Integrating Topographic Knowledge into Deep Learning for the Void-filling of DEM

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2022 EGU

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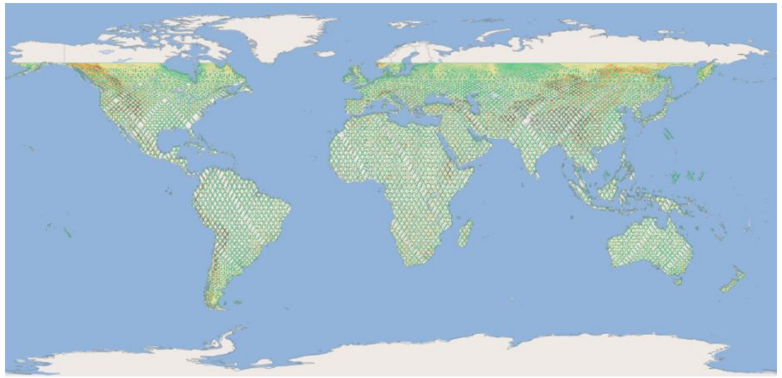
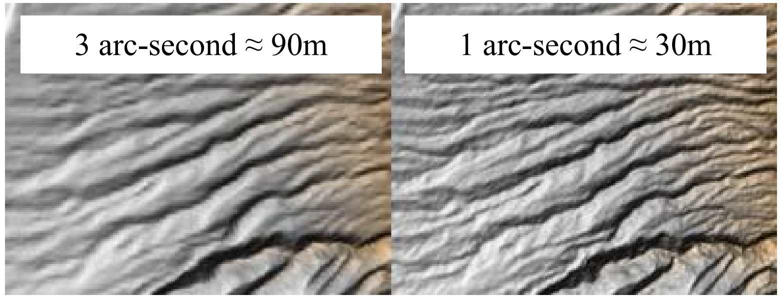
Digital Elevation Model (DEM) & Data Voids

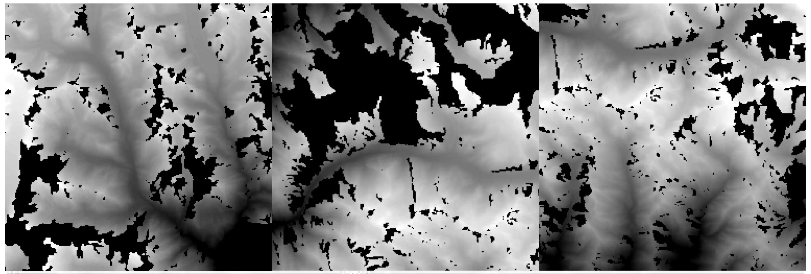
Global DEMs:
SRTM, ASTER GDEM, TanDEM…

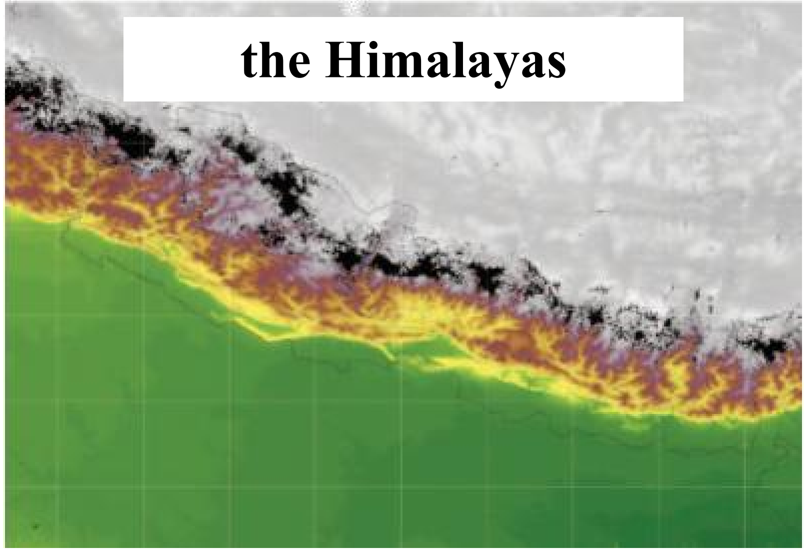
Shuttle Radar Topography Mission (SRTM)





Data Voids (Black area)





Reuter et al., 2007

- Intense terrain relief (high mountains)
- Clouds
- Surface cover (sand)

↓

Data Voids

↓

A large number of voids in mountains

Previous Studies

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Practical Approaches：

1) Field Work

Measuring and filling data voids.

2) Data Fusion

Integrating DEMs from other sources.

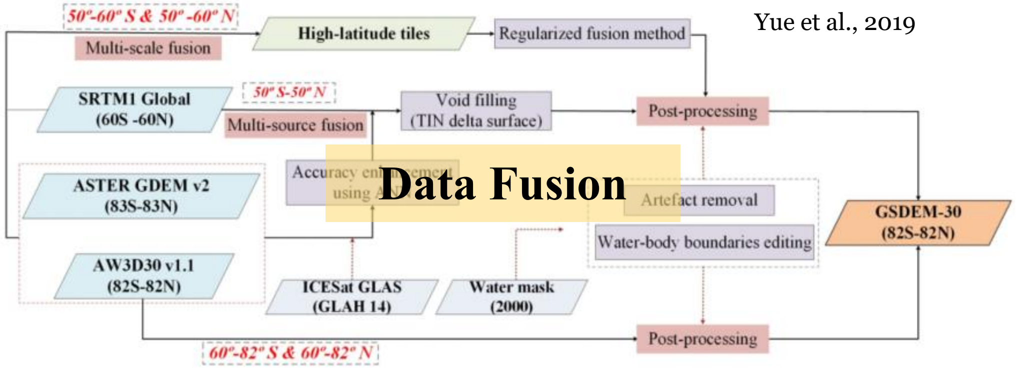
(issues: different resolutions and elevation datums)

