

# KI4FloodDamage

Fernerkundungsbasiertes KI-Verfahren für Deutschland zur automatischen  
Erkennung von Hochwasserschäden





# 1. LOCAL DATASETS

# Damage description of buildings impacted by flood hazards

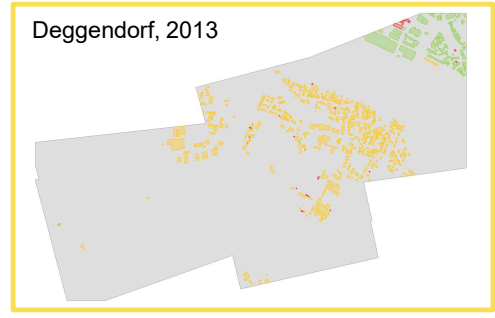
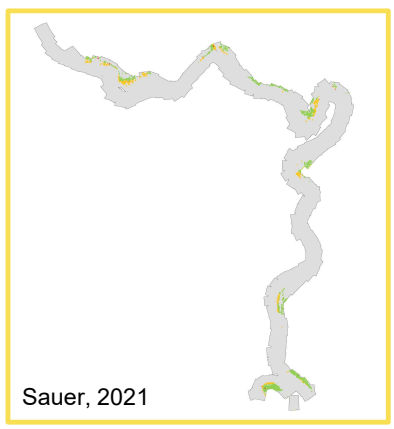
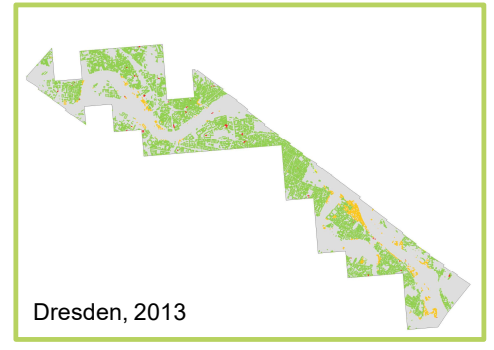
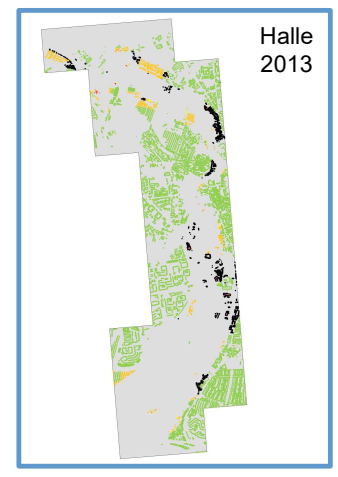
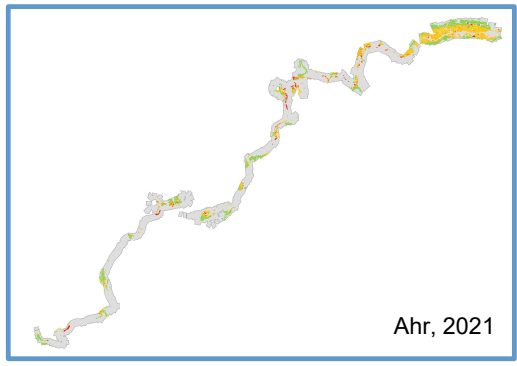


