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Leveraging Deep Learning and Crowdsourced Imagery for Urban Flood Mapping

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Motivation

URBAN FLOODING
Flooding is one of the most frequent and damaging disasters, intensified by climate change and **urbanization**.

OBSERVATIONAL GAP
Conventional methods often lack the **spatial granularity** and **immediacy** needed for real-time urban flood depth assessment.

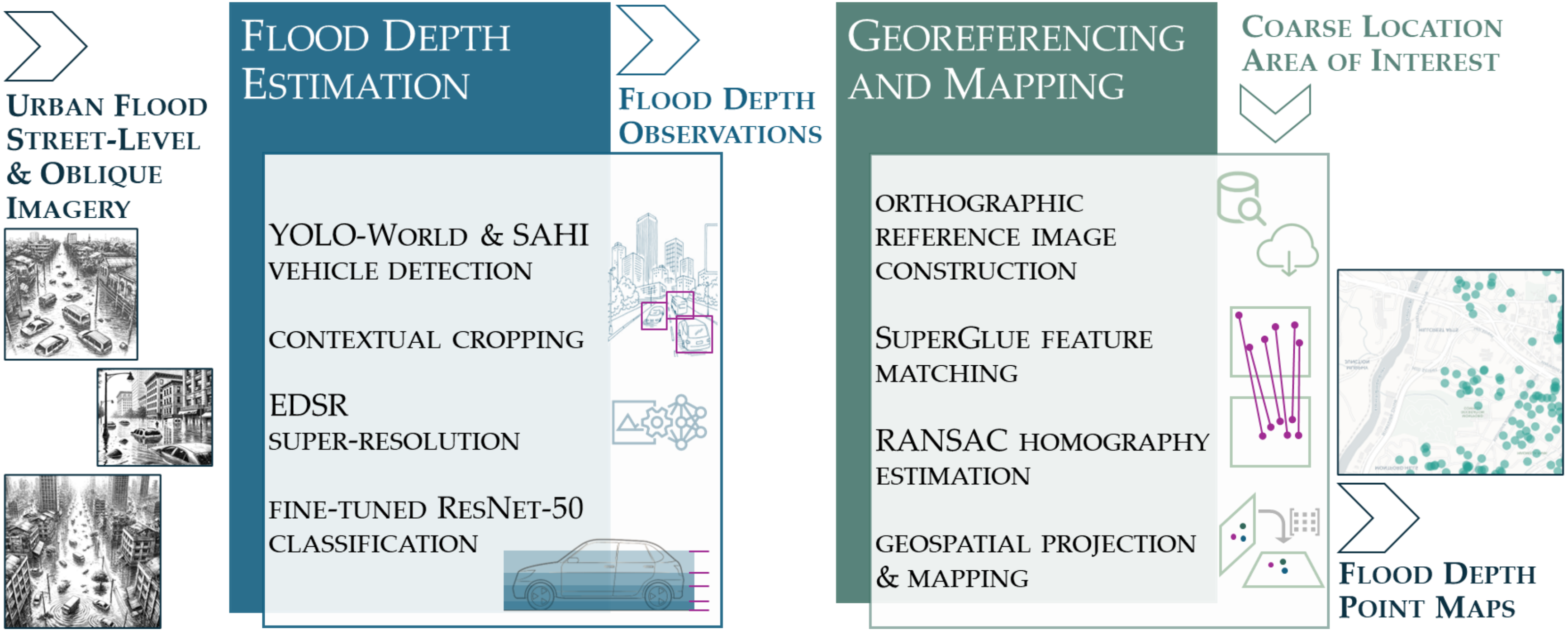
OPPORTUNISTIC SENSING
Street-level and oblique aerial imagery provides a complementary, device-independent source with broad accessibility.

STURM-FloodDepth APPROACH
We introduce an **open-source deep learning pipeline for urban flood depth estimation** and **spatial mapping** using submerged vehicles as reference objects.