3) Interpolation

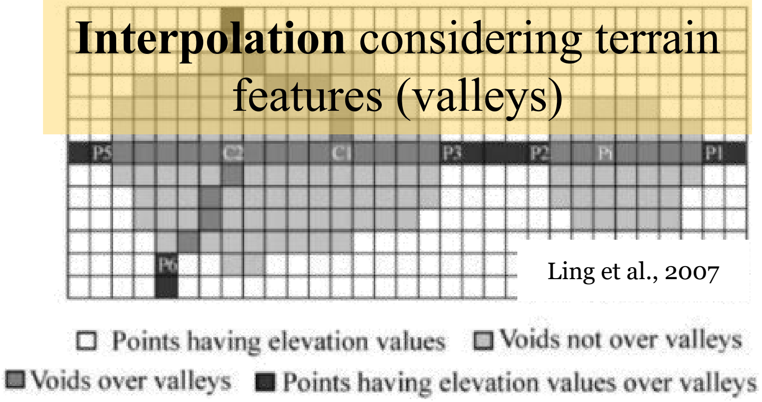
Such as IDW, spline and kriging interpolations.

4) Machine Learning/Deep Learning (ML/DL)

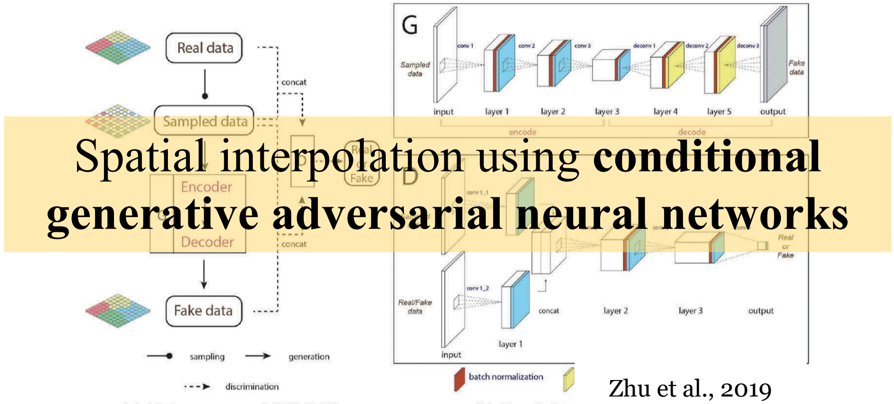
Constructing complex relationships between contextual terrain around voids and elevation in voids.



