Response to comments on Manuscript egusphere-2026-4655 (RC1)

Title: An Open-Source Python Framework for the Flexible Deployment and Advanced Applications of the Variable Infiltration Capacity (VIC) Model

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Reply on RC1:

Many thanks for taking the time and effort to review our paper. All comments from Referee #1 are addressed below with point-by-point responses.

For better readability, our replies are prefixed with "**R/**". The original reviewer comments are prefixed with "**RC-n/**" and are presented in **bold**. The revisions to be added into the revised manuscript is highlighted in red, while unchanged text from the original manuscript is shown in grey. The important parts are highlighted in **blue**. The quoted content is displayed in *italics*. All references cited in this response are listed at the end of the reply. Line numbers from the unrevised manuscript are provided where relevant.

Point-to-point response:

RC1-1/ This manuscript addresses practical challenges in deploying the VIC model, particularly the tedious preparation of input data and model parameters. The authors present Easy VIC Build (EVB), an open-source Python package that integrates these procedures into a unified workflow, and demonstrate its applicability in two real-world basins with different modeling settings. The integration of MPR further enhances the potential of EVB to support accessible spatially distributed parameterization. Overall, the manuscript is of high quality, fits well within the scope of the journal, and should be of interest to an international readership. In addition, the manuscript examines the relationship between the spatial distribution of model parameters and runoff generation from the perspective of physical plausibility, providing an indirect assessment of the rationality of the MPR approach. Although such an analysis is not commonly adopted, I find this aspect particularly interesting and believe that it deserves further discussion. I therefore minor revision, with several points regarding the presentation and wording to be addressed, as outlined below.

R/ We appreciate your positive feedback and recognition of our work. Your comments are valuable for revising and improving our paper. We fully agree that examining the **physical plausibility** of the estimated parameter from different perspectives **is important**. Following your suggestion, we will **further discuss this aspect** based on our existing findings and relevant findings reported in the literature. Below, we provide detailed responses to each of your concerns. The corresponding revisions will be incorporated into the subsequent revised manuscript.

RC1-2/ 1. As noted above, the authors examine the physical plausibility of the spatial patterns of model parameters, which is an important advantage facilitated by the application of the MPR

technique. However, the manuscript does not appear to provide sufficient discussion of the estimation of spatially distributed parameters, and thus this advantage is not fully highlighted. I therefore suggest that the authors expand the discussion of spatial parameter estimation, including (1) what alternative approaches, besides MPR, can be used to estimate spatially distributed parameters, (2) what are the major challenges and difficulties associated with spatial parameter estimation, and (3) what are the specific advantages of MPR in addressing these challenges. Such a discussion would help better contextualize the contribution of MPR and further highlight the significance of the spatial parameter patterns obtained in this study.

R/ Thank you for this valuable suggestion. We fully agree that the spatial parameter estimation enabled by MPR is one of the key components that allows EVB to effectively support distributed modelling and distinguishes it from existing model deployment frameworks. We also acknowledge that a more comprehensive discussion of spatial parameter estimation would help better highlight the significance of this advantage and strengthen the broader implications of our work.

In response to this comment, we have added **a new Section 6 entitled "Opportunities and challenges of spatial parameter estimation in distributed hydrological models"** to provide a more systematic discussion. This discussion addresses your concerns by highlighting (1) the necessity and opportunities of spatial parameter estimation, (2) the challenges associated with this process, (3) the available approaches for estimating spatially distributed parameters, and (4) the unique advantages of MPR compared with other approaches. These aspects are substantiated, to some extent, by a synthesis of previous studies and relevant literature, providing a broader context for understanding the contribution of MPR. For ease of review, the newly added discussion is provided below.

6 Opportunities and challenges of spatial parameter estimation in distributed hydrological models

The rapid growth of hydrological big data has enabled substantial advances in hydrological modelling, particularly in the development of increasingly sophisticated distributed models (Argentin et al., 2025). By explicitly representing the spatial variability of hydrological processes, distributed models can resolve the spatial patterns of hydrological states and fluxes that are unavailable from their lumped counterparts, offering valuable insights for water resources management and flood and drought risk assessment. For example, in this study we found that baseflow was generally more abundant in the southern part of the JRB, indicating potentially greater hydrological capacity to support afforestation in these areas (Fig. 9c). In contrast, the relatively lower baseflow in the northern part suggests that afforestation need to be implemented more cautiously to avoid increasing pressure on local water availability. In this context, integrating the increasingly available data sources for spatial parameter estimation presents new opportunities for fully realizing the potential of distributed hydrological modelling.