DEFINITION OF DAMAGE LEVELS				OBSERVED DAMAGE PATTERNS														
EDAC damage grade	Damage		Description	Criterion	Observation/measure	EDAC damage grade												
	Structural	Non-structural				D1	D2	D3	D4	D5	D6							
No visible damage	-	None	None															
	D1	None	Light	<ul style="list-style-type: none"> <li>Structure appears to have complete structural integrity</li> <li>Walls remain standing</li> <li>Roof is virtually undamaged</li> </ul>														
	D2	Light	Moderate	<ul style="list-style-type: none"> <li>Only wetting through</li> <li>Dirt</li> </ul>														
Damaged	D2	Light	Moderate	<ul style="list-style-type: none"> <li>Light cracking to loadbearing walls</li> <li>Doors and windows pushed in</li> <li>Washing out of foundations</li> </ul>														
	D3	Moderate	Heavy	<ul style="list-style-type: none"> <li>Larger cracking in loadbearing walls and slabs</li> <li>Settlement</li> <li>Collapse of non-loadbearing walls</li> </ul>														
	D4	Heavy	Very heavy	<ul style="list-style-type: none"> <li>Wetting-through of loadbearing and non-loadbearing walls and floor slabs</li> <li>Dirt (mud, deposits)</li> <li>Contaminations (oil, chemicals)</li> <li>Windows and doors pushed in</li> <li>Slight cracking to loadbearing walls</li> <li>Washed-out foundations</li> <li>Larger cracks and/or deformation in loadbearing walls and slabs</li> <li>Settlement</li> <li>Collapse of non-loadbearing walls</li> <li>Collapse of building elements (loadbearing walls, slabs)</li> <li>Collapse of larger parts of building</li> <li>Building completely washed away, toppled or displaced from foundation</li> </ul>														
Destroyed	D5	Very heavy	Very heavy	<ul style="list-style-type: none"> <li>Replacement of finishing</li> <li>Replacement of non-loadbearing building elements</li> <li>Replacement of loadbearing building elements</li> <li>Demolition necessary</li> </ul>														
	D6	Very heavy	Very heavy	<ul style="list-style-type: none"> <li>Dislocation: building completely washed away, toppled or displaced from foundation</li> </ul>														
	D6	Very heavy	Very heavy	<ul style="list-style-type: none"> <li>Dislocation: building completely washed away, toppled or displaced from foundation</li> </ul>														
Invalid	-	-	-	<ul style="list-style-type: none"> <li>Uncertain interpretation due to image quality (e.g. shadow or degraded resolution due to high off-nadir angle)</li> </ul>														