Key Innovations Over Prior Work

- Avoids ethical and privacy concerns (no human pose analysis)
- Ensures reproducibility (open dataset and code)
- Generalizes across perspectives, including street-level and oblique aerial images
- Moves beyond image-level aggregation, enabling object-level flood depth estimation
- Includes a georeferencing step using feature matching for spatially accurate mapping
- Works without proprietary multimodal models, enhancing transparency
- Optimizes computational efficiency for near-real-time deployment

The STURM-FloodDepth pipeline



REFERENCES

Cheng et al. (2024). *YOLO-World: Real-Time Open-Vocabulary Object Detection*. arXiv. https://doi.org/10.48550/arXiv.2401.17270

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He et al. (2015). *Deep Residual Learning for Image Recognition* (arXiv:1512.03385). arXiv. https://doi.org/10.48550/arXiv.1512.03385

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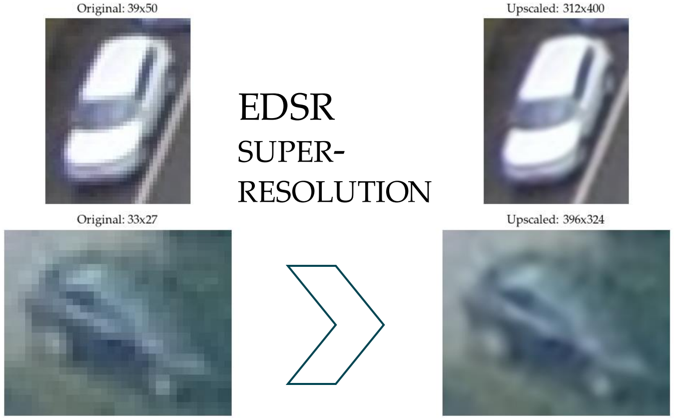
Data Preprocessing



3,367

IMAGES

of submerged vehicles

VEHICLES AS VISUAL PROXIES

Standard dimensions
Common in urban areas
Human references excluded

5

DEPTH LEVELS

based on visible car parts

REFERENCES

Wan et al. (2024). Automatic detection of urban flood level with YOLOv8 using flooded vehicle dataset. *J. Hydr.*, *639*, 131625. https://doi.org/10.1016/j.jhydrol.2024.131625

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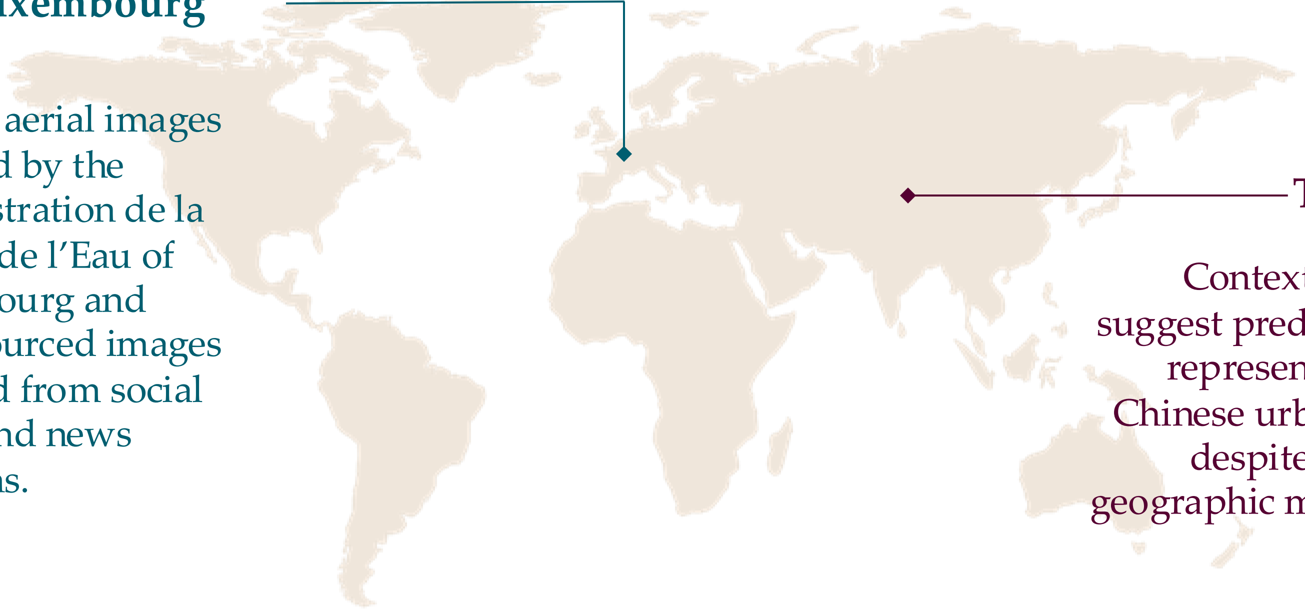
Results & Evaluation