Several fundamental challenges hinder the effective estimation of spatially distributed parameters. First, the historical reliance on the concept of "effective parameters" in hydrological modelling has resulted in many models retaining a large number of free parameters that require calibration and are implicitly assumed to be spatially homogeneous, limiting their ability to explicitly represent spatial heterogeneity. Second, introducing spatially varying parameters into traditional calibration frameworks substantially increases the dimensionality of the optimization problem, while the available observations are often insufficient to constrain such high-dimensional parameter spaces, leading to equifinality and ill-posedness. Finally, direct parameter estimation approaches generally require extensive prior information describing the relationships between parameters and environmental characteristics, while establishing such relationships requires extensive experimental investigations and coordinated efforts across multiple disciplines. Against this background, many distributed hydrological models still use spatially uniform parameters to maintain the number of free parameters at a level that can be reliably constrained through calibration, imposing substantial limitations on their capability to represent spatial heterogeneity. Our previous studies have shown that such simplifications create spatial trade-offs that undermine the physical realism of simulations and limit predictive performance (Zheng et al., 2026).

To address these challenges, several strategies have been proposed for estimating spatially distributed parameters. A straightforward approach is to aggregate the modelling domain into spatial units, such as sub-basins, and independently calibrate parameters for each unit while assuming spatial homogeneity within it. This provides an intermediate representation between fully lumped and grid-based parameterizations, with implementations including spatial clustering (Huynh et al., 2023), representative grid sampling (Sun et al., 2021), and hydrological response units (HRUs). Nevertheless, the number of calibration parameters still increases with the number of spatial units, leaving the parameter-dimensionality problem largely unresolved. Another class of approaches can be broadly termed scaling methods, which infer parameter values at one spatial scale and relate them to hydrological processes or parameters at another through scale-invariant or explicitly scale-dependent relationships (Viney et al., 2004). For example, Barrios and Frances (2012) demonstrated the feasibility of estimating mesoscale effective parameters by aggregating microscale simulation outputs and solving the inverse problem. Regionalization approaches further extend this concept and exploit similarity principles (Bao et al., 2012), establishing relationships between catchment characteristics and parameters in data-rich regions (donors) and transferring them to data-scarce or ungauged regions (receptors). More importantly, if such relationships are applied consistently across all modelling grids, they can provide an effective pathway for spatial parameter estimation.

Within the regionalization framework, MPR offers several advantages over conventional approaches. As mentioned in Sect. 3.1, MPR establishes environment–parameter relationships using transfer functions informed by existing literature. Compared with standard regionalization (SR) methods based on empirical regression or similarity measures derived from spatial distance or physical attributes, this approach allows prior knowledge from multiple disciplines to be explicitly incorporated into parameter estimation, thereby improving the plausibility and reliability of spatial parameter estimates (Mizukami et al., 2017). Meanwhile, the limited number of adjustable parameters in transfer functions maintains the parameter dimensionality within a practically calibratable range. In terms of cross-scale issues, MPR first derives high-resolution parameter fields and then aggregates them to the target modelling scale, shifting the scale transformation from environmental inputs to parameters across different resolutions. This provides the benefit of minimizing uncertainties associated with environmental data aggregation and improving the representation of subgrid parameter heterogeneity. As evidenced by Samaniego et al. (2010), MPR exhibited superior performance to SR in maintaining water balance and preserving the spatial patterns of simulated variables, whereas the latter introduced larger deviations during the upscaling process. Given these advantages, MPR was selected as the default spatial parameter estimation approach in EVB. Beyond this implementation, we envision that future developments of EVB should further investigate scale-aware parameterization by incorporating scaling factor into transfer functions, allowing nonlinear upscaling relationships to be integrated into the spatial parameter estimation procedure. In our view, advancing spatial parameter estimation approaches in this direction represents one of the key priorities for hydrological model development over the coming decade.