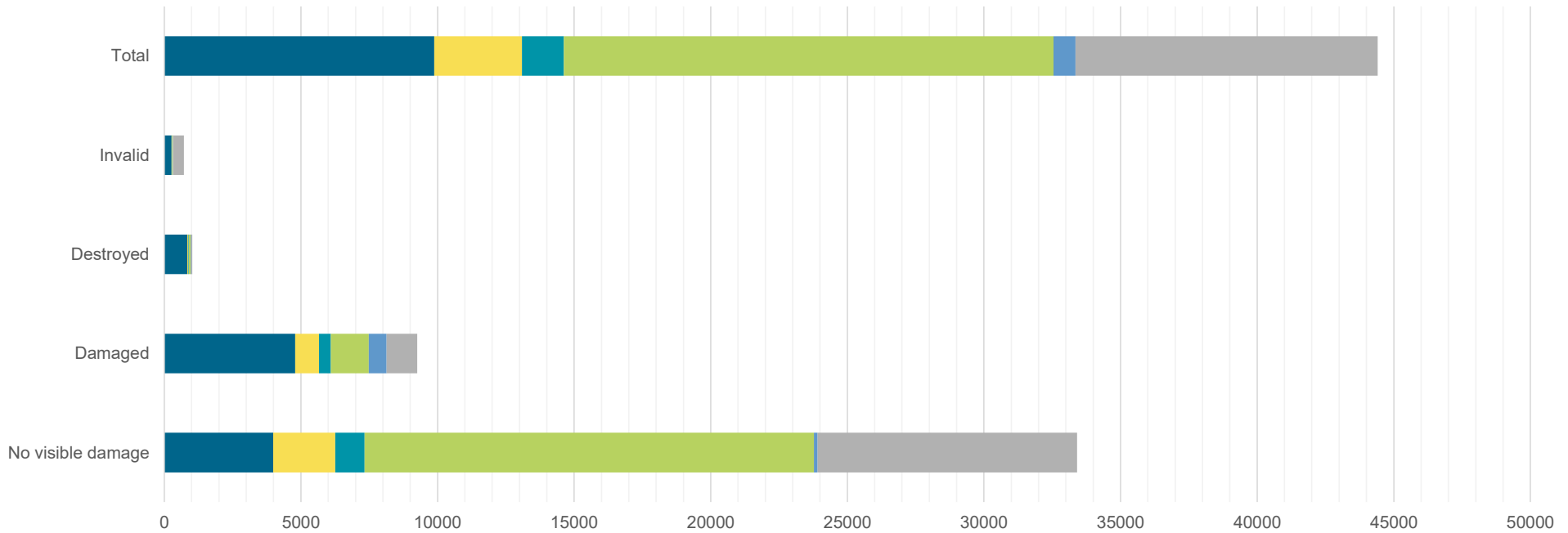
# Building damage classification scheme



# Building damage dataset for Germany



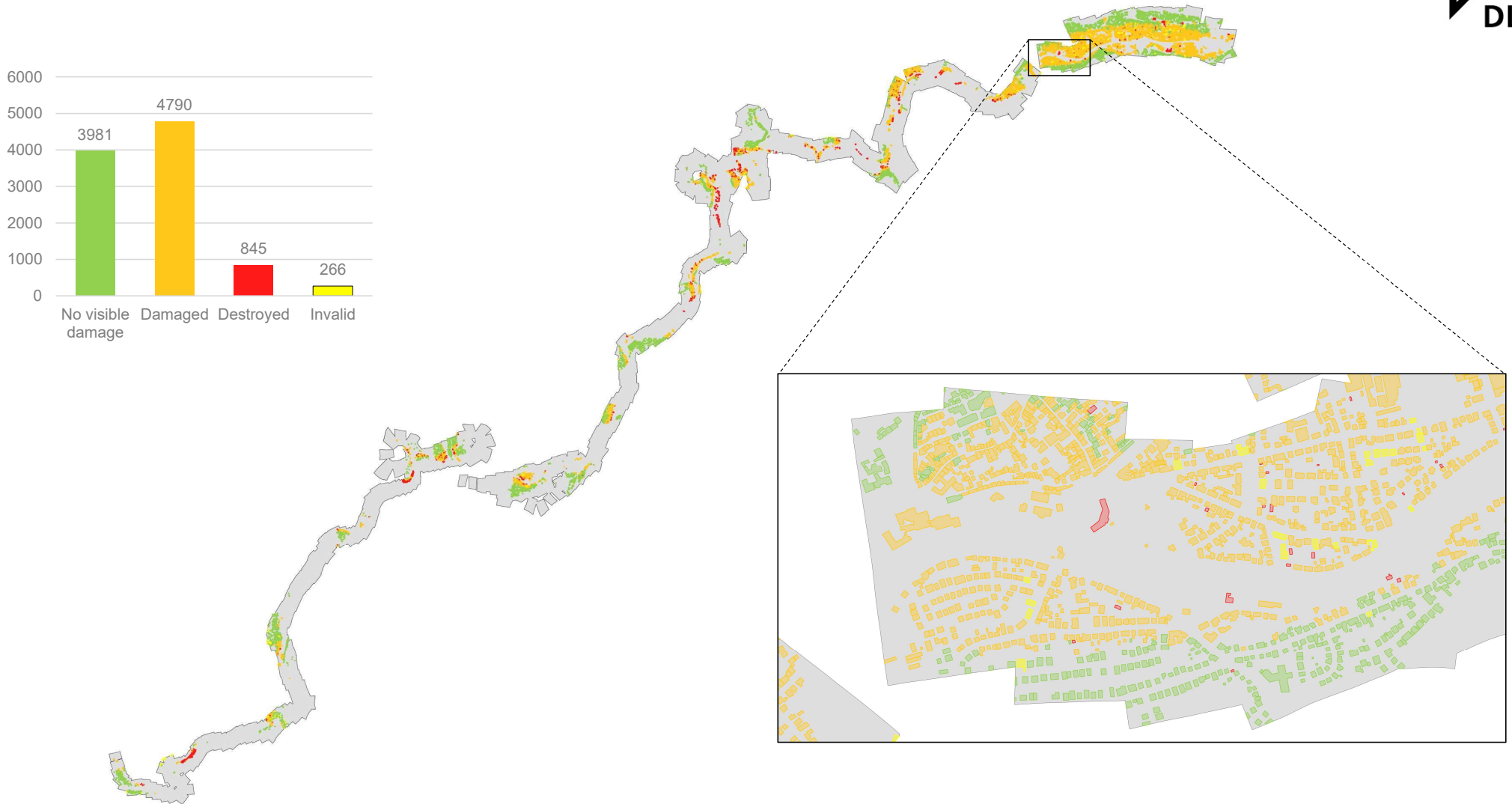
# Building damage dataset for Germany



	No visible damage	Damaged	Destroyed	Invalid	Total
■ Ahr	3981	4790	845	266	9882
■ Kyll	2274	877	39	21	3211
■ Sauer	1075	425	17	13	1530
■ Dresden	16450	1392	66	12	17920
■ Deggendorf	130	651	22	0	803
■ Halle	9497	1121	40	410	11068