Real-World Use Case 2021 Luxembourg Floods

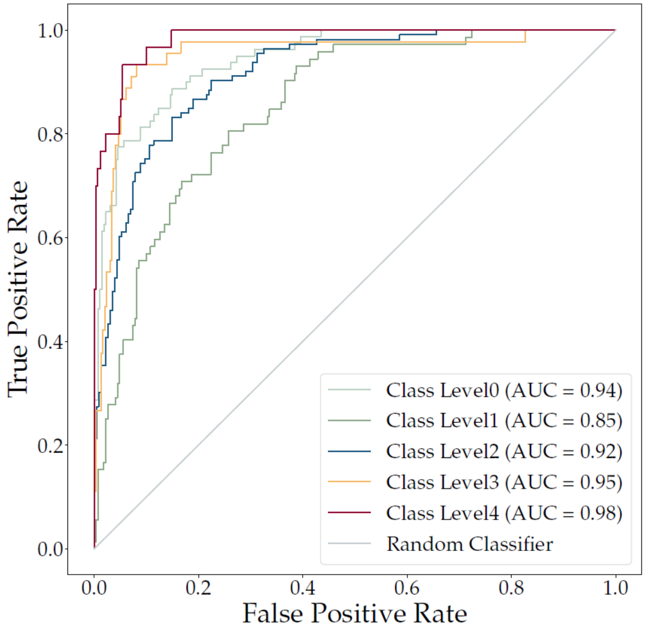
Oblique aerial images provided by the Administration de la Gestion de l'Eau of Luxembourg and crowdsourced images retrieved from social media and news platforms.

Test Set

Contextual cues suggest predominant representation of Chinese urban areas despite missing geographic metadata.

Results & Evaluation

Receiver operating characteristic curves
for the fine-tuned ResNet-50



	Precision	Recall	F1-Score	Support
Level0	0.83	0.78	0.80	80
Level1	0.62	0.56	0.58	72
Level2	0.76	0.80	0.78	113
Level3	0.69	0.89	0.78	45
Level4	0.83	0.63	0.72	30
Accuracy			0.74	340
Macro Avg	0.74	0.73	0.73	340
Weighted Avg	0.74	0.74	0.74	340

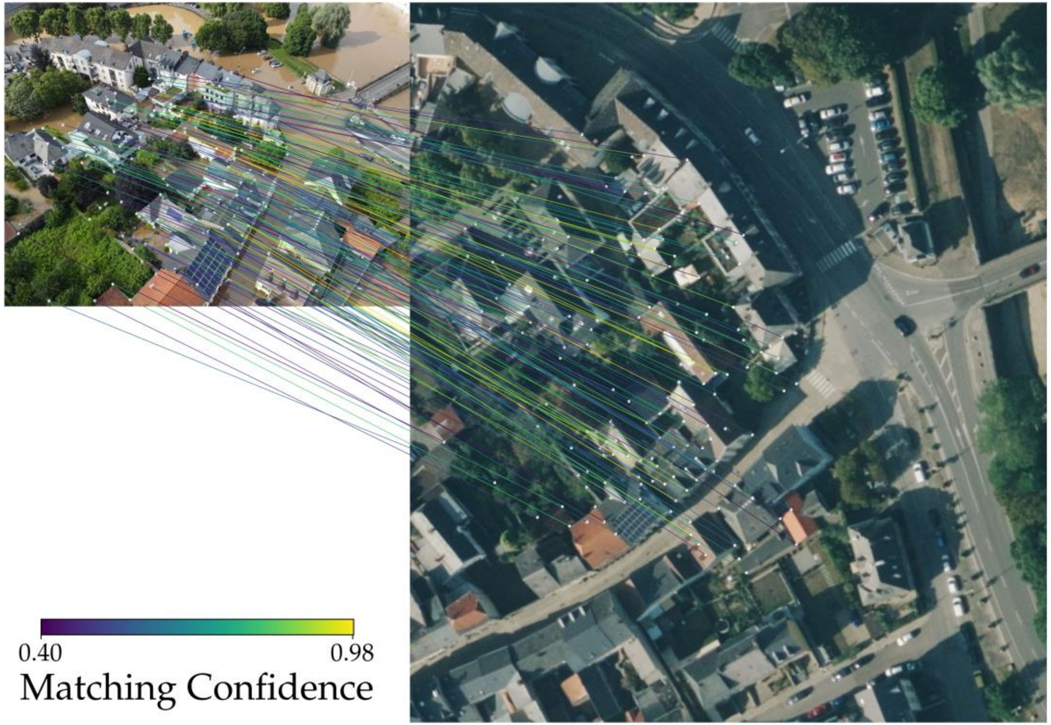
	Predicted Label	L0	L1	L2	L3	L4
	**Level 4**	1.00%	1.66%	0.96%	4.74%	**91.63%**
	**Level 1**	9.90%	**56.29%**	28.85%	2.61%	2.35%
	**Level 1**	2.00%	**50.24%**	39.61%	6.42%	1.73%