RC1-3/ 2. A key aspect that is currently missing from the manuscript is a clear description of the transfer functions, particularly which predictor variables are used to estimate each model parameter. I suggest that the authors provide a summary table in Section 3.1 specifying the predictor-parameter relationships. The corresponding transfer functions could also be presented explicitly, similar to those given in Eqs. (2)–(4). Providing this information would make the parameter estimation procedure more transparent and help readers better understand the implementation of the proposed approach.

R/ Thank you for pointing out this important omission. In the previous version, the transfer functions were primarily encapsulated in the code implementation, which we now recognize could make the parameter estimation procedure less transparent and potentially cause confusion for readers. Following your suggestion, we have **added a summary table of the transfer functions in the Appendix A**, explicitly specifying the predictor–parameter relationships for all model parameters.

In addition, we have **standardized the notation** of all model parameters and predictor variables and carefully revised the corresponding descriptions throughout the manuscript to ensure consistency and clarity. For your convenience, the newly added table of transfer functions is also provided below.

Table A2. Summary of the transfer functions and their formulation sources for VIC-specific parameterization in EVB.

Parameter	Description	Unit	Predictors	Transfer function	Reference
b_{infilt}	The exponent of the variable infiltration capacity curve	[1]	Standard deviation of elevation (σ_{ele}), g_4, g_5	$b_{infilt} = \frac{\log \sigma_{ele} - g_4}{\log \sigma_{ele} + 10g_5}$	Dumenil and Todini (1992); Hurk and Viterbo (2003); Balsamo et al. (2009)
K_s	Saturated hydrologic conductivity	[mm/day]	Sand content fraction (f_{sand}), clay content fraction (f_{clay}), g_6, g_7, g_8	$K_s = 10^{g_6+g_7 f_{sand}+g_8 f_{clay}} \times 25.4 \times 24$	Cosby et al. (1984)
θ_s	Saturated water content	[m^3/m^3]	f_{sand}, f_{clay}, g_9, g_{10}, g_{11}	$\theta_s = (g_9 + g_{10} f_{sand} + g_{11} f_{clay})/100$	Cosby et al. (1984)
ψ_s	Saturation matric potential	[kPa]	f_{sand}, clay content fraction (f_{silt}), g_{12}, g_{13}, g_{14}	$\psi_s = -10^{g_{12}+g_{13} f_{sand}+g_{14} f_{silt}} \times 0.0980665$	Cosby et al. (1984)
b_{ret}	Slope of Campbell's retention curve in log space	[1]	f_{sand}, f_{clay}, g_{15}, g_{16}, g_{17}	$b_{ret} = g_{15} + g_{16} f_{clay} + g_{17} f_{sand}$	Cosby et al. (1984)
b	Exponent in Campbell's equation for hydraulic conductivity	[1]	b_{ret}, g_{18}, g_{719}	$b = g_{18} + g_{19} b_{ret}$	Campbell (1974)
θ_{fc}	Field capacity	[m^3/m^3]	θ_s, field-capacity matric potential (ψ_{fc}), ψ_s, b_{ret}, g_{20}	$\theta_{fc} = g_{20}\theta_s \left(\frac{\psi_{fc}}{\psi_s}\right)^{-\frac{1}{b_{ret}}}$	Campbell (1974)
D_4	Exponent of the nonlinear part of the outflow curve	[1]	g_{21}	$D_4 = g_{21}$	Mizukami et al. (2017)
D_1	Linear reservoir coefficient	[day^{-1}]	K_s, mean slope angle (S), normalization factor of soil moisture (S_f) set to one, g_{22}	$D_1 = \frac{K_s S}{10^{g_{22}} \times S_f}$	Mizukami et al. (2017)
D_2	Nonlinear reservoir coefficient	[day^{-D4}]	K_s, S, S_f, g_{23}	$D_2 = \frac{K_s S}{10^{g_{23}} \times S_f^2}$	Mizukami et al. (2017)
D_3	Soil moisture at which baseflow transition occurs from linear to nonlinear	[mm]	θ_{fc}, layer thickness of the third soil layer (h_3), g_{24}	$D_3 = g_{24}\theta_{fc} h_3$	Mizukami et al. (2017)
d_p	Soil thermal damping depth	[m]	g_{25}	$d_p = 4g_{25}$	VIC documentation
ψ_b	Bubbling pressure of soil	[cm]	b, g_{26}, g_{27}	$\psi_b = g_{26} b + g_{27}$	Schaperow et al. (2021)
f_{quartz}	Quartz content of soil	[1]	f_{sand}, g_{28}	$f_{quartz} = g_{28} f_{sand}/100$	Peters-Lidard et al. (1998)
ρ_b	Bulk density of soil layer	[kg/m^3]	Reference bulk density in soil dataset ($\rho_{b,ref}$), g_{29}	$\rho_b = g_{29}\rho_{b,ref}$	Empirical adjustment
ρ_s	Soil particle density	[kg/m^3]	g_{30}, g_{31}, g_{32}	$\rho_{s,i} = 2685 g_{3i}, i = 0,1,2$	VIC documentation