Yue et al., 2019



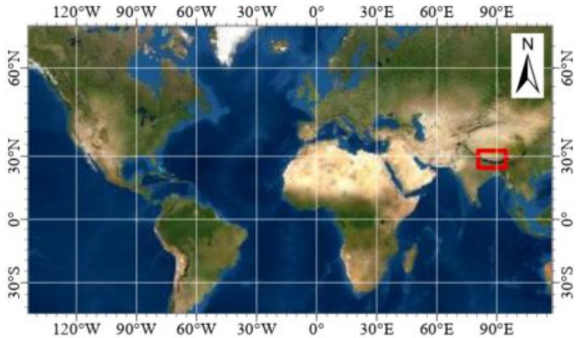
Ling et al., 2007

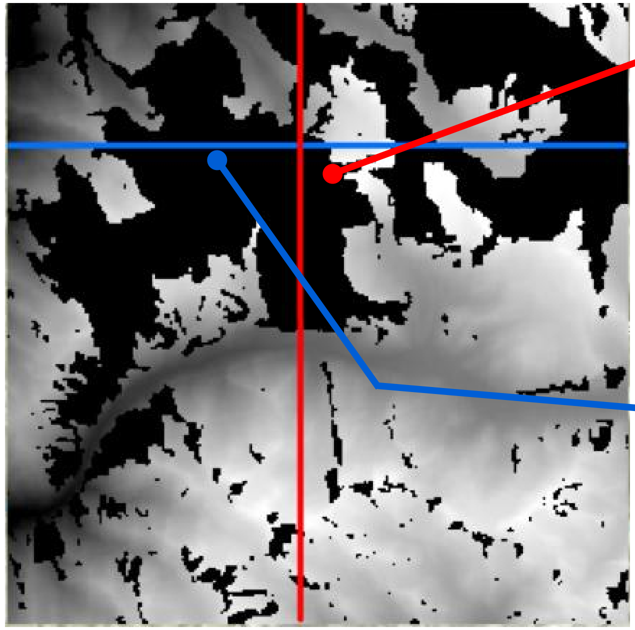


(a) Main structure of CEDGAN (b) Detailed in

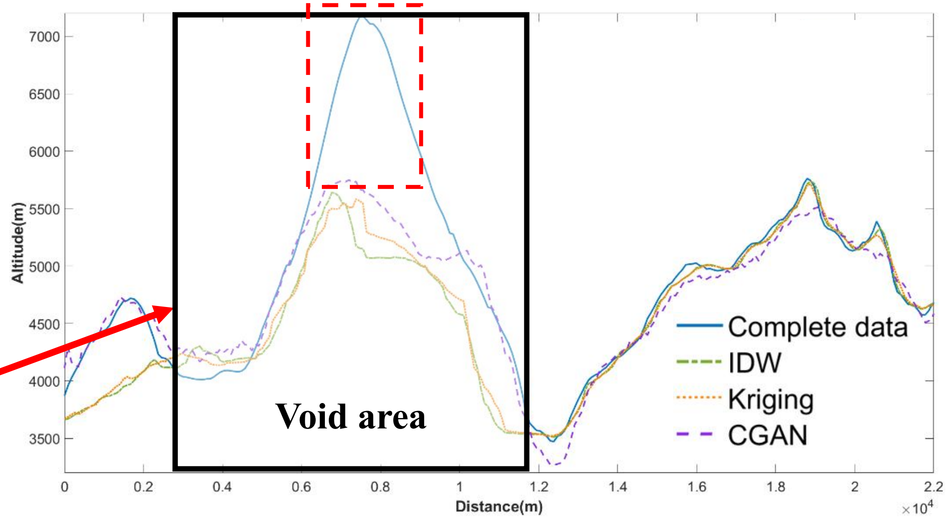
Zhu et al., 2019

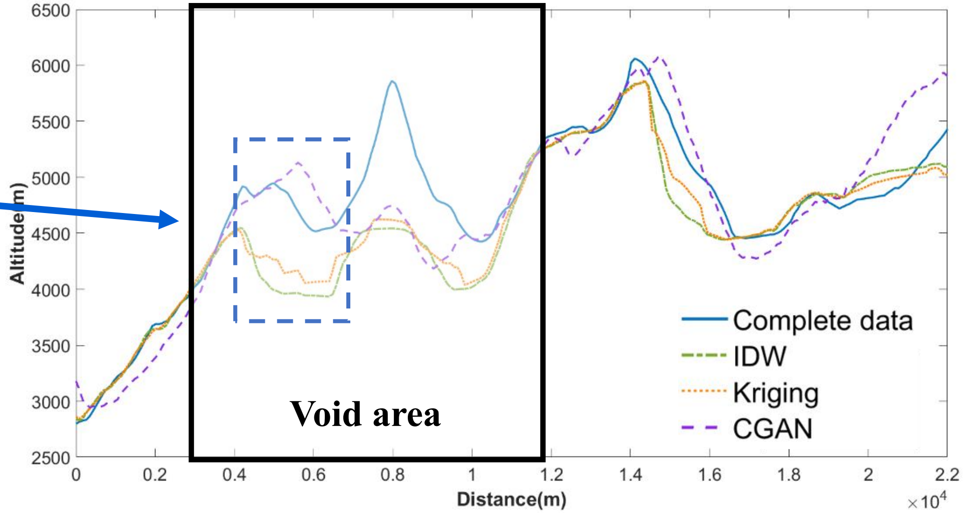
These methods are difficult to reconstruct the (relatively) accurate terrain, especially in the area with intense terrain relief.

