IDW-ResUNet Framework
for Ground-Level Radioactive Contamination Estimation Using UAV-Based Airborne Radiation Data

IDW-ResUNet 프레임워크 기반 무인항공기 관측데이터를 활용한 지표면 방사능 오염 분포 추정

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UNIST UCIM

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1. Introduction

Research Background & Motivation

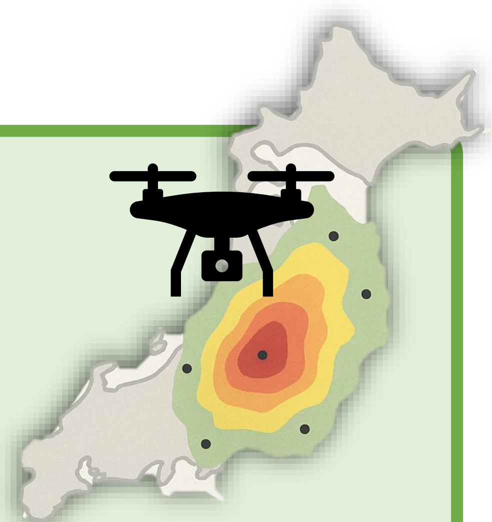
Restricted access to contaminated zones after nuclear accidents [1][2]
(e.g., Chernobyl 1986, Fukushima 2011)

Essential to assess contamination for safety and recovery.

UAV (Unmanned Aerial Vehicle)

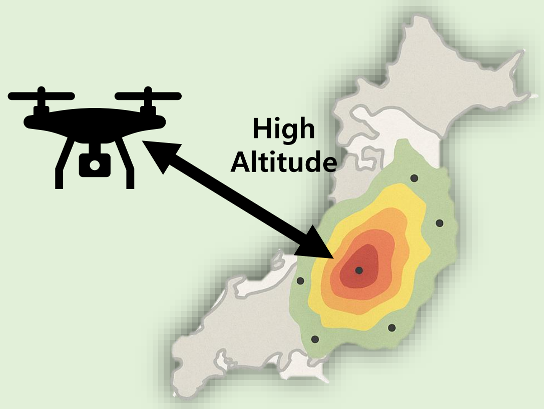
Advantages[3]

- No equipment failure issues
- Not limited by terrain
- Can quickly scan large areas

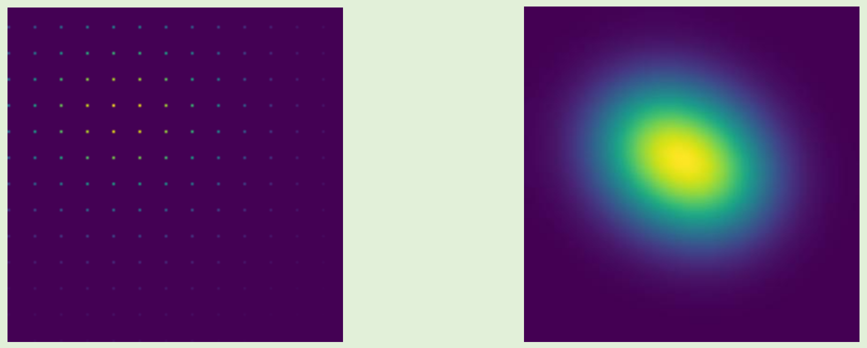


Limitations of UAV

UAV sensors are Far from ground
Lower accuracy[4]



Few measurement points << Total ground area



sparse measurement vs contamination map

Need reconstruction methods (e.g., interpolation)
to estimate full contamination map!

Our research focuses on precise ground-level contamination estimation from UAV data

[1] Saveliev, M., Shtefan, V., Proskurin, O., Pantin, M., Martin, P. G., Grechaninov, V., & Havrylko, Y. (2024). Multi-Robot Radiation Reconnaissance in the Chornobyl NPP Exclusion Zone. Ядерна та радіаційна безпека, (4 (104)), 41-49.
[2] Shozugawa, K., Hori, M., Johnson, T. E., Ishigaki, Y., & Matsumoto, Y. (2025). Projections of future ambient dose rates in a mountainous area in the Fukushima evacuation zone, Japan. Journal of Radioanalytical and Nuclear Chemistry, 334(2), 1643-1648.
[3] Geelen, S., Camps, J., Olyslaegers, G., & Schroeyers, W. (2024). Drone-borne dosimetry in a radiological or nuclear scenario. Radiation Measurements, 170, 107042.
[4] Sasaki, M., Sanada, Y., Katengeza, E. W., & Yamamoto, A. (2021). New method for visualizing the dose rate distribution around the Fukushima Daiichi Nuclear Power Plant using artificial neural networks. Scientific Reports, 11(1), 1857.

Related Work & Need for Deep Learning

1 IDW / Kriging

- **Linear interpolation**

$input = [x_1, x_2, x_3 \ldots]$ → $output = w_1 \times x_1 + w_2 \times x_2 + w_3 \times x_3 + \cdots$

- **Limitations**[5]

  Struggle with complex nonlinear relationships

2 Classical ML

- **Feature-engineered models**
- **Limitations**[6]

  Depend on handcrafted features

→ Deep Learning

Deep learning enables nonlinear estimation and automatically extracts features from data, capturing patterns beyond handcrafted models[6]

[5] Alam, M. M., & Nuruzzaman, M. (2025). Comparative analysis of interpolation methods commonly used in bathymetric data generation. World J. Adv. Res. Rev, 25(3), 2018-2029.
[6] Lai, Y. (2019, October). A comparison of traditional machine learning and deep learning in image recognition.

Research Gap & Approach

Deep Learning Paper for UAV-based Radiation Mapping

- [7] Sasaki, M., & Sanada, Y. (2022). Improvement of training data for dose rate distribution using an artificial neural network. Journal of Advanced Simulation in Science and Engineering, 9(1), 30-39.
- [8] Sasaki, M., Sanada, Y., Katengeza, E. W., & Yamamoto, A. (2021). New method for visualizing the dose rate distribution around the Fukushima Daiichi Nuclear Power Plant using artificial neural networks. Scientific Reports, 11(1), 1857.