Parameter	Description	Unit	Predictors	Transfer function	Reference
θ_c	Fractional soil moisture content at the critical point	[1]	θ_{fc}, θ_s, g_{33}	$\theta_c = \frac{g_{33}\theta_{fc}}{\theta_s}$	Empirical adjustment
θ_{wp}	Wilting point	[m^3/m^3]	θ_s, b_{ret}, ψ_s, g_{34}	$\theta_{wp} = g_{34}\theta_s(-\frac{1500}{\psi_s})^{-\frac{1}{b_{ret}}}$	Campbell (1974); Mizukami et al. (2017)
f_{wp}	Fractional soil moisture content at the wilting point	[1]	θ_{wp}, θ_s, g_{35}	$f_{wp} = \frac{g_{35}\theta_{wp}}{\theta_s}$	Mizukami et al. (2017)
z_{0s}	Surface roughness of bare soil	[m]	g_{36}	$z_{0s} = 0.001g_{36}$	Schaperowet al. (2021)
$z_{0,snow}$	Surface roughness of snowpack	[m]	g_{37}	$z_{0,snow} = 0.0005g_{37}$	Schaperowet al. (2021)
v	Average flow velocity within each grid	[LT^{-1}]	Accumulated upstream area (acc), S, g_{38}, g_{39}, g_{40}	$g_{38}acc^{g_{39}}S^{g_{40}}$	K et al. (2005); Duc et al. (2007); Chen et al. (2019)
D	Average diffusion coefficient within each grid	[L^{2}T^{-1}]	Flow distance within each grid (d), v, g_{41}	$g_{41}dv$	Yang et al. (2016)

*Note: Units are S (%), h_3 (m), acc (km^2), and d (m). ψ_{fc} is set to -33, -20, and -10 kPa when $f_{sand} \leqslant 50\%$, $50\% < f_{sand} \leqslant 70\%$, and $f_{sand} > 70\%$, respectively. The source of VIC documentation is: https://vic.readthedocs.io/en/master/.

RC1-4/ 3. Given the length of the manuscript, I suggest that the authors consider reducing or streamlining some of the less essential content to improve the overall readability and focus of the manuscript. The space saved through these revisions could instead be used to further strengthen several aspects that are more closely related to the scientific contribution of the study. Specifically:

Section 2.1.3: This subsection could be removed from the main text or reduced to a brief description and incorporated elsewhere, as the current level of detail does not appear essential to understanding the main contribution of the study.

Section 3.3: I suggest merging and substantially condensing the subsections under this section to provide a more concise description of the workflow and improve readability.

Section 4.1: This section could also be shortened, as the detailed description of the case-basin setup does not appear to be central to the main findings of the manuscript.

Section 5.3.2: I suggest expanding the discussion of spatially distributed parameter estimation as mentioned above, particularly the challenges associated with this process and the advantages of the MPR approach.

Abstract and Conclusion: I recommend further strengthening these sections by incorporating more quantitative results, such as specific model performance metrics and the accuracy achieved through cross-scale parameter transfer. Including these quantitative findings would allow readers to more readily assess the effectiveness and broader applicability of the proposed approach.

R/ Thank you for your constructive comments and valuable suggestions on improving the writing and organization of the manuscript. Following your recommendations, we have revised the manuscript accordingly and addressed each point as follows:

(1) Section 2.1.3: Following your suggestion, we have **removed this subsection** and moved the necessary

information to the relevant sections.