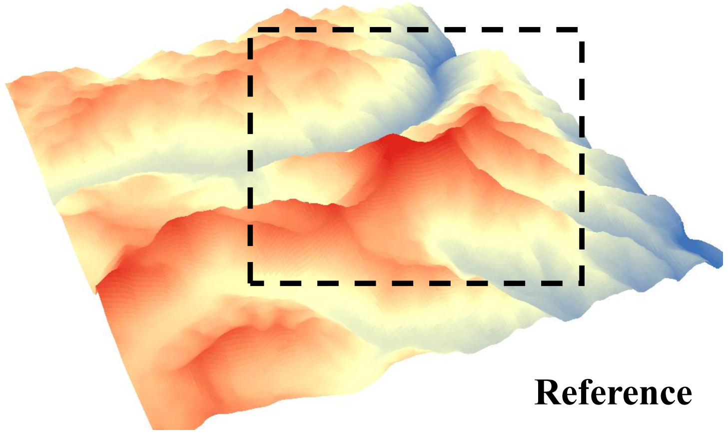




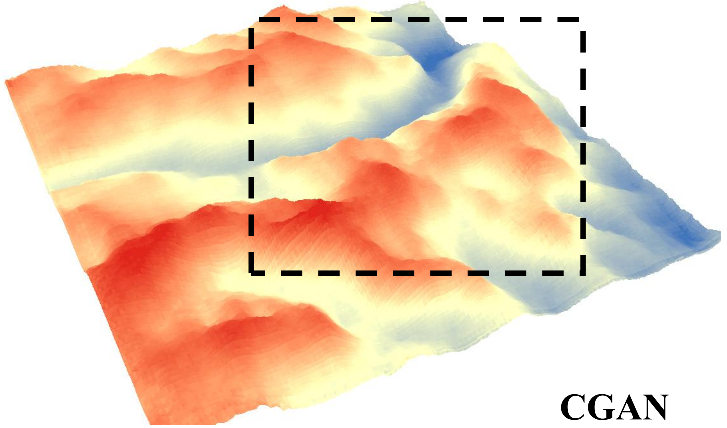
Line 1 Line 2







Reference

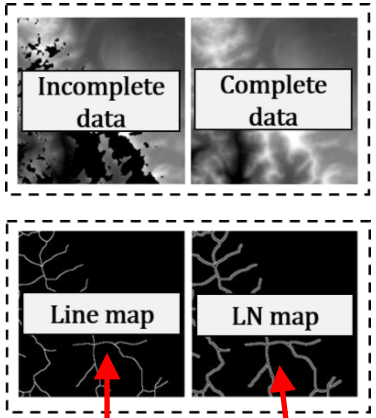


CGAN

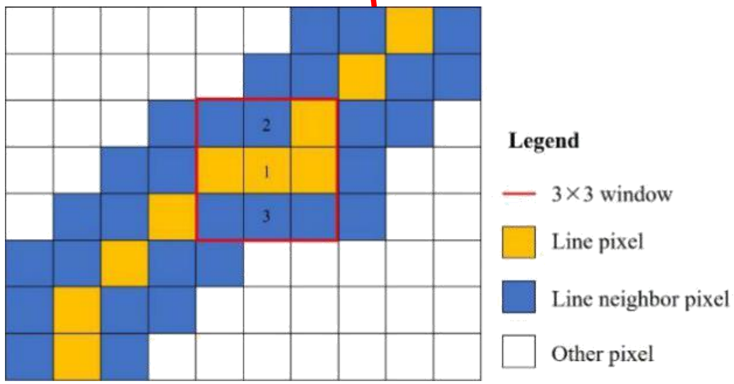
IDW=Inverse Distance Weighted interpolation; CGAN=Conditional Generative Adversarial Networks

Flowchart

Input



Ridge and Valley



Loss Function

(1) $Optimal(G,D) = \min_{G}\min_{D} L_{CGAN}$

(2) $L_H = |\ln(\Delta H^{R}_{output})| + |\ln(\Delta H^{V}_{output})|$

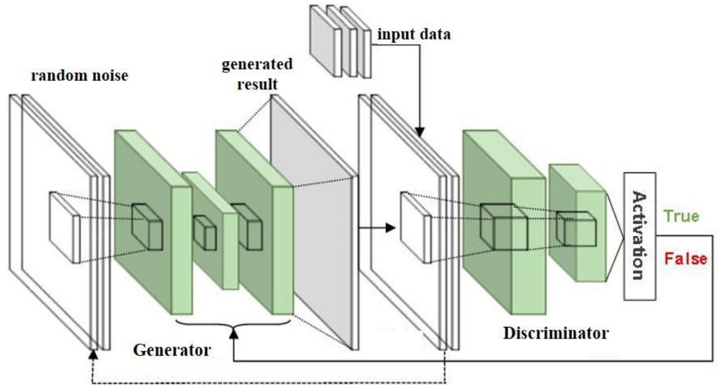
(3) $L_N = ln|N_R \times \beta| + ln|N_V \times \beta|$

(4) $L_E = \sum_{x\in X_R} |H_{output}(x) - H_{target}(x)| + \sum_{x\in X_V} |H_{output}(x) - H_{target}(x)|$

(5) $L_{EN} = \sum_{x\in X_{RN}} |H_{output}(x) - H_{target}(x)| + \sum_{x\in X_{VN}} |H_{output}(x) - H_{target}(x)|$

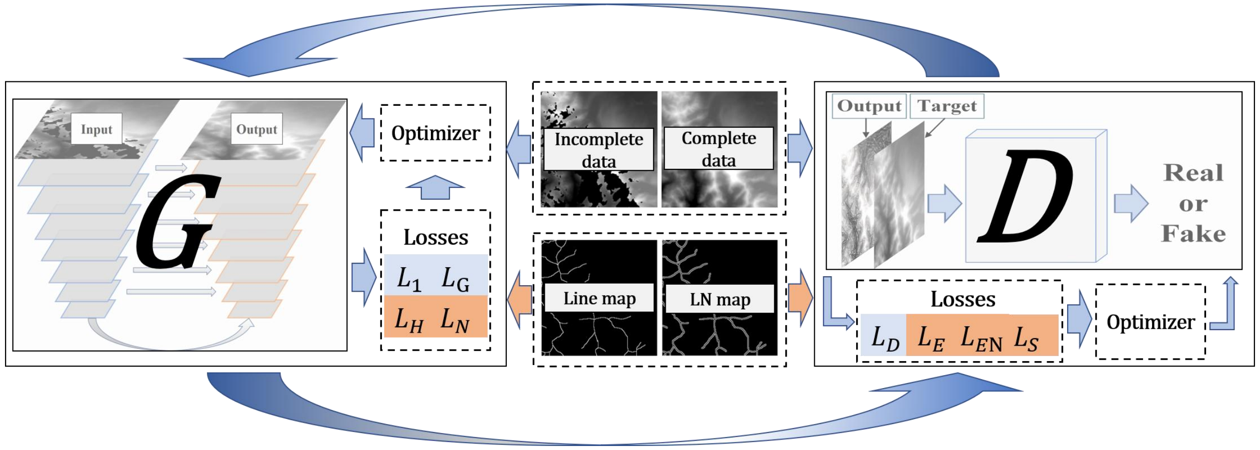
(6) $L_S = |\Delta H^{R}_{output} - \Delta H^{R}_{target}| + |\Delta H^{V}_{output} - \Delta H^{V}_{target}|$

CGAN



TKCGAN

Topographic knowledge-constrained CGAN



Loss Functions for Terrain Reconstruction

Considering:

1) Elevation (pixel value)

improving the value accuracy of each pixel

2) Terrain Relief

improving the accuracy of relief intensity and slope shape

Loss Functions

(1) $Optimal(G,D) = \min_{G}\min_{D} L_{CGAN}$

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(4) $L_E = \sum_{x \in X_R} |H_{output}(x) - H_{target}(x)| + \sum_{x \in X_V} |H_{output}(x) - H_{target}(x)|$

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(6) $L_S = |\Delta H^R_{output} - \Delta H^R_{target}| + |\Delta H^V_{output} - \Delta H^V_{target}|$

for Elevation:

Function (1) the original loss functions of CGAN

Through this competition, G and D obtain the capability to generate realistic data and distinguish generated data from the ground truth data, respectively.