Application to the 2021 Luxembourg Floods

Flood depth estimation in street-view and oblique imagery

Image sources: Zorica Antic Facebook; Ville D'Echternach Facebook.

Application to the 2021 Luxembourg Floods
Georeferencing and Mapping

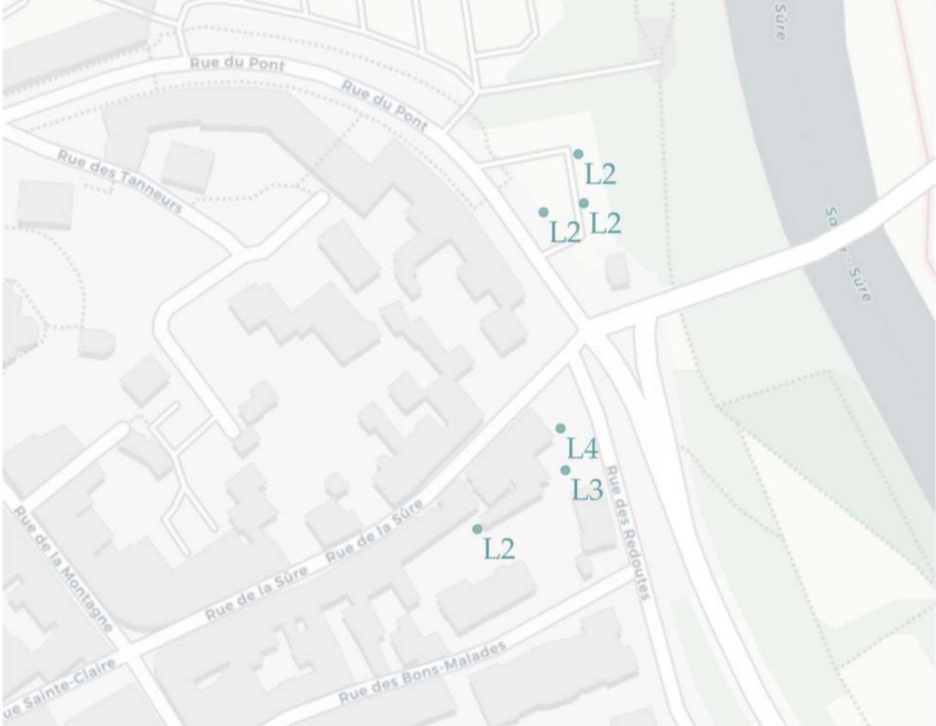


Cross-view image matching between a flood-affected oblique aerial image and an orthorectified aerial image using the SuperGlue algorithm.

Image sources: Ville D'Echternach Facebook; Microsoft Bing Maps - Vexcel Imaging.

REFERENCE
Sarlin et al. (2020). *SuperGlue: Learning Feature Matching with Graph Neural Networks.* https://doi.org/10.48550/arXiv.1911.11763

Application to the 2021 Luxembourg Floods
Georeferencing and Mapping



Base image sources: OpenStreetMap – CARTO; Microsoft Bing Maps.