(2) Section 3.3: We have **merged and substantially condensed the subsections within this section** to provide a more concise description of the workflow and improve the overall readability. The revised section is provided below:

3.3 Workflow for VIC model deployment

Figure 1b presents the VIC model deployment workflow within the EVB framework, which consist of seven sequential steps. This deployment process follows the guidelines outlined in the official VIC documentation (https://vic.readthedocs.io/) and focuses on the image driver version of VIC-5. The workflow is described in detail below, with all files involved in the deployment process managed through EVB's built-in Evb_dir class. This class provides unified path management for the definition, modification, and transfer of file and directory paths, thereby ensuring consistent and efficient file handling throughout the deployment.

The workflow first processes the required spatial and attribute data according to the selected modelling domain and spatial discretization. Users construct Grids and Basins instances and provide them to the corresponding dpc instances, where data source-specific extraction and processing are performed. The resulting basin- and grid-level information is stored as instance attributes for subsequent deployment steps. Based on the processed level-1 data, the build_Domain utility then generates the VIC domain file in NetCDF format, including grid area, basin fraction, and grid-edge information.

VIC parameter files are subsequently generated using the MPR-based parameterization scheme embedded in EVB. The scheme maps level-0 basin characteristics to spatially distributed parameters at the selected modelling scale, while the g-parameters can be calibrated to account for basin-specific conditions. Meteorological forcing is generated from the processed dpc instances using the buildMeteForcing function. The required VIC forcing variables are prepared and converted when necessary, for example, deriving vapor pressure from specific humidity and wind speed from its zonal and meridional components. The resulting forcing files are stored in NetCDF format and can be directly used by VIC.

For runoff routing, EVB uses the Python implementation of RVIC to generate routing parameter files. This procedure first derives the hydrological topology from the level-1 DEM and then generates the required routing inputs, including the pour point and unit hydrograph. Users can select either the Nash or GUH unit hydrograph, while flow velocity and diffusion parameters can be regionalized using the MPR scheme and calibrated when required. A global parameter file is finally generated and managed through the GlobalParamParser, which facilitates the specification and modification of model input/output paths and runtime options.

The final step is VIC model calibration. Although MPR provides spatially distributed parameter estimates, calibration remains necessary to account for uncertainties in regionalized parameters and their scaling across spatial resolutions. EVB provides both the Covariance Matrix Adaptation Evolution Strategy (CMA-ES; Hansen and Ostermeier, 2001) and the Non-dominated Sorting Genetic Algorithm II (NSGA-II; Deb et al., 2002) through the DEAP library for single- and multi-objective calibration, respectively, allowing users to calibrate selected model parameters against streamflow and, where available, additional hydrological observations.

(3) Section 4.1: We have **shortened the description of the case-basin setup** by retaining only the essential information required for understanding the modelling experiments. The corresponding revisions are shown below:

4.1 Basin setup A: case basin from large-sample dataset

In response to the call for large-sample hydrological research highlighted by Gupta et al. (2014), we assess whether the EVB framework can contribute to this research direction. To this end, we selected a case basin from the widely used Catchment Attributes and Meteorology for Large-sample Studies (CAMELS) dataset (Newman et al., 2015; Addor et al., 2017) to demonstrate the implementation of VIC modelling within the EVB framework. Employing a simple model setup with streamflow-only calibration, we investigated the parameter transferability to evaluate the efficiency of applying EVB in large-sample basin contexts. The case basin is located within Missouri, USA, and is known as the Gasconade River Basin (GRB; USGS gauge ID: 06934000), with a total drainage area of approximately 8,268 km2. Fig. 2 provides an illustrative map of the basin, showcasing the topography, outlet, and land surface properties in the area. The local temperate continental climate is typical and characterized by distinct seasonal variations. Under the combined effects of climate, topography, and vegetation, streamflow in this area exhibits pronounced seasonal variability, with the peak flow occurring in the spring and a low flow observed in the late summer and autumn. Notably, the current EVB implementation, once demonstrated in this case basin, can be seamlessly extended to the entire CAMELS basin collection.

(4) Section 5.3.2: In response to your suggestion, we have **added a new discussion section** of spatially distributed parameter estimation, which covers its necessity, major challenges, alternative approaches, and the specific advantages of MPR. Further details regarding this revision are provided in our response to **RC1-2**.