⋮

Used only **MLP** (basic ANN) for contamination estimation

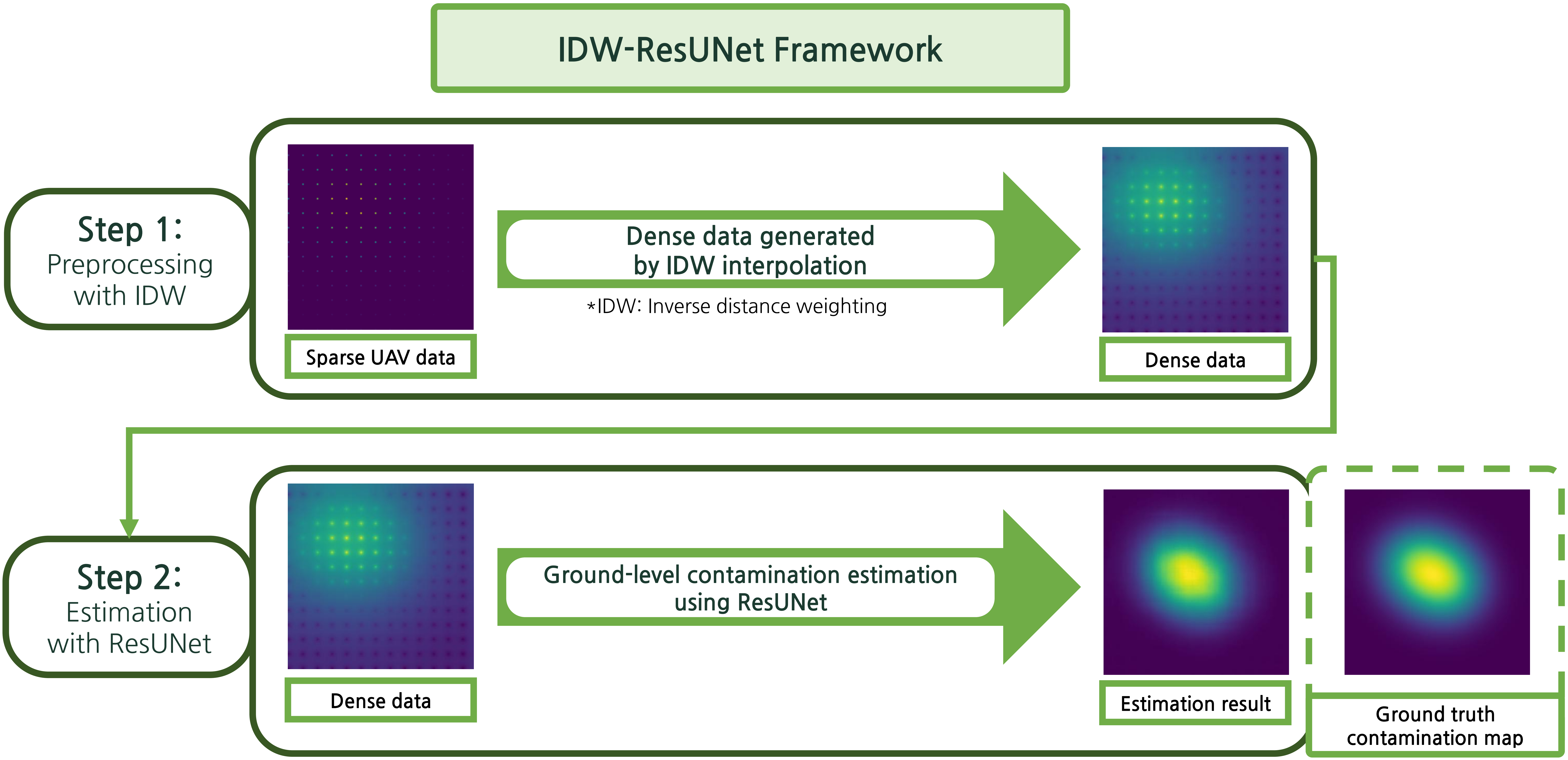
- No clear studies applying advanced deep learning models (beyond MLP) to UAV-based radiation data (Google Scholar search: UAV + radiation + deep learning)

Apply Residual UNet[9] (estimation-specialized model)

- Widely used in medical imaging and remote sensing for image restoration[10][11]
- Applied to reconstruct sparse seismic data[12]

[9] Diakogiannis, F. I., Waldner, F., Caccetta, P., & Wu, C. (2020). ResUNet-a: A deep learning framework for semantic segmentation of remotely sensed data. ISPRS Journal of Photogrammetry and Remote Sensing, 162, 94-114.
[10] Jinka, H., Shaji, J., John, S., Menon, S. R., Pradeep, A., PB, J., ... & Puzhakkal, N. (2024, February). SART-Res-UNet: Fan Beam CT Image Reconstruction from Limited Projections using attention-enabled residual U-Net. In Asian Conference on Machine Learning (pp. 598-613). PMLR.
[11] Vijay Kumar, S., Sun, X., Wang, Z., Goldsbury, R., & Cheng, I. (2023). A U-Net approach for InSAR phase unwrapping and denoising. Remote Sensing, 15(21), 5081.
[12] Tang, S., Ding, Y., Zhou, H. W., & Zhou, H. (2020). Reconstruction of sparsely sampled seismic data via residual U-Net. IEEE Geoscience and Remote Sensing Letters, 19, 1-5.