Functions (4) & (5)

Emphasizing the accuracy of elevation value at each location

for Terrain Relief:

Functions (2) & (6)

Emphasizing the terrain relief around feature lines (ridges and valleys). The parameter α can control the relief intensity.

Function (3)

Emphasizing the slope shape around feature lines. The parameter β can reflect the shape of slope surface.

Results – Visual Inspection & Accuracy Indices

TKCGAN achieves better results especially in the area with large voids.

original voids & simulating voids

indicating that DL-based methods could achieve the prediction of terrain patterns or terrain relief through "imitating contextual terrain"

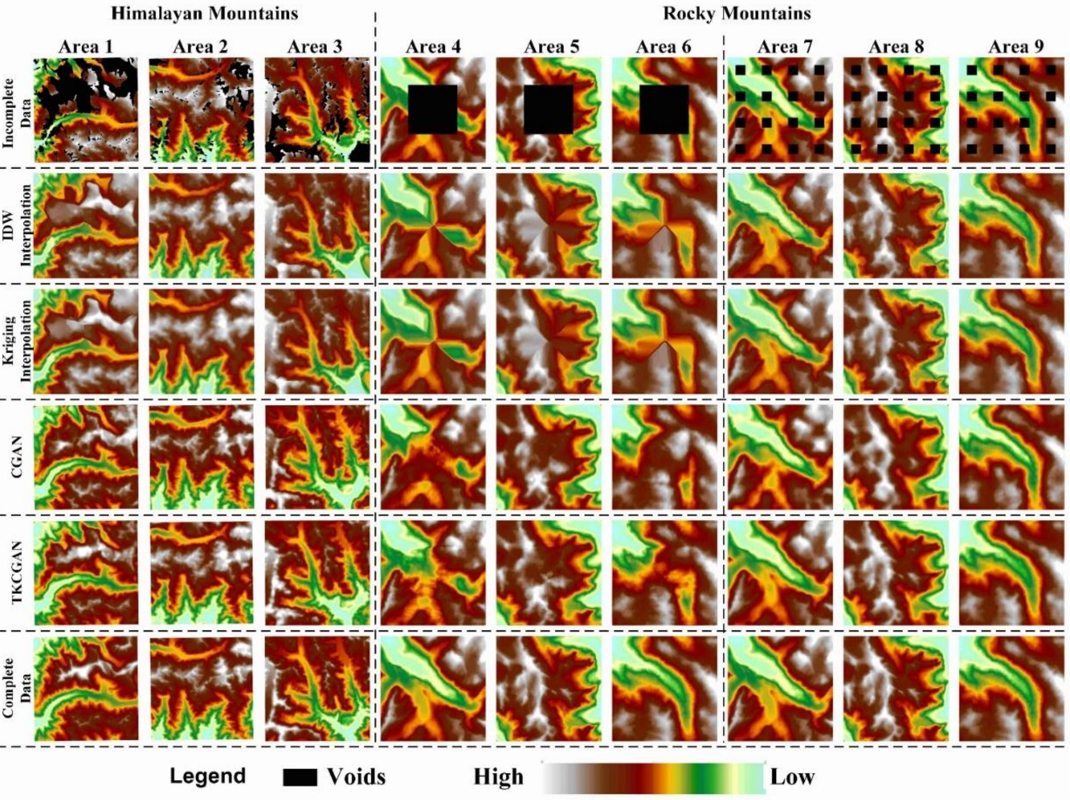


Table 2
Elevation accuracy of the reconstruction results in void areas (the best performances are highlighted in bold.)

	RMSE (m)					MAE (m)			
	IDW	Kriging	CGAN	TKCGAN		IDW	Kriging	CGAN	TKCGAN
Area 1	103.62	102.59	104.46	**102.91**	Area 1	86.30	85.95	90.65	**85.37**
Area 2	93.96	95.28	101.46	**93.08**	Area 2	77.18	79.14	87.53	**76.34**
Area 3	106.18	104.09	108.82	**99.38**	Area 3	89.67	88.15	92.78	**85.16**
Area 4	84.03	84.52	112.13	**75.24**	Area 4	64.28	64.88	103.12	**61.56**
Area 5	87.79	**86.12**	96.74	89.95	Area 5	72.46	**71.24**	72.93	75.74
Area 6	86.88	87.19	90.79	**81.04**	Area 6	66.84	67.16	74.51	**65.49**
Area 7	40.68	**30.44**	46.57	37.13	Area 7	27.53	**19.84**	31.71	27.39
Area 8	50.91	**38.52**	42.33	41.16	Area 8	36.17	**26.24**	64.14	49.77
Area 9	27.57	**26.84**	49.03	28.74	Area 9	20.58	**20.39**	36.00	23.81

