Response to Anonymous Referee#1

We would like to thank the Referee for his/her constructive comments that concerns five major subjects and several minor issues. Through a careful study on the comments, we have made modifications accordingly. The responds to the comments and the main modifications to the paper are as following:
(Review comments are reported in red.)

Major Comments:

1. Making the introduction more accessible to a general audience and in the process explaining or removing much of the technical jargon.

Response:
The Introduction section is reorganized by removing some technical terms and statements are reconstructed into direct, short sentences accordingly.

2. Validation across varied resolutions....Compute the surface accuracy statistics across a wide range of resolutions and point densities. These could be added to Table 1 or as a plot.

Response:
We have carried extra experiments on those two LiDAR derived DEMs with varied resolutions. The added resolutions are ranged from 5% to 0.1% (as ranged from 3.1% to 0.6% setting in [1]). The comparison results of the surface accuracy statistically are added to Tab.1, and we copy them here for clarification:

Tab. 1Interpolated elevation RMSEs (m) at varied scale transformation *Ratios*

Dataset	Approx. Method	5%	1%	0.5%	0.1%
St. Helens	cCVT	0.636	1.614	2.455	5.772
	HFPR	1.028	2.371	4.006	11.779
UTM11	cCVT	1.239	3.773	6.593	19.997
	HFPR	3.087	6.712	10.137	28.460

From the results we could see that, under the same resolution (point density), transformed DEM surface from cCVT method is generally more precise than that from HFPR method. While all surface approximation precision (compared to the original) decrease as the resolution coarsened. We have added these modifications to the manuscript (P10, L23-24).

For further analysis of to what extent (though roughly) cCVT could be comparable to existing models, cCVT-based terrain adaptive grid models (TAM) with varied resolutions are subjected to fixed-resolution grid models for comparison. This experiment is taken out on flood inundation simulation, where topography condition dominates the well-known shallow-water process. Lots of methods have been proposed in this domain to generate terrain-following computational grids, here we select two most classical grid (mesh) models for comparison, that is, block-structured mesh (BM) [2] and transfinite interpolation mesh (TIM) [3].

The selected topography comes from the Okushiri tsunami experiment (c.f. Fig. 1). The BM grid (c.f. Fig. 2 a) and TIM grid (c.f. Fig.2 b) for this experiment come from ANUGA[1] validation case and TELEMAC[2] validation case respectively, both are publicly available from their official websites. TAM grid from cCVT is illustrated as Fig. 2 (c). For rough analysis, we build TAM grids with varied resolutions ranged from 24K triangles to 7.8K triangles, and compute different surface approximation metrics for comparison with the fixed-resolution BM grid (with 21K triangles) and TIM grid (with 25K triangles). The result are listed in Tab. 2.

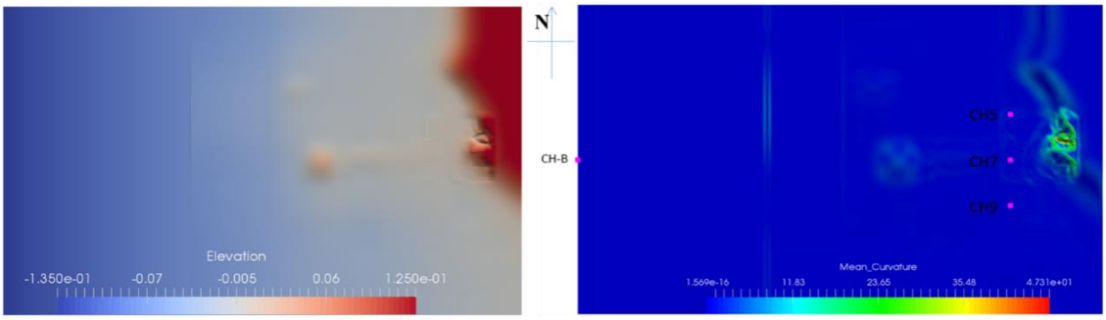

Fig. 1 Topography of Okushiri Tsunami experiment. Left, elevation rendering; Right, mean curvature rendering. (CH-B, CH-5-7-9 marks the four gauge locations)