■ Ahr ■ Kyll ■ Sauer ■ Dresden ■ Deggendorf ■ Halle

# Building damage dataset for Germany, Ahr Valley 2021





## 2. DOMAIN ADAPTATION

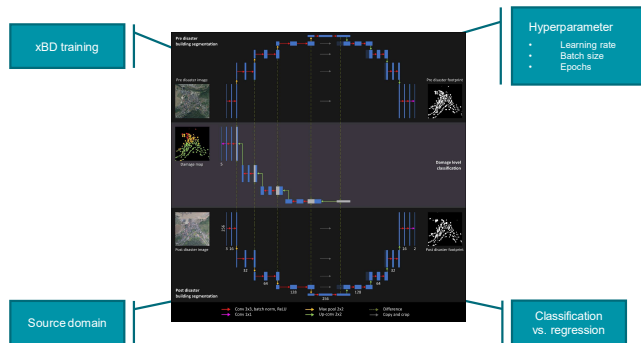
More information: <https://doi.org/10.1016/j.srs.2025.100287>

# Domain adaptation



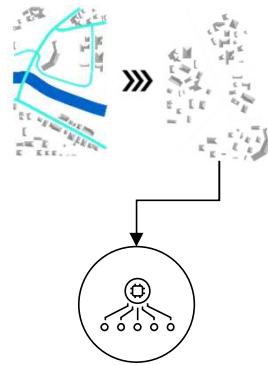
Experiment 1

*Inference*



Experiment 2

*Semi-supervised domain adaptation*



Experiment 3

*Semi-supervised domain adaptation + disaster intensity*



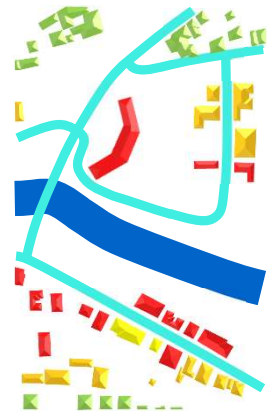
Experiment 4

*Supervised domain adaptation*



Experiment 5

*Supervised learning*



Accuracy

# Results



Method	$F_1^{\text{weighted}}$ (%)	Class-specific $F_1$ (%)							
		No visible damage		Damaged		Destroyed		Invalid	
1 Baseline	44.1 +0%	55.1 +0%	39.2 +0%	29.6 +0%	1.6 +0%				
2a CyCADA	45.6 +5%	55.8 +4%	38.9 -1%	<b>60.2 +83%</b>	0.2 -27%				
2b FACT	46.9 +9%	58.4 +17%	39.6 +1%	48.9 +52%	2.2 +11%				
3a Model-based footprints	65.0 +66%	56.2 +6%	76.2 +89%	45.7 +44%	0.0 -31%				
3b External footprints	<b>71.3 +86%</b>	<b>67.2 +63%</b>	<b>79.0 +96%</b>	52.4 +62%	0.0 -31%				
4a 5 buildings per class	53.6 +30%	51.7 -18%	59.3 +48%	43.2 +37%	0.4 -23%				
4b 75 buildings per class	56.3 +39%	50.8 -23%	62.2 +56%	57.4 +75%	<b>3.2 +31%</b>				
5 Benchmark	75.6 +100%	74.1 +100%	80.6 +100%	66.7 +100%	6.8 +100%				

Accuracy metrics of the proposed domain adaptation techniques on the Ahr valley (target domain) dataset. The percentages show the performance gain compared to the upper performance limit (benchmark). The highest metric within each damage class is highlighted in grey.