Application to the 2021 Luxembourg Floods

Average computational performance per pipeline component on a consumer-grade laptop

Pipeline Component	Throughput (item/s)	Latency (s/item)	Item
Flood Depth Estimation			
Vehicle detection with YOLO-World and SAHI	0.16	6.25	image
Contextual cropping	61.84	0.02	detection
Super-Resolution with EDSR	0.19	5.21	crop
Classification with the fine-tuned ResNet-50	10.85	0.09	crop
Geo-referencing and Mapping			
Orthographic Reference Image Construction	0.28	3.51	image
Feature Matching with SuperGlue	0.26	3.93	image pair
RANSAC Homography + Transformation	9.00	0.11	image
GeoJSON Export	1000	<0.01	image

Conclusions and future directions

- The proposed pipeline effectively estimates and geolocates object-level urban flood depth observations from street-level and oblique imagery.
- The method generalizes across diverse conditions and demonstrates potential for real-world deployment in urban flood monitoring.
- Limitations include approximations from discretized depth classes and reliance on visible vehicles for estimation. Spatial accuracy may be reduced in scenes with limited aerial reference data.

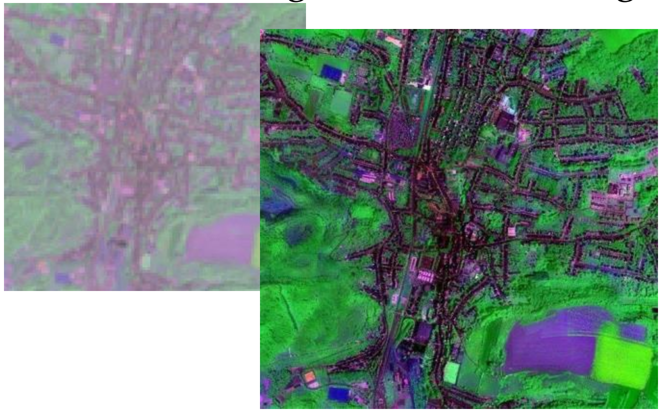
- The method exhibits a high level of technological readiness, is cost-effective, computationally efficient, scalable, and fully open-source.
- It provides a viable solution for enhancing early warning systems, especially in data-limited urban environments.

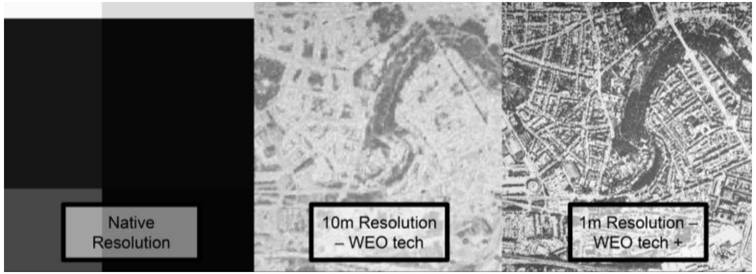
Future developments

Quantitative validation against authoritative data	Advance WKT/GPS-free cross-view geolocation techniques	Integration with ancillary data (e.g., DEMs, RS flood maps)

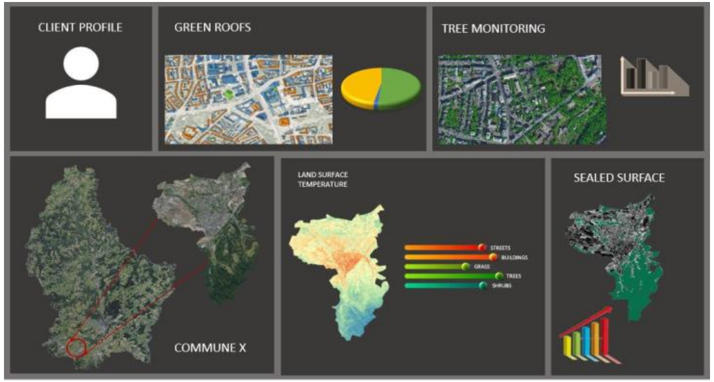
Towards a sustainable future with impactful EO environmental solutions for all

DL-based high resolution insights





Data driven approach



https://www.weo-water.com

Thank you for your attention

References and Materials

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· Notarangelo, N. M., Wirion, C., & van Winsen, F. (2025). A Deep Learning Pipeline for Urban Flood Depth Estimation from Street-Level Imagery., EGU General Assembly 2025 https://doi.org/10.5194/egusphere-egu25-4320

· Notarangelo, N. (2025). STURM-FloodDepth Flooded Cars [Data set]. Zenodo. https://doi.org/10.5281/zenodo.14833532

· https://github.com/STURM-WEO/

· Project Website: https://sturm-weo.github.io/


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