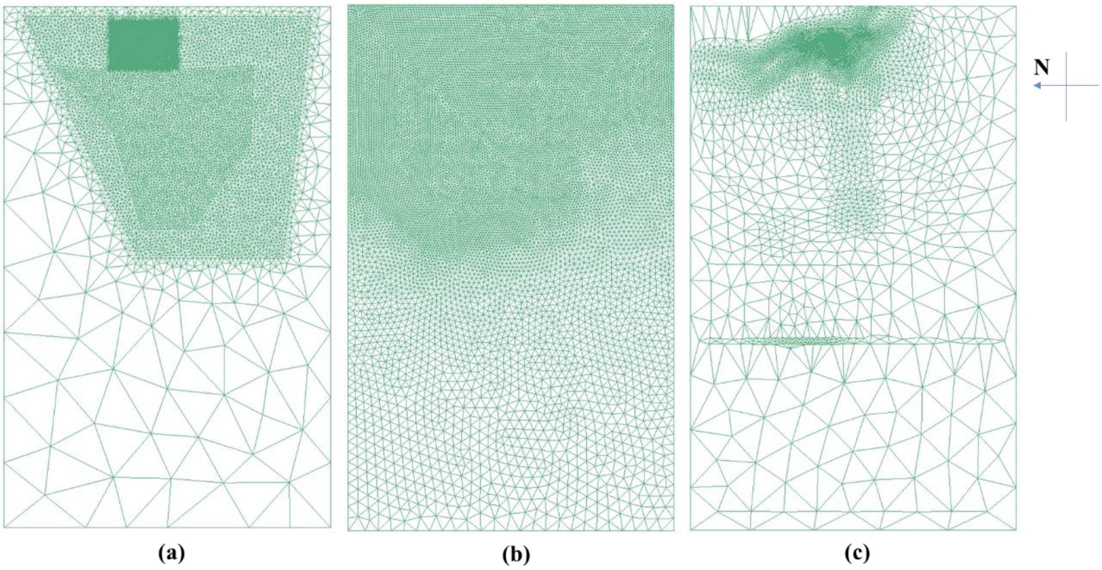

Fig. 2 Different Computational grid models. (a) Block-structured grid, (b) Transfinite interpolation grid, (c) Terrain adaptive grid.

From Tab. 2, we can see that, under the same resolution, for any approximation metrics as

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[1] ANUGA is a general-purposed hydrodynamic modelling tool developed by Australia National University and Geoscience Australia, https://anuga.anu.edu.au/.

[2] TELEMAC is an integrated solver suite for free surface flow, http://www.opentelemac.org/

Hausdorff distance, barycenter elevation interpolation (which is commonly adopted by finite volume methods), or random elevation interpolation, TAM grid (A0) approximates the original terrain surface best. TAM grid with only half samples (TAM A1) to that of BM grid or TIM grid performs approximation fairly well to that of the two comparing grids.

Tab.2 Approximation precision comparison for different grids.

Approx. Metric	BM, 21K	TIM, 25K	TAM A0, 24K	TAM A1, 12K	TAM A2, 7.8K
Hausdorff Dist.(1e-2)	4.147	1.205	0.304	0.354	1.400
Bary RMSE(1e-4)	4.127	2.414	1.653	2.315	3.035
Rand RMSE(1e-4)	3.942	2.823	2.024	2.844	3.947

3. How does the selection of feature points effect the results? (e.g. what if this was done poorly)

Response:

CVT works under the variational framework. The result of CVT optimization relies on initial conditions and boundary conditions. For DEM transformation, the effects of selected feature points can be summarized from two aspects:

(1) In general, if the feature points are not well selected for initial samples, we can still get improved surface approximation precision. But the feature points (critical points as well) may not be accurately positioned, this means kinds of structural distortion. The result thus may be acceptable from surface approximation precision expectation, but may not be acceptable from feature retention aspect.

(2) If the initial samples are extremely ill-positioned, CVT may fail to recover good surface approximation either. To illustrate this, we built feature points based cCVT and random points based cCVT on the former Okushiri topography (the resolution is set at 1% point density). The result surfaces are illustrated as Fig. 3 and Fig.4. The Hausdorff distance and barycenter interpolation RMSEs for the two surface are listed in Tab. 3.

