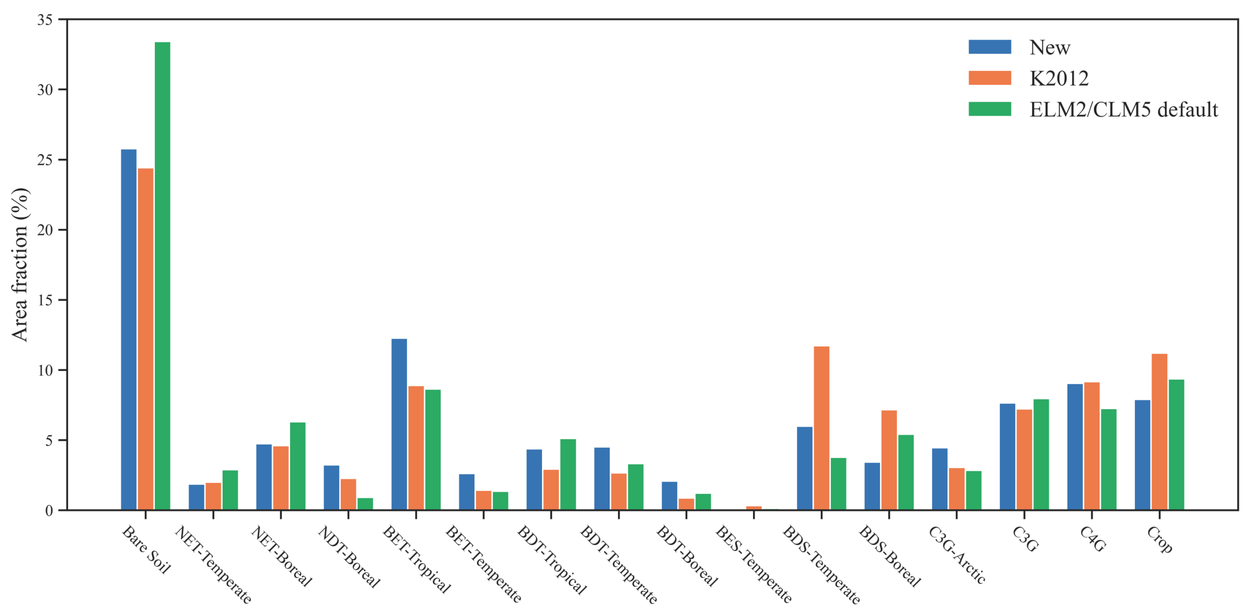

Figure 4. The global average area fractions of PFTs for three land surface parameter datasets. PFT abbreviations used on the X-axis are displayed in Figure 2.

The global distributions of non-vegetated land covers of lake, glacier and urban areas vary among the datasets (Figure S17–S19). The new dataset shows slightly less lake coverage than K2012, but both are smaller than ELM2/CLM5 default, particularly in high-latitude North America (Figure S17). Glacier coverage in the new parameter is around 0.7% smaller than K2012, with noticeable differences in the Arctic North America, while ELM2/CLM5 default shows more extensive glacier coverage in Antarctica (Figure S18). Regarding urban areas, K2012 has the smallest urban coverage in the Northern Hemisphere compared to both the new dataset and ELM2/CLM5 default (Figure S19). Meanwhile, ELM2/CLM5 default exhibits more expansive urban areas in India and China than the new dataset and K2012.

The global annual mean LAI exhibits similar spatial patterns among the new parameter, K2012, and ELM2/CLM5 (Figure 5). The overall global mean LAI for the new parameter (1.28 m^2/m^2) is slightly higher than that of K2012 (1.14 m^2/m^2) and the ELM2/CLM5 default data (1.24 m^2/m^2). In terms of spatial pattern, the new LAI, relative to K2012 (Figure S20a), shows lower values in the NET-Boreal PFT over the northern hemisphere, but higher values in the BET-Tropical PFT over the tropics. Similarly, compared with the ELM2/CLM5 default LAI (Figure S20b), the new LAI also presents smaller values in both the NET-Boreal and NDT PFTs over the northern hemisphere, but larger values in the BET-Tropical PFT regions.