Overview

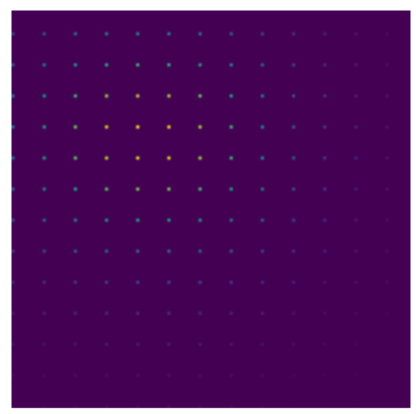

IDW-ResUNet Framework
Step 1:
Preprocessing
with IDW
Sparse UAV data
Dense data generated
by IDW interpolation
*IDW: Inverse distance weighting
Dense data
Step 2:
Estimation
with ResUNet
Dense data
Ground-level contamination estimation
using ResUNet
Estimation result
Ground truth
contamination map

Step 1: Preprocessing with IDW

Note

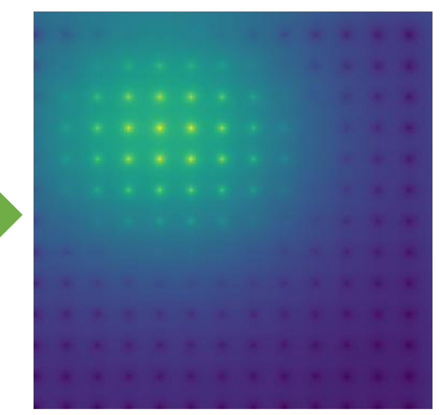
ResUNet (CNN-based)

- Learns **spatial patterns** & **relationships between neighboring pixels**[13]
- **Fills** unobserved areas with **meaningful values** → **better estimation**[14]

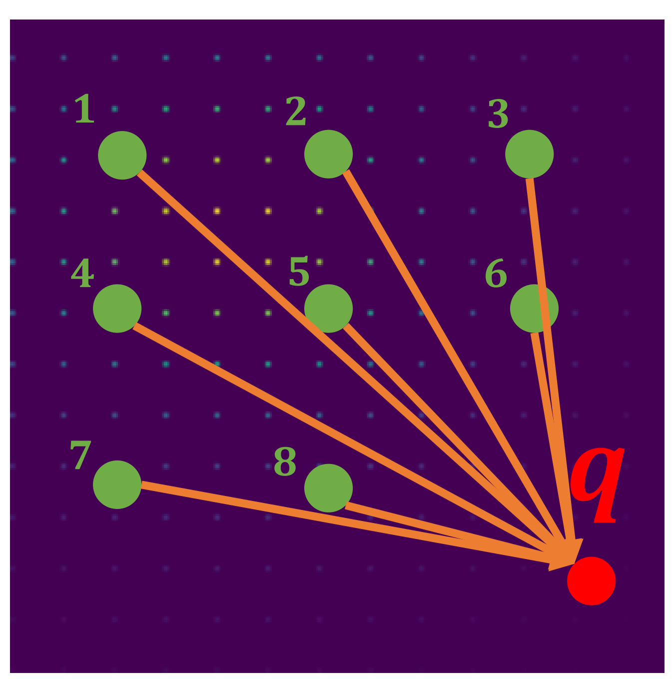


Sparse UAV data

Dense data generated by IDW interpolation



Dense data



Altitude 10m plane

Inverse Distance Weighting formula

$$\hat{Z}(q) = \frac{\sum_{i=1}^{N} \frac{M_i}{d(q,i)^p}}{\sum_{i=1}^{N} \frac{1}{d(q,i)^p}}, p = 1.5$$

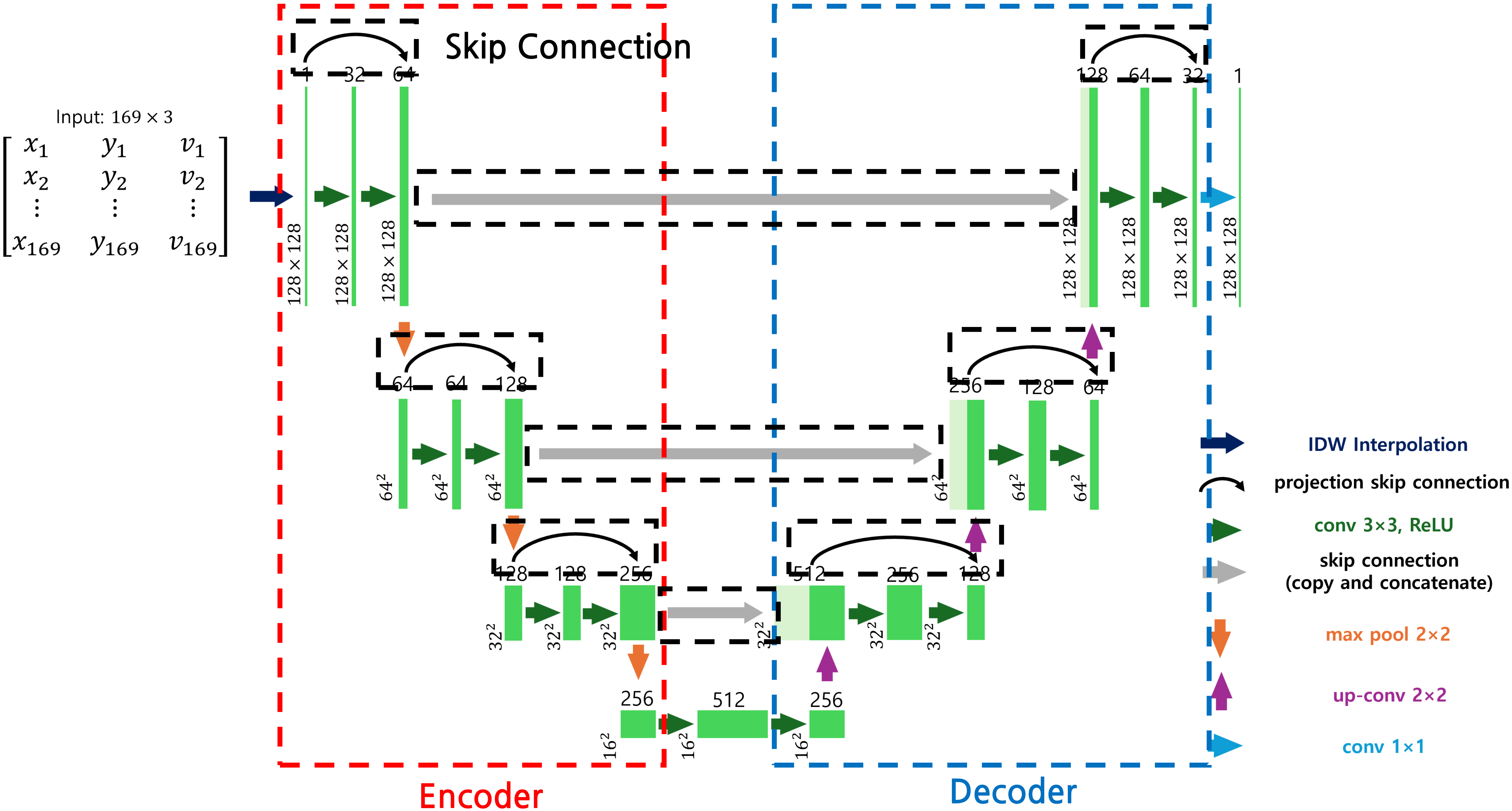
$\hat{Z}(q)$: Estimated radiation intensity at position q, where i = 1, 2, ⋯ are UAV observation points