(5) Abstract and Conclusion: We have strengthened these sections by **incorporating additional quantitative results** to better demonstrate the effectiveness of the proposed framework. The revised versions of the Abstract and Conclusion are provided below:

Abstract. The development of the Variable Infiltration Capacity (VIC) model to version 5 has endowed it with enhanced land-surface-modelling features, establishing it as a modern and cutting-edge tool for hydrological research. However, its adoption is limited by challenges in complex data processing and parameter preparation. To address this issue, this study proposes the Easy VIC Build (EVB) framework, an open-source Python package with an object-oriented, modular design, developed for efficient and flexible VIC deployment. The Multiscale Parameter Regionalization (MPR) and the General Unit Hydrograph (GUH) provide the underlying approaches for spatial parameter estimation and routing parameterization, forming the methodological basis for VIC model deployment within EVB. Two real-world basin setups were selected for model application to validate the efficiency and effectiveness of the EVB framework. The results indicate that the estimated spatial parameters were transferable across spatial scales, with transfers from coarser- to finer-resolution models resulting in KGE degradation of less than 0.1, while their spatial patterns were consistent with those of simulated runoff and reference soil parameter datasets, supporting their physical plausibility. The capability for multi-objective calibration and simulation was also demonstrated. Under three-objective calibration, the model captured the seasonal variations of multiple hydrological variables well, with KGE values exceeding 0.7 for streamflow and 0.8 for actual evapotranspiration, and a soil moisture correlation coefficient above 0.85 against observations. Overall, The EVB framework provides a well-suited workbench for advanced applications of the VIC model, promising to further leverage the value of VIC-5 in hydrology and related fields.

7 Conclusion

This study was motivated by the need for a standardized and reproducible approach to VIC model deployment. Although the restructuring of VIC-5 has enhanced its flexibility and maintainability, it has introduced additional technical complexity for model implementation. To overcome these limitations, we developed an open-source Python framework, Easy VIC Build (EVB), which provides a flexible and efficient solution for automated VIC model deployment. The EVB framework adopts a modular object-oriented architecture and integrates advanced techniques for VIC model deployment, including the Multiscale Parameter Regionalization (MPR) and the General Unit Hydrograph (GUH). Through the implementation of several core classes—such as Grids and Basins for storing and processing geographic information, dpc for managing forcing and general input data, and Evb_dir for organizing file paths—together with a layered abstraction strategy based on information-level division, EVB enables efficient data management and seamless information transfer throughout the model deployment workflow.

The efficiency of the EVB framework was evaluated through several real-world modelling applications implemented across two distinct basin setups. For the first basin setup, EVB-estimated parameters showed robust transferability across spatial resolutions, with transfers from coarser to finer resolutions resulting in KGE degradation of less than 0.1 and largely preserving the spatial patterns of simulated runoff. For the second basin setup, the capability of EVB-deployed VIC models for multi-objective calibration and simulation was demonstrated, with KGE values exceeding 0.7 for streamflow and 0.8 for actual evapotranspiration, and correlation coefficients for soil moisture exceeding 0.85 against observations. More importantly, this study provides evidence for the effectiveness and physical plausibility of MPR-derived spatial parameter estimation, as the estimated parameter patterns showed strong consistency with the spatial distribution of simulated runoff and with independent reference soil parameter dataset. In terms of deployment efficiency, data preprocessing and meteorological forcing generation are the main time-consuming steps, but their one-time execution makes these costs acceptable. Overall, we anticipate that the EVB framework will facilitate broader applications of the VIC model by improving compatibility with VIC-5 and providing standardized, flexible, and efficient deployment capabilities beyond those offered by existing tools.

RC1-5/ 4. The manuscript also contains several minor formatting and writing issues that should be addressed. For example:

Line 417: A line break appears to be missing. Please check and correct the formatting accordingly.

Appendix C: The title appears to be identical to that of Appendix B. Please verify the correct title and revise it accordingly.

R/ Thank you for your careful and thorough review. In accordance with your suggestions, we have carefully checked the entire manuscript and **revised the identified writing and formatting issues** throughout the text to improve its overall clarity and consistency. We have also **corrected the duplicated title of Appendix C** and verified the formatting, including the missing line break noted in the comments. For your convenience, the corrected title of Appendix C is provided below.

Appendix C VIC streamflow simulations at 8 km and 6 km using parameter transferred from 12 km calibration

Finally, we would like to once again thank the Editor and all the Reviewers for your thorough review and support of our paper. If you have any questions, suggestions, or discussions, please feel free to contact us.