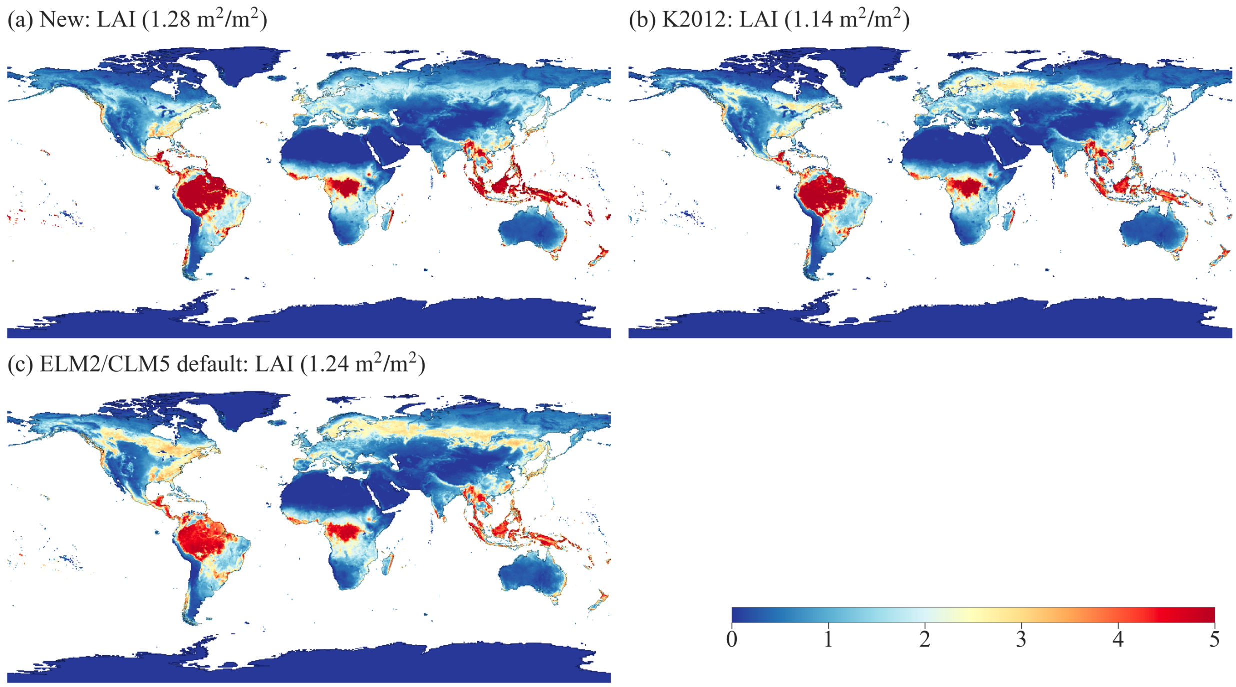

Figure 5. Comparison of global annual mean LAI for (a) new, (b) K2012, and (c) ELM2/CLM5 default parameters. The global average is indicated in the subplot title.

Soil parameters exhibit significant differences between the new and ELM2/CLM5 default datasets (Figures 6a-bc, S21, and S22). The global mean absolute differences between the new and ELM2/CLM5 default for percent sand, percent clay, and organic matter are 14.1%, 8.1%, and 30.5 kg/m³, respectively. Generally, the new soil parameters are spatially distributed more smoothly than those from ELM2/CLM5 with more patchy patterns (Figure 6a vs. 6b). Specifically, the new percent sand is higher in regions like Europe, Siberia, South Africa, and Southern Australia, but lower in areas such as the Lower Mississippi River Basin, North Africa, and Central and Southeastern Asia (Figure 6c). The new percent clay shows larger values in the Western US, North Africa, Central Asia, and Australia, but smaller values in Alaska and Eastern Europe (Figure S21). For organic matter, the new parameter indicates smaller values in the Northern

Hemisphere but larger values in other global regions compared to the ELM2/CLM5 default (Figure S22).

Topography-related parameters exhibit broadly similar spatial patterns but with notable differences between the new and ELM2/CLM5 default parameters, as seen in Figures 6d-6f and S23. The new slope parameter generally shows a larger slope relative to the ELM2/CLM5 default, particularly in mountainous regions (Figure 6f). This could be attributed to the new 1 km slope being calculated from a finer 90 m resolution elevation. Differences in elevation between the new and ELM2/CLM5 parameters are more pronounced in areas such as various mountainous regions, Greenland, the Amazon Basin, the Tibetan Plateau, and Australia (Figure S23).