Why IDW?

- Simple formula, **fast computation** → **efficient for dataset generation**[15]

[13] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. nature, 521(7553), 436-444.
[14] Yang, Y. Q., Wang, P. S., & Liu, Y. (2021). Interpolation-aware padding for 3d sparse convolutional neural networks. In Proceedings of the IEEE/CVF international conference on computer vision (pp. 7467-7475).
[15] Lu, G. Y., & Wong, D. W. (2008). An adaptive inverse-distance weighting spatial interpolation technique. Computers & geosciences, 34(9), 1044-1055.

Step 2: Estimation with ResUNet

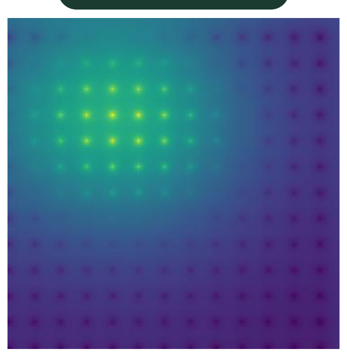


2. Methodology

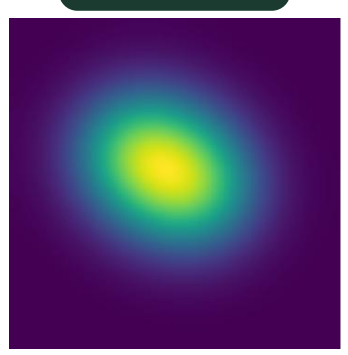
Step 2: Estimation with ResUNet

Training Data Format

Input (128 × 128)



Label (128 × 128)



×12,000

▶ Loss Function

- Mean Squared Error (MSE)