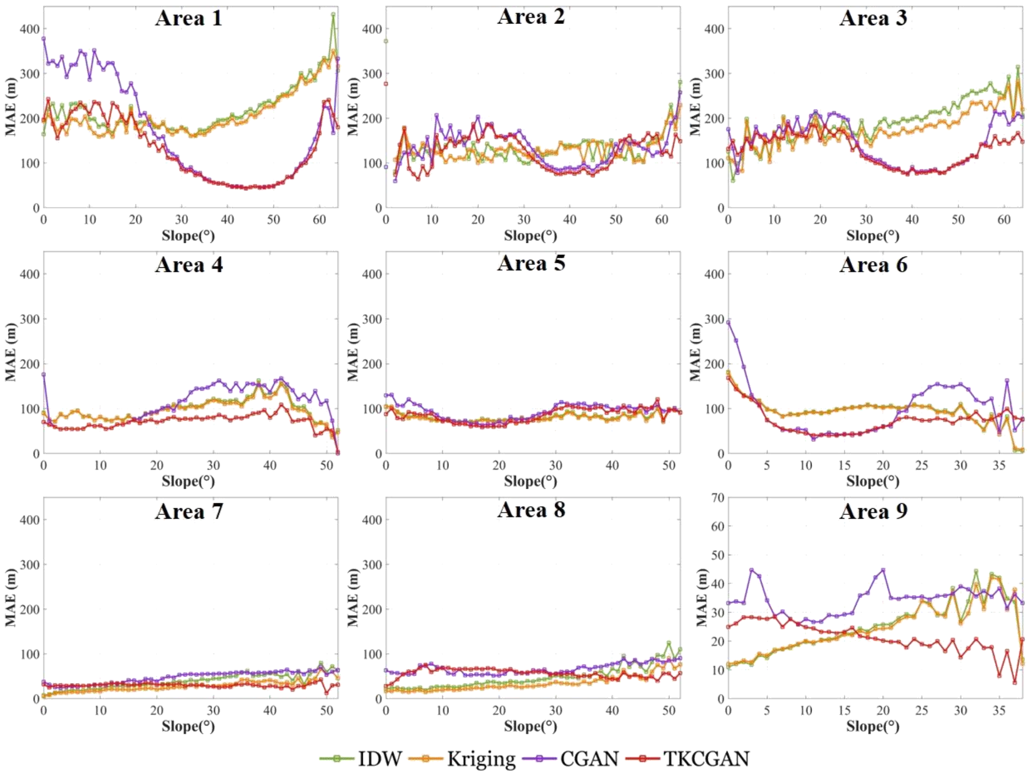
Table 3
Surface slope accuracy of the reconstruction result in void areas (the best performances are highlighted in bold.)

	RMSE (°)					MAE (°)			
	IDW	Kriging	CGAN	TKCGAN		IDW	Kriging	CGAN	TKCGAN
Area 1	17.13	17.04	14.49	**14.11**	Area 1	13.26	13.01	11.36	**11.19**
Area 2	12.21	**11.60**	14.07	11.99	Area 2	9.83	**9.00**	11.24	9.51
Area 3	13.85	14.66	16.20	**13.21**	Area 3	11.02	11.24	12.92	**10.25**
Area 4	16.53	15.82	**11.72**	11.96	Area 4	12.59	11.89	**9.33**	9.75
Area 5	17.55	16.93	12.84	**12.29**	Area 5	13.41	13.05	10.41	**10.33**
Area 6	18.57	18.90	9.73	**9.14**	Area 6	12.51	13.19	7.88	**7.34**
Area 7	14.96	11.99	11.37	**7.43**	Area 7	11.03	8.60	9.39	**6.15**
Area 8	15.82	12.94	12.75	**9.46**	Area 8	12.34	9.94	10.42	**7.73**
Area 9	13.71	12.60	9.14	**6.91**	Area 9	10.34	9.68	7.65	**5.69**

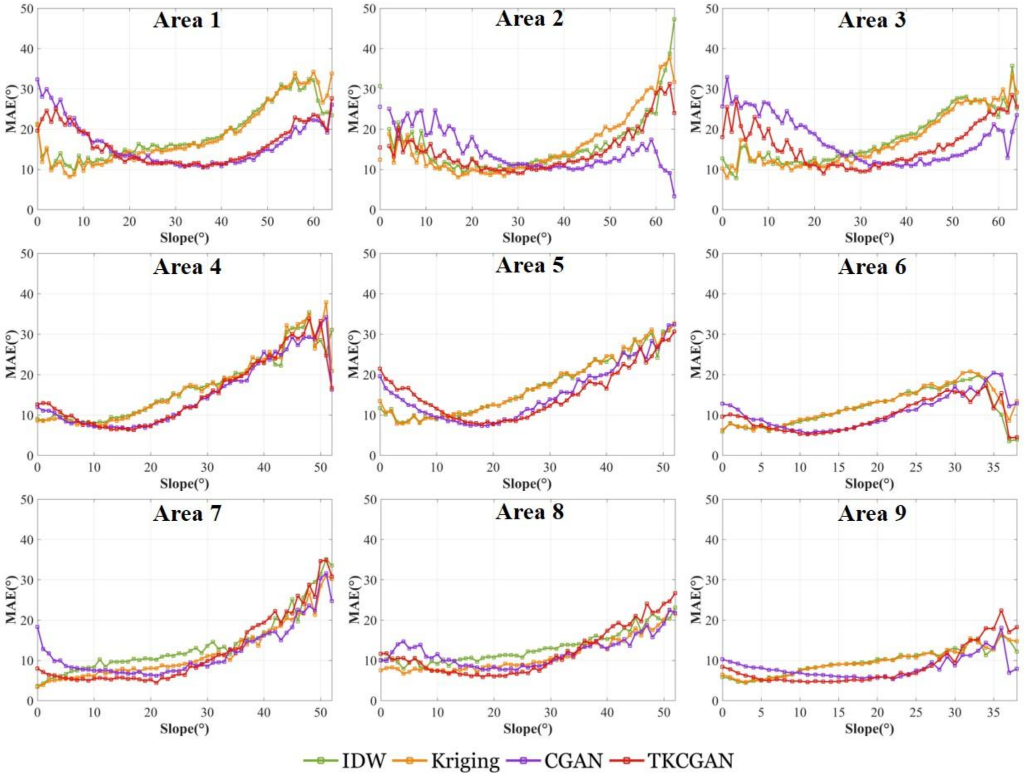
Results – Elevation & Slope Errors

- calculating slope (gradient) based on reconstructed DEMs
- analyzing the relationships between the elevation and slope (gradient) error and slope (gradient) calculated based on reference data.