# Results



Pre disaster    Post disaster    Reference mask



Background  
No visible damage  
Damaged  
Destroyed

Baseline

Semi-supervised DA

Hazard intensity-based DA

Supervised DA

Benchmark

(1) Inference

(2a) CyCADA

(2b) FACT

(3a) Model-based  
footprints

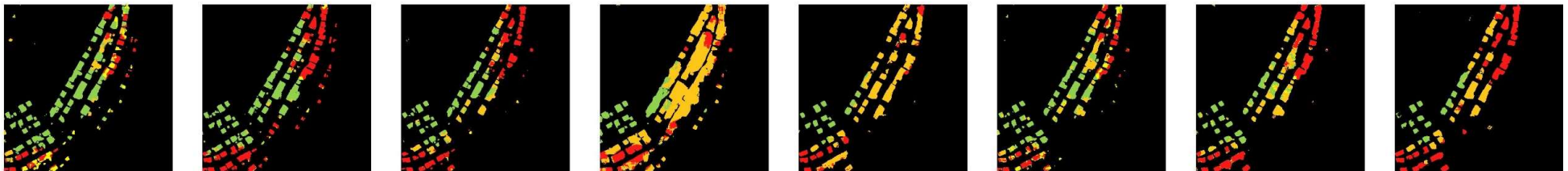
(3b) External  
footprints

(4a) 5 buildings  
per class

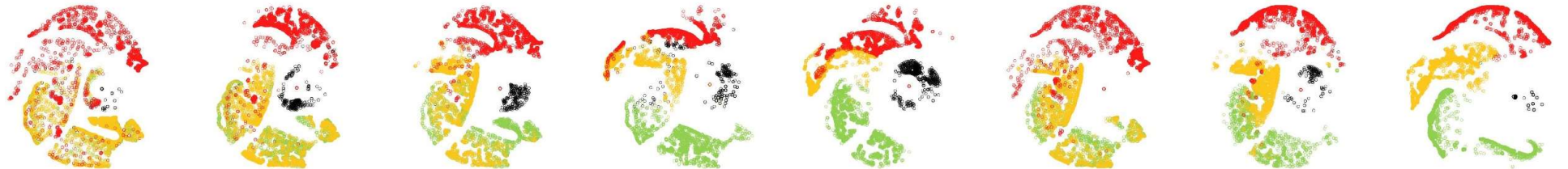
(4b) 75 buildings  
per class

(5) Supervised  
learning

(a)

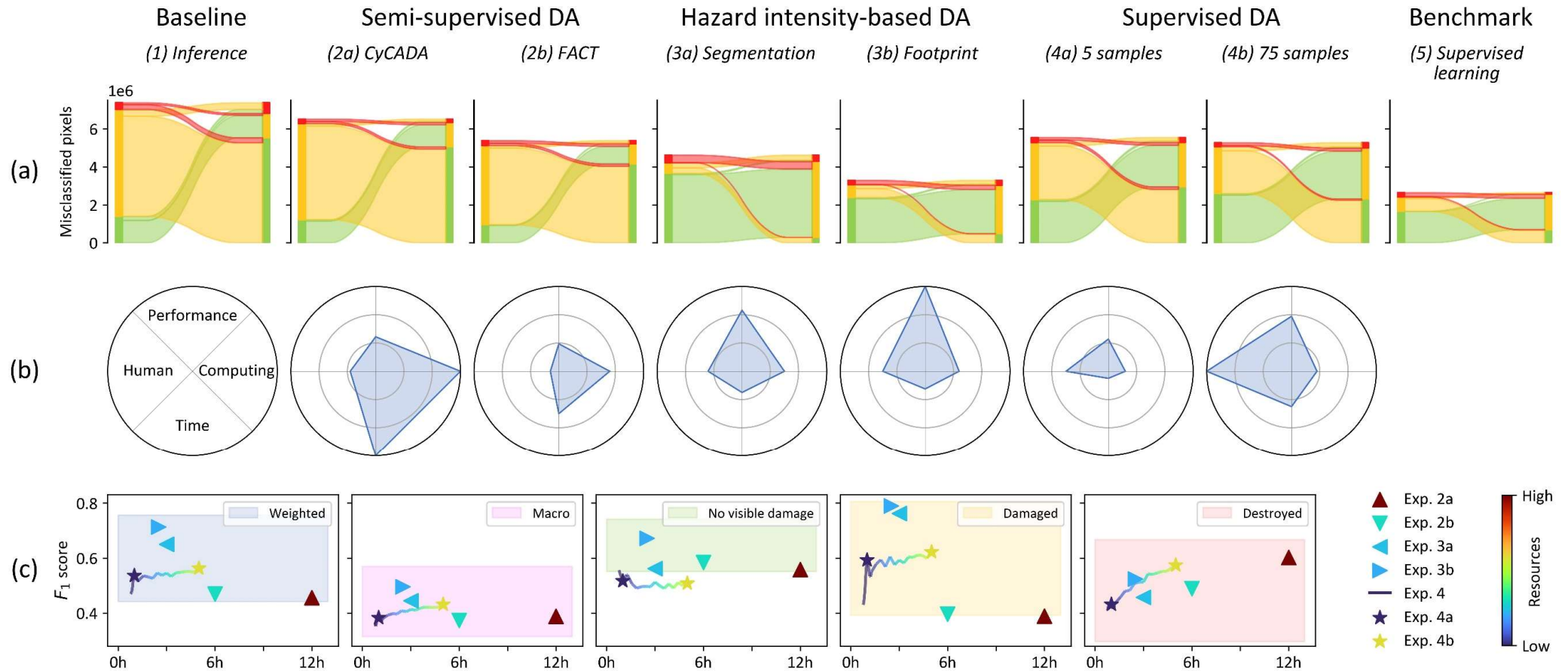


(b)



Example of the Ahr valley data: (a) model predictions. (b) t-SNE plots of the last model layer.