From Fig.3, Fig.4, and the comparison results of Tab. 3, we can see that, though both approaches show good structural feature capturing capability, however the ill-positioned samples (i.e., weak feature capturing capability) affects the surface precision and sample points distribution greatly. As regards to the negative indices, surface approximation precision from Hausdorff distance is more evident than that from barycenter elevation interpolation RMSEs (computed independently).

These facts imply two important issues: (1) CVT might be used for surface feature extraction, i.e., terrain generalisation purpose; (2) Feature points based approach is essential to the cCVT implementation, auxiliary input points or computed structures are still useful for DEM transformation.

We have add some modifications to the manuscript to stress these points. (Section 2.3.2)

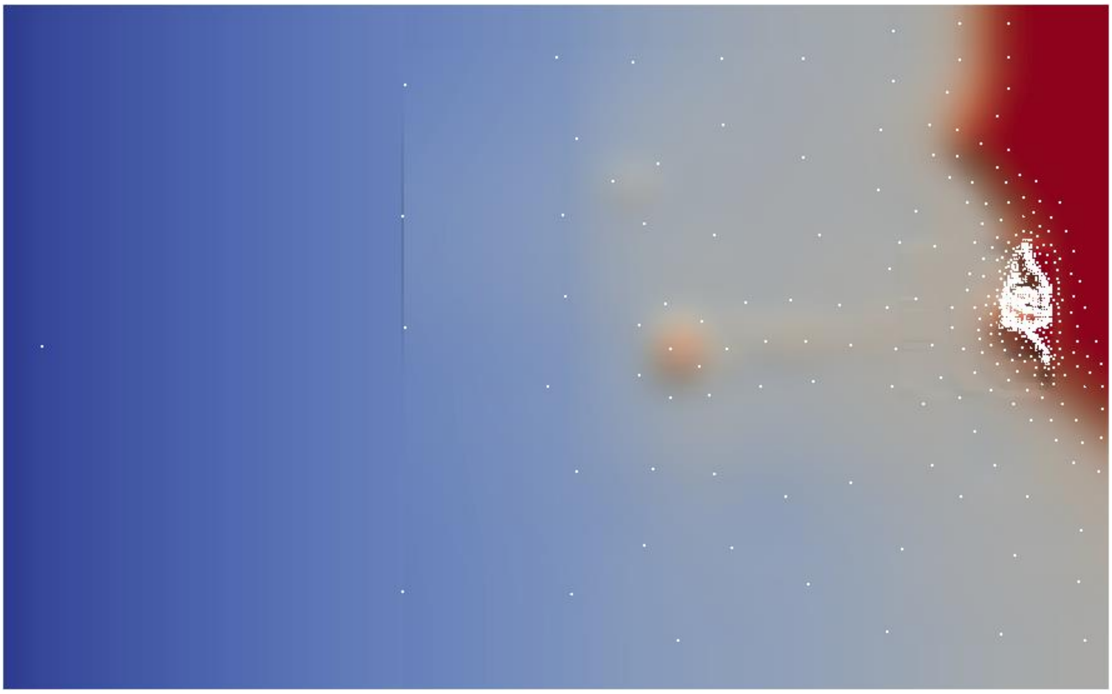

Fig. 3 Feature points as samples and converged distribution

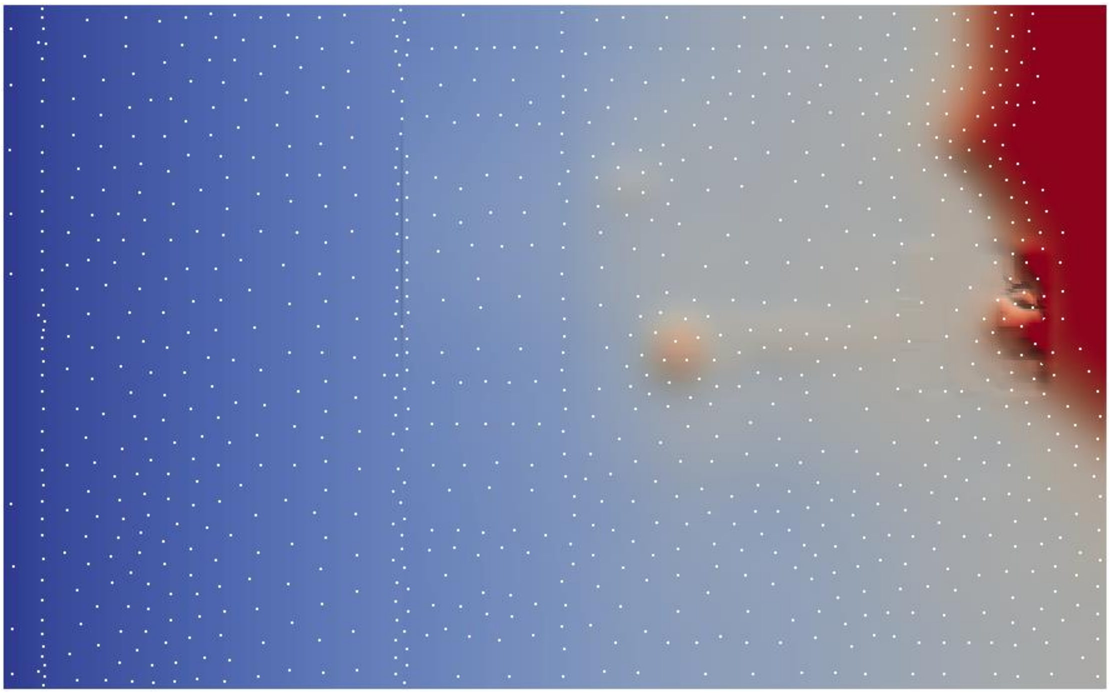

Fig. 4 Random points as initial samples and converged distribution

Tab.3 Surface approximation comparison for feature points based CVT and random points based CVT.

Approx. Metric	Feature Points CVT, 2K	Random Points CVT, 2K
Hausdorff Dist.(1e-2)	1.216	2.392
Bary RMSE (1e-3)	1.220	1.322

4. What can cCVT not be compared to previousCVT methods.

Response:

cCVT aims at the intrinsic properties of the terrain surface geometry, while CVT could be applied to a wide variety of application domains, even not confined to geometry space.

For the implementation of the proposed cCVT, we develop an extra energy referring through exact geometry clipping technique. The exact clipping is due to several considerations such as numeric instabilities, fast convergence, and quality grid.

The keys to the popular CVT implementation is to cluster facets without surface reconstruction, and it relies on existing vertices rather than generating new ones. This may result in bad grid quality as exemplified by Fig. 5 (b), which is generated by the clustering approach. This grid can be further optimized by cCVT method and the result is shown as Fig.5 (c), from which we can observe improved grid quality with smooth transition.

The exact geometric clipping functions on the presumption of the 2.5 dimensionality of DEM surface. In such circumstance, it cannot be applied to arbitrary geometric domains as clustering CVTs can.