TKCGAN outperforms in the areas with medium and large slope (gradient).

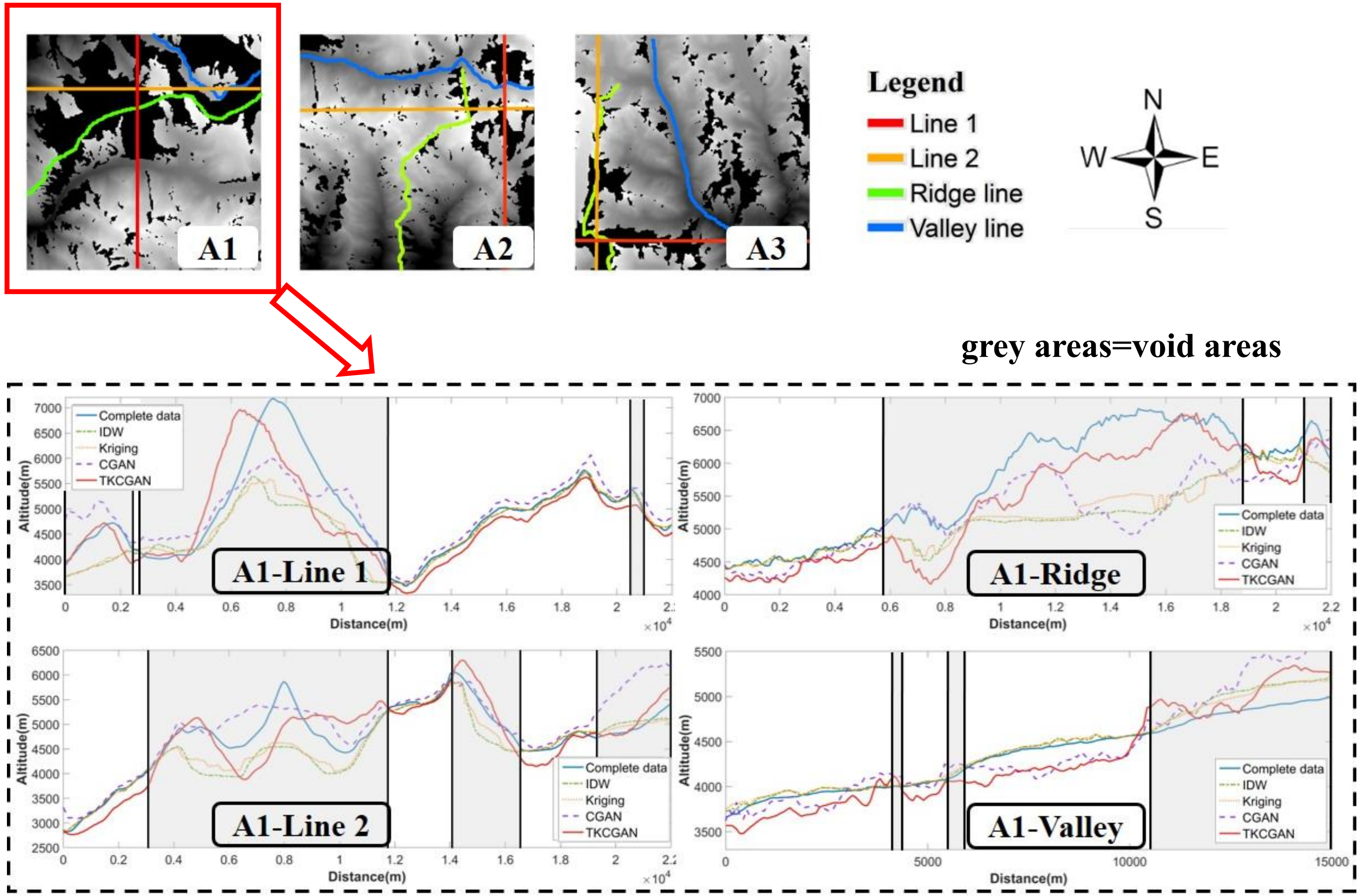


Elevation error



Slope error

Results – Cross Section



Advantage

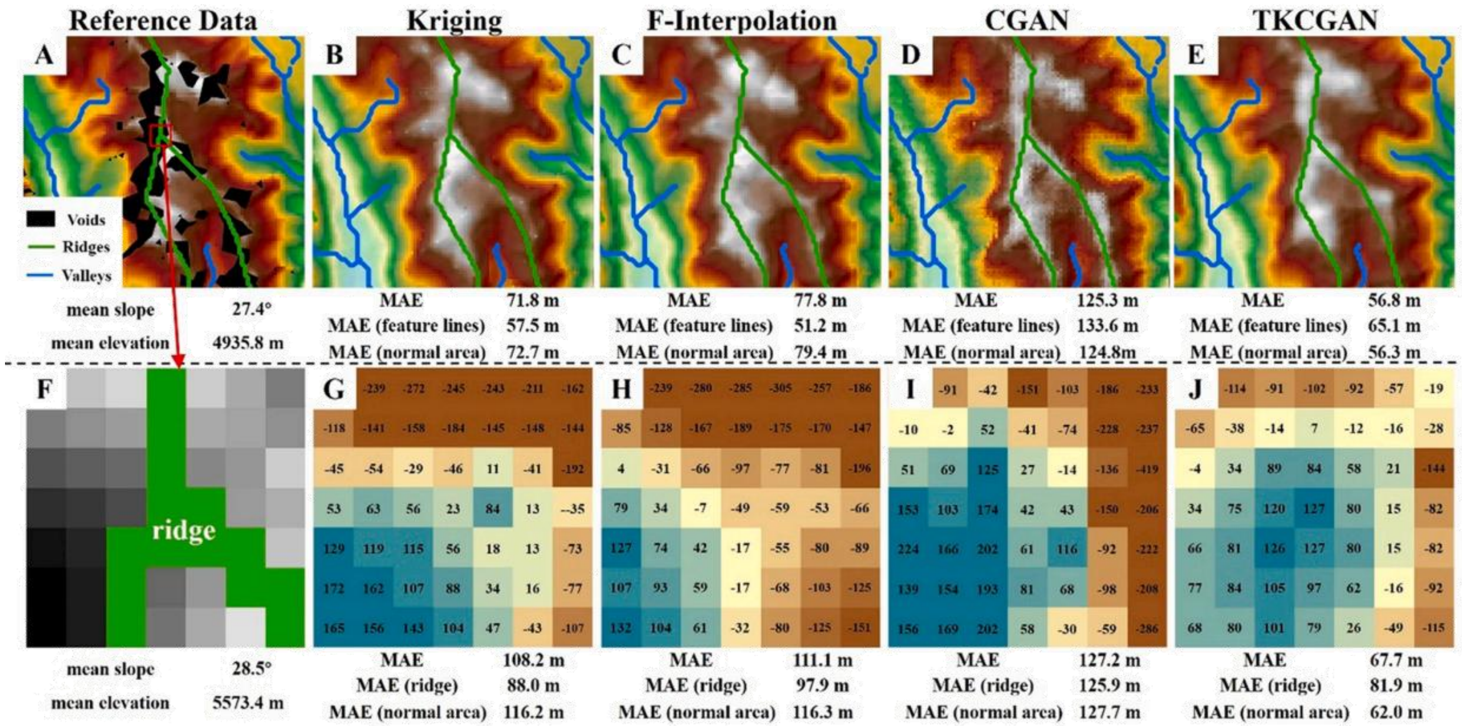
TKCGAN achieves better results in the area with intense terrain change (for example, the peak in A1-Line1 and ridge in A1-Ridge.

Disadvantage

Our method “underestimates” the elevation in valleys (A1-Line2). This could result from the new loss functions that overemphasize the intense terrain relief.

Results – Details

Mapping the elevation error in ridge areas (ridge line and its adjacent areas).



1. Classical interpolations contain significant errors.
2. The interpolation considering the terrain feature lines has small errors on lines but contains large errors in the adjacent area.
3. TKCGAN achieves significantly better results in areas around ridges

Summary

Finding

the topographic controlling through the addition of loss functions is practical to improve the accuracy of void-filling DL-based methods.