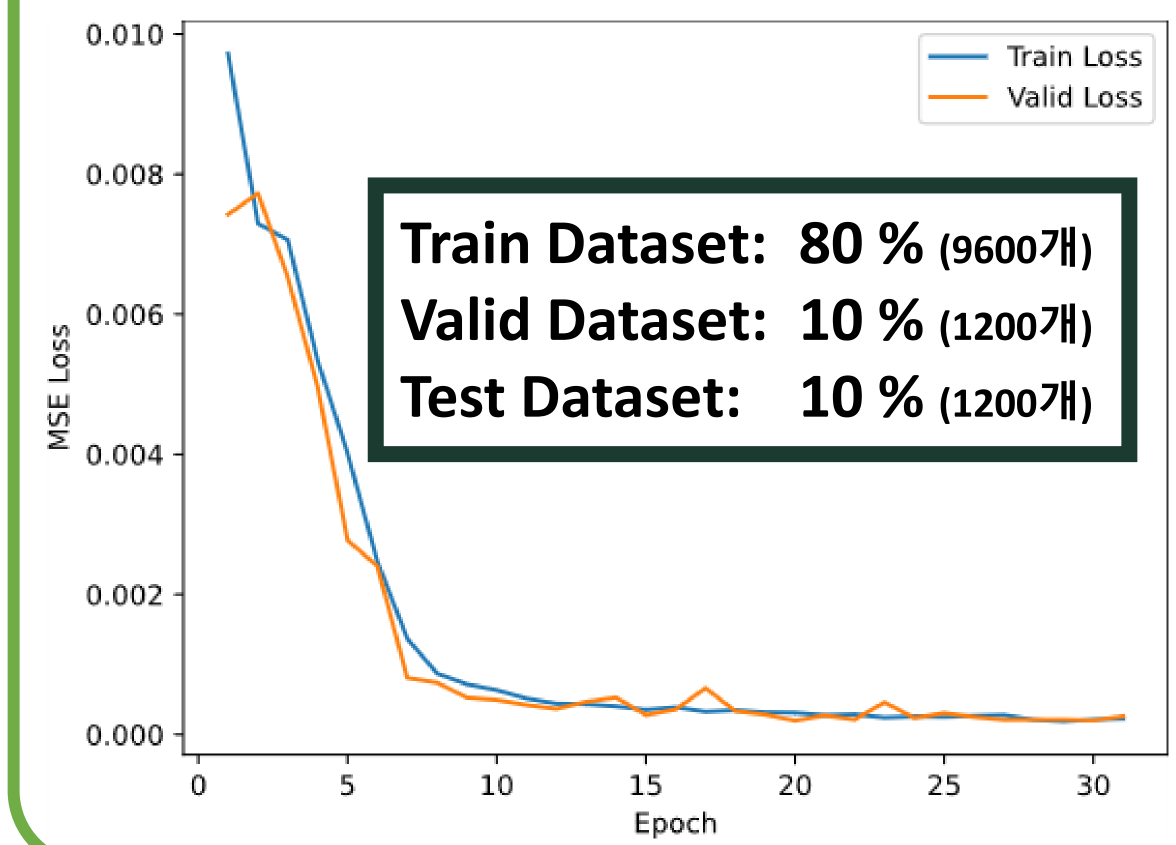
▶ Optimizer

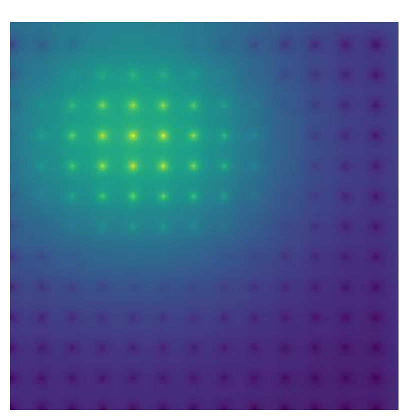
- Adam optimizer with a learning rate of 0.001

▶ Hardware and Environment

- CPU: Intel Core i7-12700F (12th Gen)
- Memory: 48 GB
- GPU: NVIDIA GeForce RTX 3080 Ti

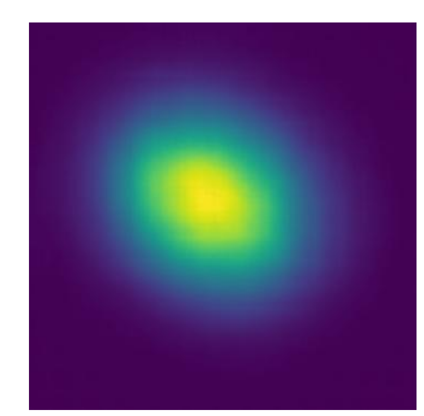
Fig. 3. Training and validation MSE Loss curves over 31 epochs. The similar decreasing trends of training and validation losses indicate that the model was trained stably without overfitting.





Dense data

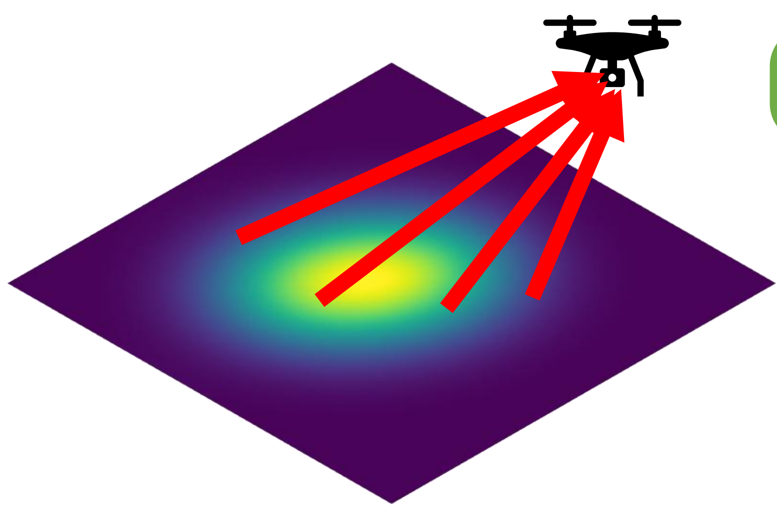
Ground-level contamination estimation using ResUNet



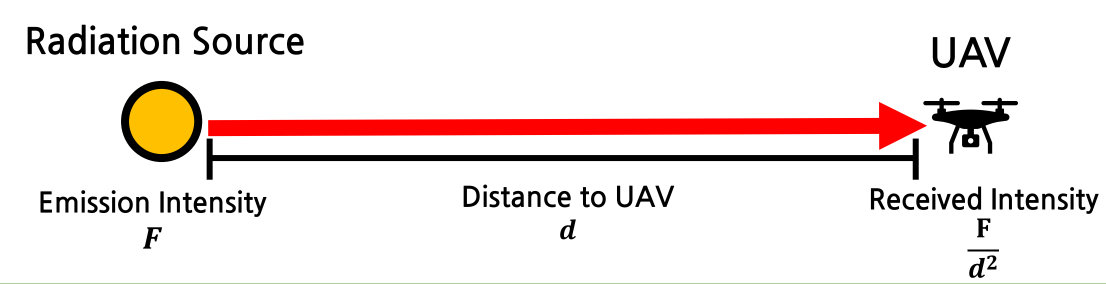
Estimation result

2. Methodology

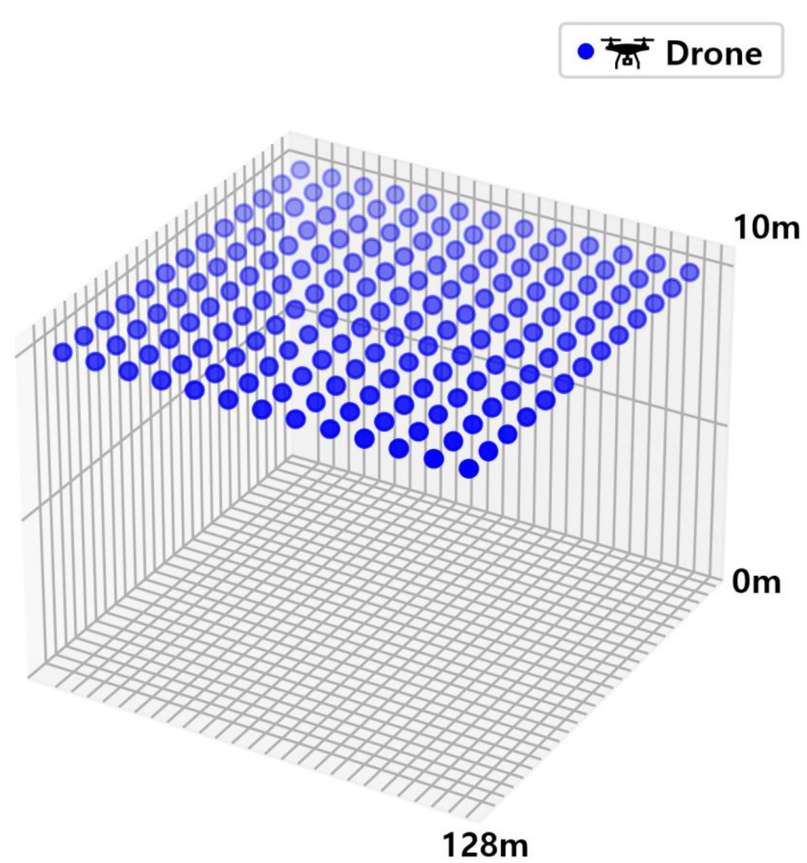
Ground Contamination Generation



Inverse-Square Law



UAV Observation Locations



Elliptical contamination sources (12,000 samples)