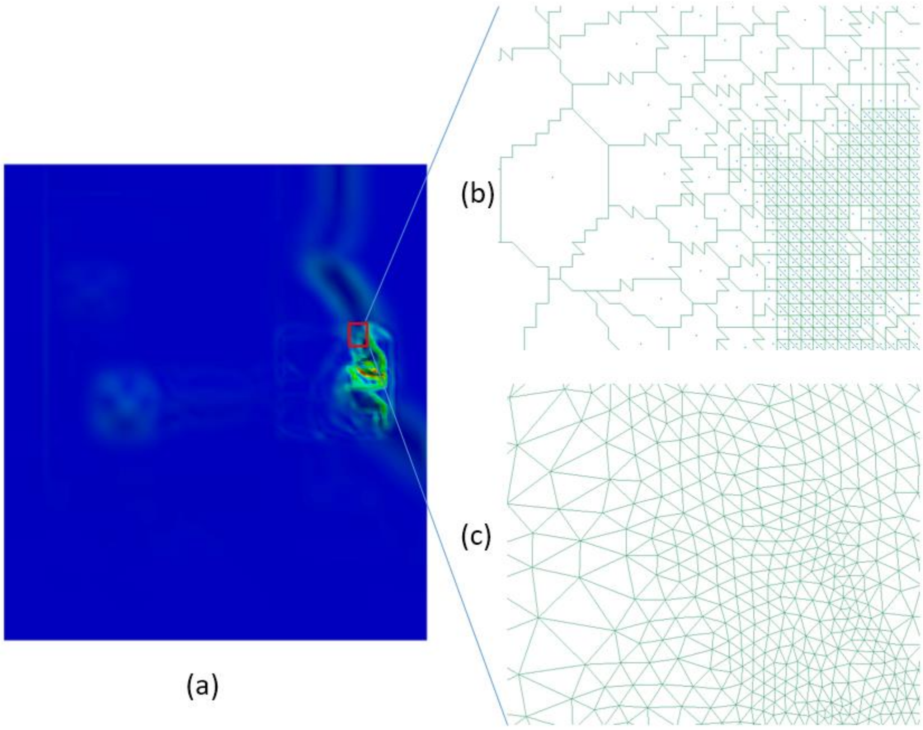

Fig. 5Grid quality comparison of classical CVT clustering (b) and exact energy referring (c). They are subtracted from the former Okushiri topography (a) example.

5. How would the method compare to an optimal estimator such as kriging?

Response:

Both the Kriging method and the cCVT method consider the samples' impact from either spatial domain or frequency domain. But Kriging method is usually utilized for the situation of data scarcity and it is essentially an interpolation approach, while cCVT method considers the data redundancy problem and it is thus usually a coarsening approach.

Specific points:

1. increasingly improved resolution (P2L9)

Response:
We have replaced it with "finer resolution".

2. for clearance of confusions and distractions (P3L13)

Response:
We modified this sentence as:
"As surface approximation precision and terrain feature retention are competitive for the redistribution of feature points, DEM (digital elevation model) generalisation is differentiated from terrain generalisation for its emphasis on surface approximation as a whole, with the aim of providing precise surface interpolation (Guilbert et al., 2014)."

3. Section 1.3: For a general geoscience audience

Response:
The Section 1.3 is reconstructed to state aims and contributions. The involved technical considerations, underlying principles of CVT are rearranged into section 2.3, where three new sub-sections are added, for a clearer statements.

4. Section 2.3, hydrological model, curvature-generated drainage networks (P7 L22-25)

Response:
Thanks for the Referee's reminding, we modified the confusing "hydrological model" as the commonly used "flow accumulation model", and the statements is reorganized as:
"compared to the results of the flow accumulation model, curvature based delineation of drainage networks has not limited to one pixel thickness and requires no depression filling (Kennelly, 2008)".

5. The localization makes geometrical operation costs minimized (P7L32)

Response:
This section has been reconstructed into three new sub-sections for a clearer statements. The related statements here are rearranged as:
"... By this exactly clipped referring patch we compute accurate energy estimation for new approximated sites. The global clipping computation is localized using a *kd-tree* structure.
The localization and accurate referring energy computation makes cCVT iteration converge fast. The efficiency of the cCVT approximation as a whole is comparable to that of the elegant clustering approach. We go no further for the complexity analysis but however provide an implementation of the classical clustering with the same settings as the cCVT in the attachment."

6. Section 3.3: To what extent is the accuracy effected by the scale transformation ratio of the HFPR method

Response:
This has been supplied as response to the major comment#2.

7. "more natural transition effect" of cCVT optimized grid (P11 L5)

Response:
We modified the "natural transition effect" as "smooth grid transition".

We may still use the Okushiri computational meshes to explain this effect. In Fig.2 (c), the cCVT generated TAM mesh has smooth transition areas all over the domain, while block-structured mesh has abrupt transition areas. This kind of smoothness are also presented in Fig. 4 (b), compared to rigid transition grid of Fig. 4(c).

8. Do you mean precision or accuracy of the general approximation? (P11 L9)

Response:
Here we refer to approximation precision, not accuracy.

References:
[1] Zhou, Q. and Chen, Y.: Generalization of DEM for terrain analysis using a compound method, ISPRS Journal of Photogrammetry and Remote Sensing, 66, 38-45, 2011, doi:10.1016/j.isprsjprs.2010.08.005.
[2] Nikolos, I. K. and Delis, A. I.: An unstructured node-centered finite volume scheme for shallow water flows with wet/dry fronts over complex topography, Computer Methods in Applied Mechanics and Engineering, 198, 3723-3750, 2009, doi:10.1016/j.cma.2009.08.006.
[3] Li, Y., et al.: An orthogonal terrain-following coordinate and its preliminary tests using 2-D idealized advection experiments. Geosci. Model Dev., 7(4), 1767-1778, 2014, doi: 10.5194/gmd-7-1767-2014.