Issues

the number and quality of input feature lines can influence the reconstructed results.

Can we integrate the topographic information carried by remote sensing **imagery**?

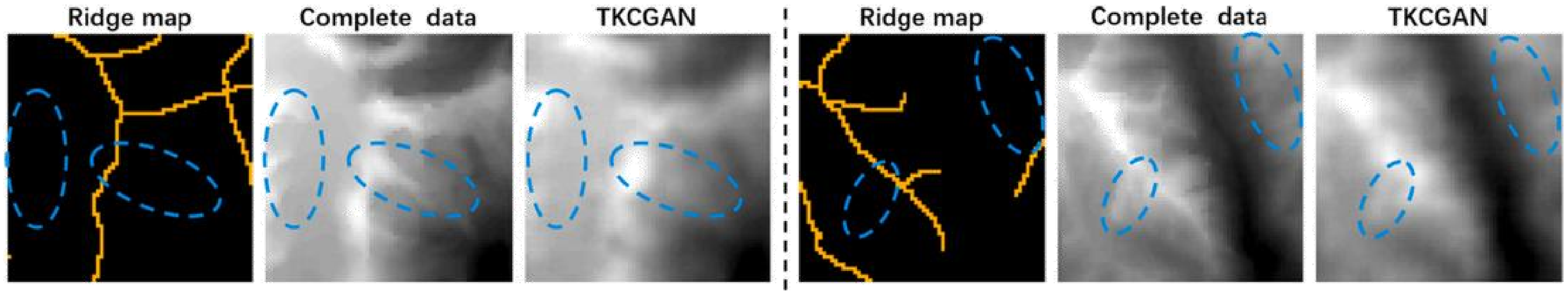


Fig. 13. Inaccurate reconstruction was performed because of the lack of corresponding ridge lines. Some detailed topographic features in the blue circles are missed through the generation process because of the lack of corresponding input data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Li, S., Hu, G., Cheng, X., Xiong, L., Tang, G., & Strobl, J. (2022). Integrating topographic knowledge into deep learning for the void-filling of digital elevation models. Remote Sensing of Environment, 269, 112818.

Thank you!

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Acknowledgement

Guanghui Hu, Liyang Xiong, Guoan Tang

Josef Strobl

Xinghua Chen

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