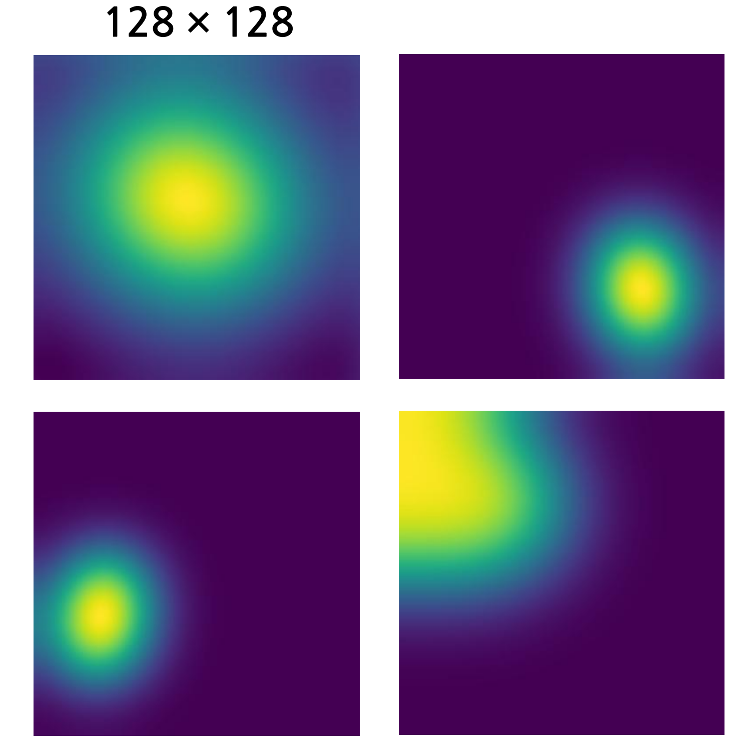
$$C(x,y) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{x'^2 + y'^2}{2\sigma^2}\right)$$

$$;\frac{x'^2}{3^2} + \frac{y'^2}{2^2} \leq r_{max} \quad \begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{pmatrix} \begin{pmatrix} x - x_c \\ y - y_c \end{pmatrix}$$

- Center coordinates: (x_c, y_c)
- Rotation angle: θ
- Maximum diffusion distance: $r_{\max}$
- Spread factor: σ

128 × 128

e.g.



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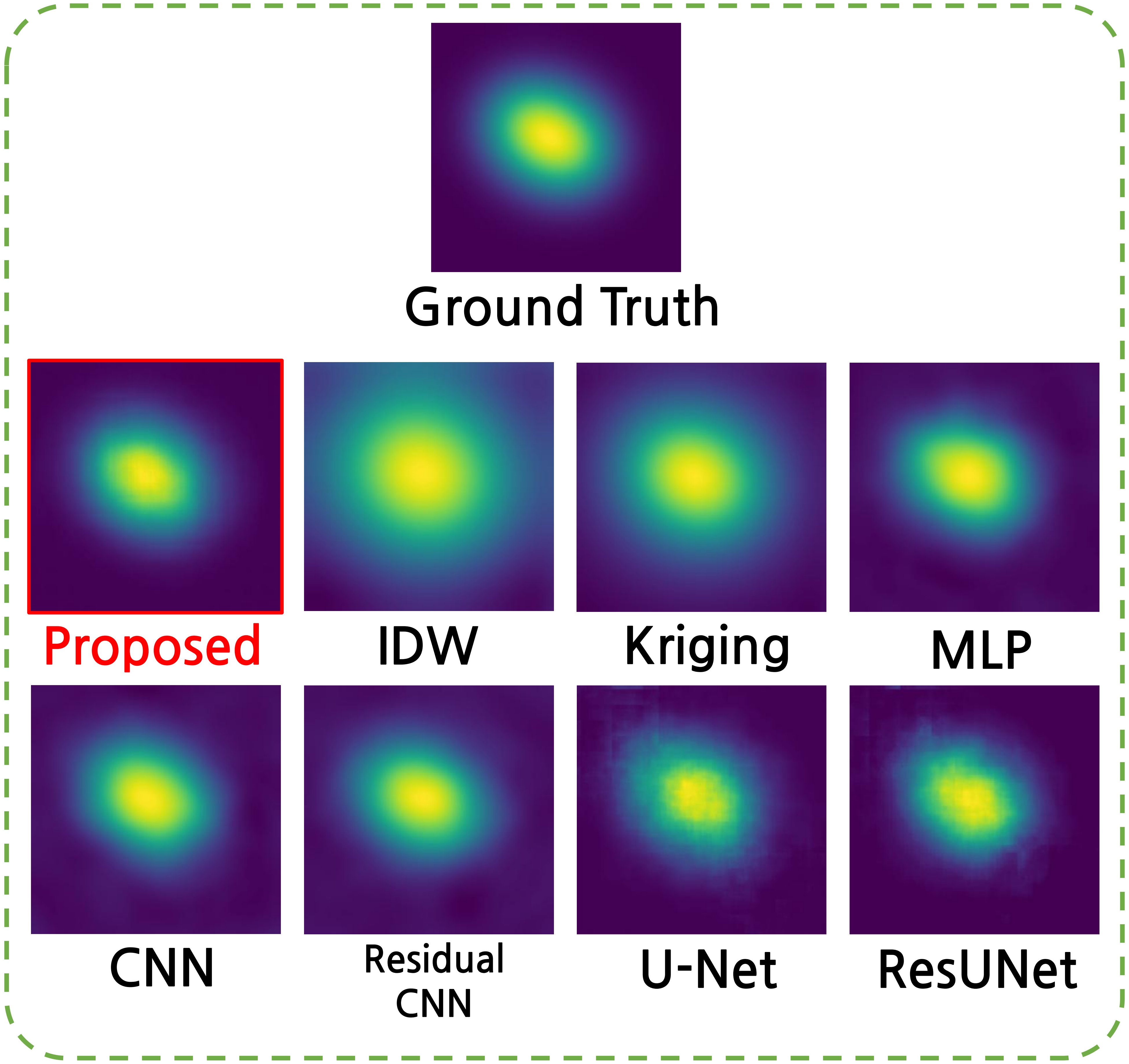
3. Result