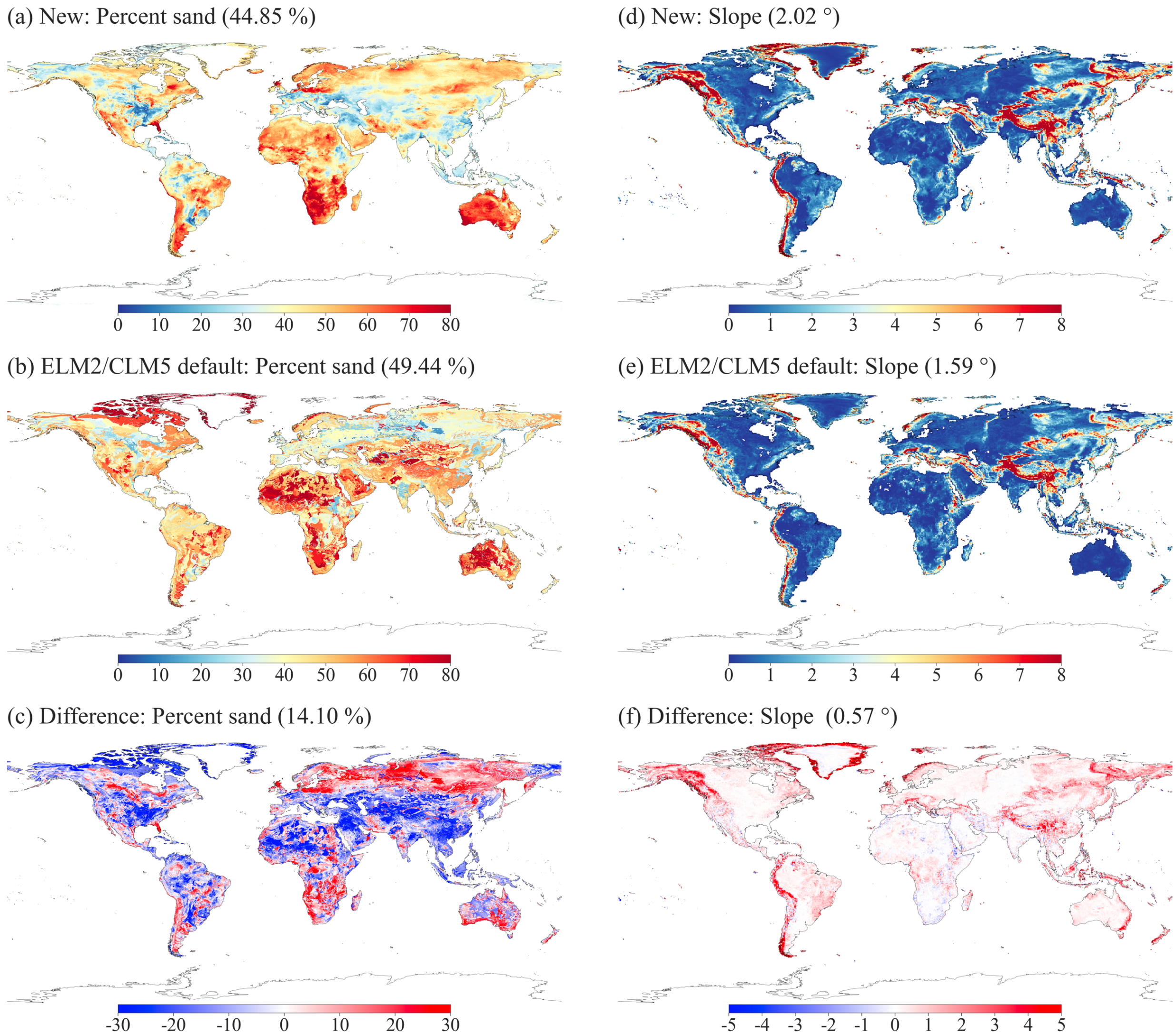

Figure 6. Comparisons of percent sand and slope. (a) new and (b) ELM2/CLM5 default percent sand, along with (c) their difference (new – ELM2/CLM5 default) for percent sand; (d) new, (e) ELM2/CLM5 default, and (f) their difference for slope. The global average is shown in the subplot titles, with the global average of the absolute difference provided for (c) and (f).

- In the supplementary, corresponding Figures S1 to S23 have been added.

- In L566–584, the first paragraph of the discussion section has been updated.