Table I: Error and Score analysis[16]

Method \ Metrics	MSE	MAE	PSNR	SSIM
IDW	0.060352	0.196762	12.474	0.2768
Kriging	0.018677	0.107056	17.545	0.3444
MLP	0.001275	0.021881	30.362	0.7115
CNN	0.001294	0.021936	30.998	0.6863
Residual CNN	0.001275	0.021797	31.309	0.6722
U-Net	0.003118	0.020981	27.285	0.8958
ResUNet	0.002378	0.018303	28.027	0.9244
Proposed	***0.000258***	***0.007237***	***37.768***	***0.9783***



Note

- MSE/MAE ↓, PSNR/SSIM ↑ → Better performance

[16] Prodan, M., Vlăsceanu, G. V., & Boiangiu, C. A. (2023). Comprehensive evaluation of metrics for image resemblance. Journal of Information Systems & Operations Management, 17(1), 161-185.

4. Conclusions

Proposed Framework

- IDW interpolation → fill sparse UAV data
- ResUNet → restore ground contamination distribution

Performance

- Outperforms IDW, Kriging, MLP, CNN, U-Net, ResUNet
- Best results in MSE, MAE, PSNR, SSIM

Implications

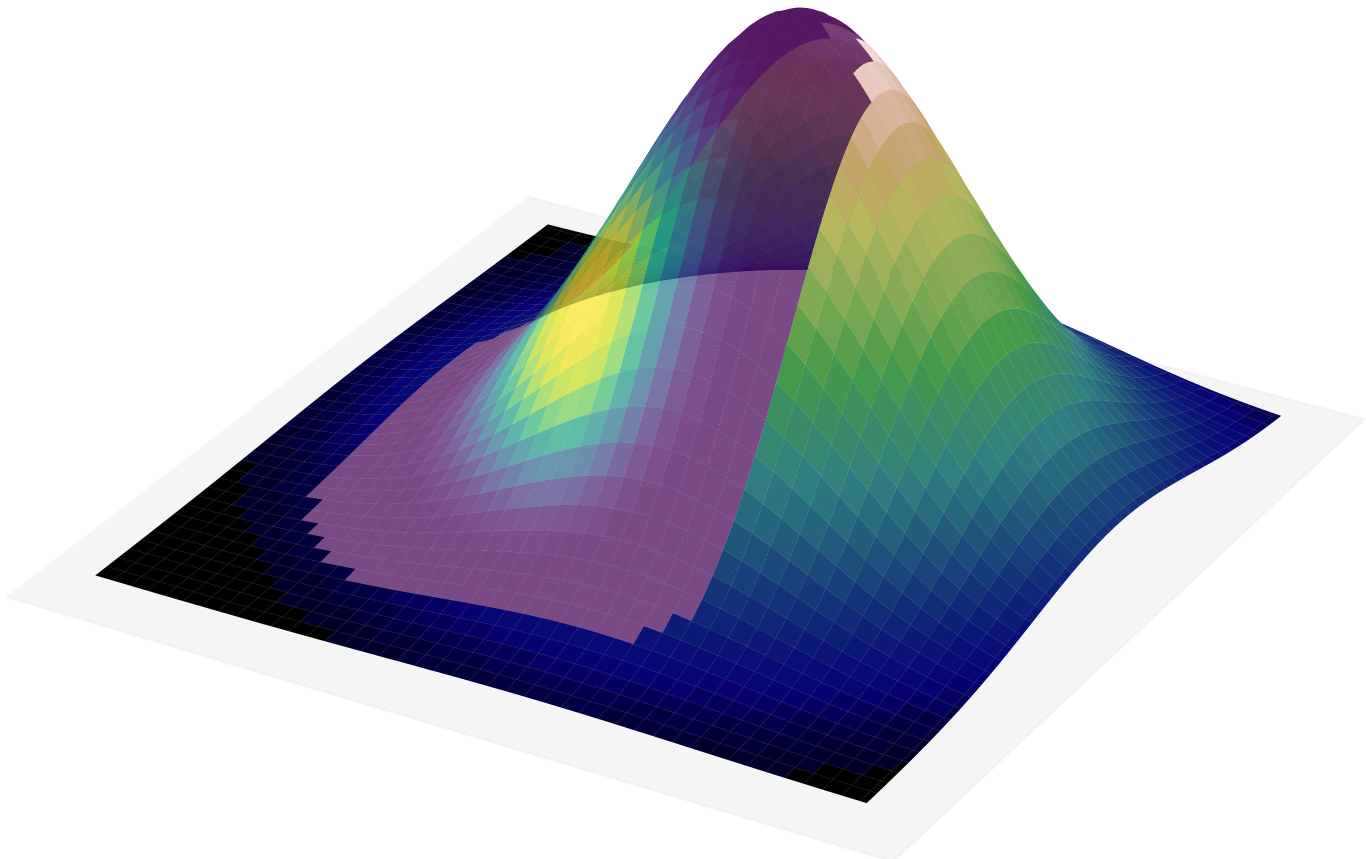
- Enables accurate contamination mapping from UAV data
- Potential to support emergency response & recovery planning

Limitations

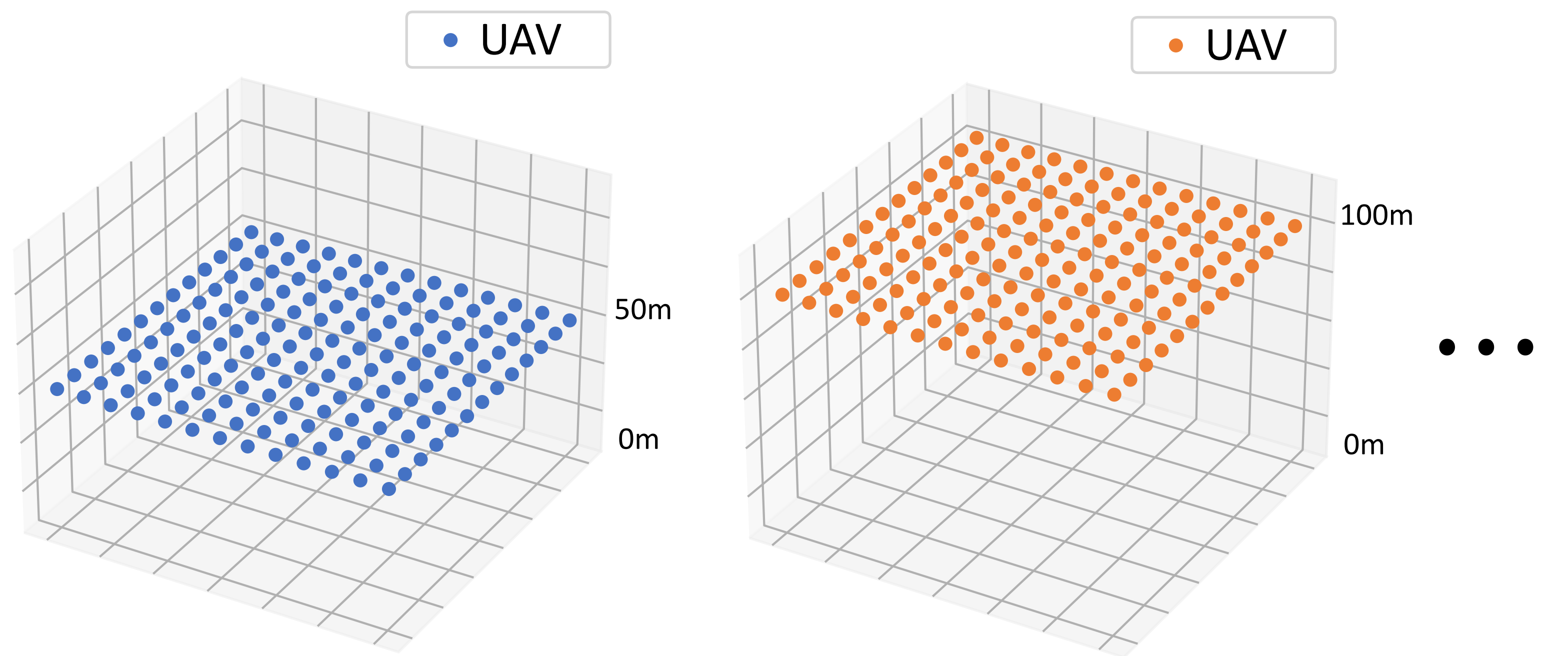
- Flat terrain & inverse-square law only (simplified simulation)

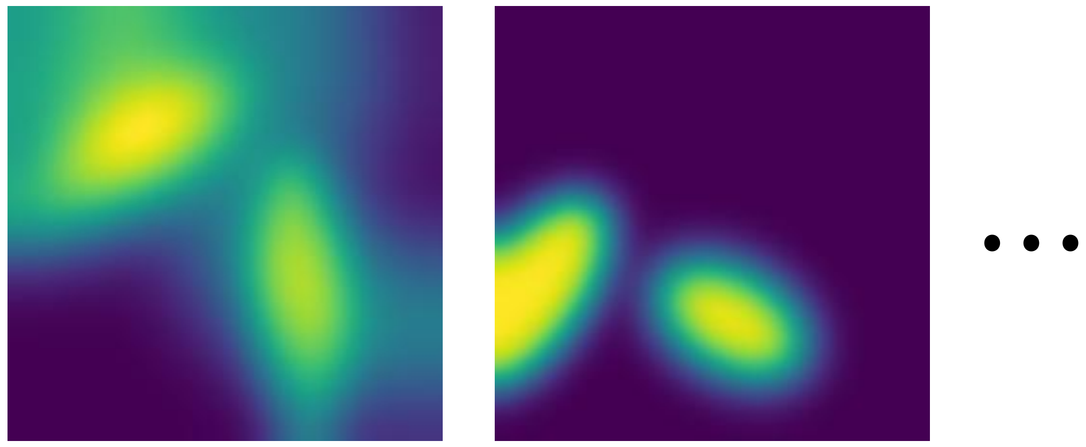
5. Future Work

- Need to include terrain, scattering, shielding, and noise



- Analyze altitude / source variations





- Large-scale dataset acquisition for advancing deep learning performance

Reference

[1] Saveliev, M., Shtefan, V., Proskurin, O., Pantin, M., Martin, P. G., Grechaninov, V., & Havrylko, Y. (2024). Multi-Robot Radiation Reconnaissance in the Chornobyl NPP Exclusion Zone. Ядерна та радіаційна безпека, (4 (104)), 41-49.
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[16] Prodan, M., Vlăsceanu, G. V., & Boiangiu, C. A. (2023). Comprehensive evaluation of metrics for image resemblance. Journal of Information Systems & Operations Management, 17(1), 161-185.

Thank you