The development of new 1 km land surface parameter datasets in this study marks a substantial improvement over commonly used land surface parameters such as CLM5 and K2012, leveraging the latest high-resolution data sources with rigorous validation, including MODIS PFTs, enhanced LAI and canopy height, soil properties, and topography factors. When compared with K2012 and ELM2/CLM5 default datasets, the new 1k parameters exhibit notable differences, suggesting potential improvement due to the use of more advanced data sources. Distinct features of the new parameters include a reduction in bare soil compared to ELM2/CLM5, especially in regions like North America and Central Asia, and diverse coverage of specific PFTs such as NDT and BET-Tropical in areas like Siberia and South America. The LAI of the new parameters diverges from K2012 and ELM2/CLM5, showing lower values in NET-Boreal PFTs of the northern hemisphere but higher BET-Tropical PFTs in the tropics. The soil parameters, particularly in regions like Europe, Central Asia, and the Western US, show significant differences between the new and ELM2/CLM5 defaults. Moreover, the new parameters indicate larger slopes in mountainous regions and more distinct elevation differences in areas such as Greenland and the Tibetan Plateau compared to ELM2/CLM5. These differences potentially highlight enhanced accuracy and sophistication of the new 1k parameters. Their enhanced resolution and rigorous validation suggest a substantial capacity to improve ESMs modeling. Additionally, the richness of multi-year data for LULC, LAI, and SAI in these datasets is especially valuable for examining land use and cover changes, urbanization trends, deforestation impacts, and agricultural transformations.

The remaining portions of the initial first paragraph in the discussion have been relocated and revised as the fifth paragraph, now found in lines 681–695.

There are certain opportunities for future development of 1k parameters. The urban extension may vary based on data sources, urban definitions, and the algorithms employed, such as those derived from harmonized nighttime lights (Zhao et al., 2022), global artificial impervious area (GAIA, Li et al., 2020b; Gong et al., 2020), urban expansion (Liu et al., 2020; Kuang et al., 2021), necessitating careful consideration in specific modeling applications. Additionally, urban classification in J2010, based on global building height data, is limited by the lack of a consistent and publicly accessible global dataset, despite available regional data for Europe (Frantz et al., *2021), the US (Li et al., 2020a), and China (Cao and Huang, 2021; Yang and Zhao, 2022), thus posing challenges to future urban classification enhancements. Incorporating local climate zones offers a promising approach for urban classification and modeling. Moreover, the multiple-year high-resolution PFT maps like the ones developed by the European Space Agency's Climate Change Initiative could be used to further extend this dataset for a longer period (Harper et al., 2023). Soil color, crucial for soil albedo and surface energy balance, lacks extensive global datasets for ESMs modeling, but the global soil color map derived by Rizzo et al. (2023) offers potential for further kilometer-scale ESMs and LSMs modeling.*

Another important issues is about the citation in the text. The citation should be thoroughly revised. For instance, the list of more than 10 references in a line can provide readers no accurate information and a clear relation between the reference and the mentioned information. e.g. L49-L50 ... and biogeochemical cycles, as well as land and atmosphere coupling (Giorgi and Avissar, 1997; Chaney et al., 2018; Zhou et al., 2019; Liu et al., 2017; Bou-Zeid et al., 2020; Chen et al., 2020; Nitta et al., 2020; Vrese et al., 2016)…These references should be clearly cited and explained. Personally, I do not suggest a list of more than 3 references in a line. The citations in the text are poor and all citations throughout the manuscript should be double-checked and revised to the right form.

Thank you for your valuable feedback and suggestions on improving the manuscript. We have meticulously updated the references as advised and conducted a thorough review of the manuscript to ensure accuracy of all citations.

Specifically, in L50–L53:

High-resolution modeling can better capture the land surface heterogeneity and could improve simulations of terrestrial water and energy cycles (Giorgi and Avissar, 1997; Chaney et al., 2018; Xu et al., 2023), biogeochemical cycles (Chaney et al., 2018), as well as land–atmosphere coupling (Liu et al., 2017; Zhou et al., 2019; Bou-Zeid et al., 2020).

In L685–L689:

Additionally, urban classification in J2010, based on global building height data, is limited by the lack of a consistent and publicly accessible global dataset, despite available regional data for Europe (Frantz et al., 2021), the US (Li et al., 2020a), and China (Cao and Huang, 2021; Yang and Zhao, 2022), thus posing challenges to future urban classification enhancements.

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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Dai, Y., Zeng, X., Dickinson, R. E., Baker, I., Bonan, G. B., Bosilovich, M. G., et al.: The common land model, BAMS, 84(8), 1013-1024, https://doi.org/10.1175/BAMS-84-8-1013, 2003.

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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).