# Results



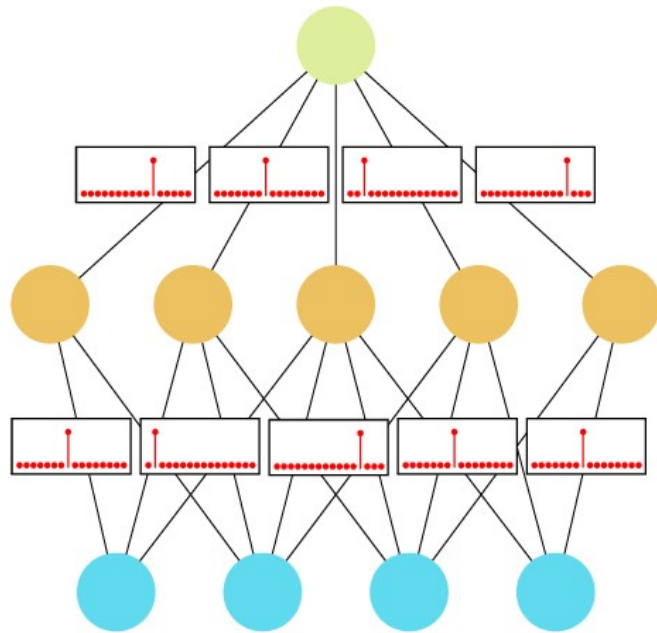
Experiment comparison: (a) pixel-based misclassification flows between reference (left) and model prediction (right). (b) qualitative resource trade-off for model selection. (c) performance and aggregated resources over time.



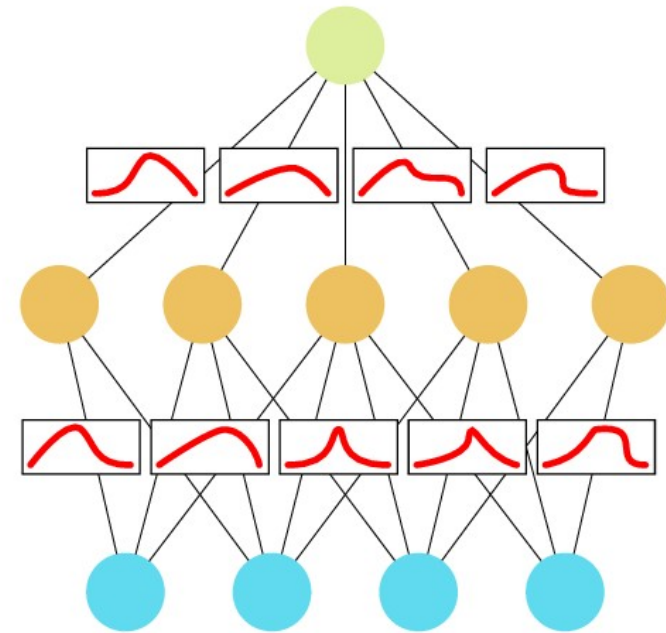
# 3. UNCERTAINTY QUANTIFICATION

More information: <https://doi.org/10.1016/j.jag.2025.104759>

# Deterministic vs probabilistic model architectures

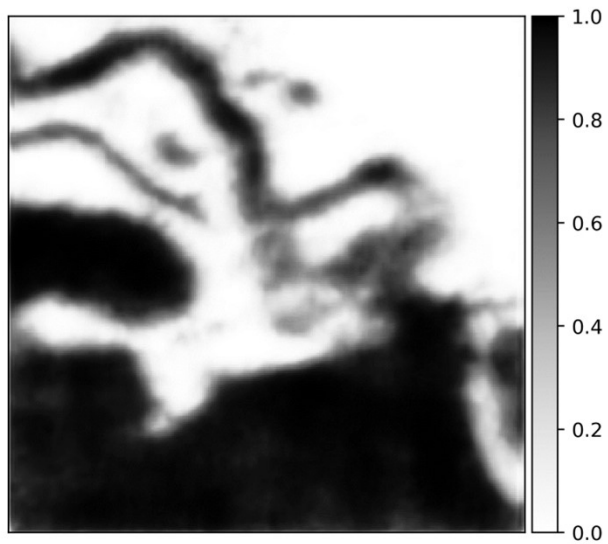


a) CNN: Single value weights

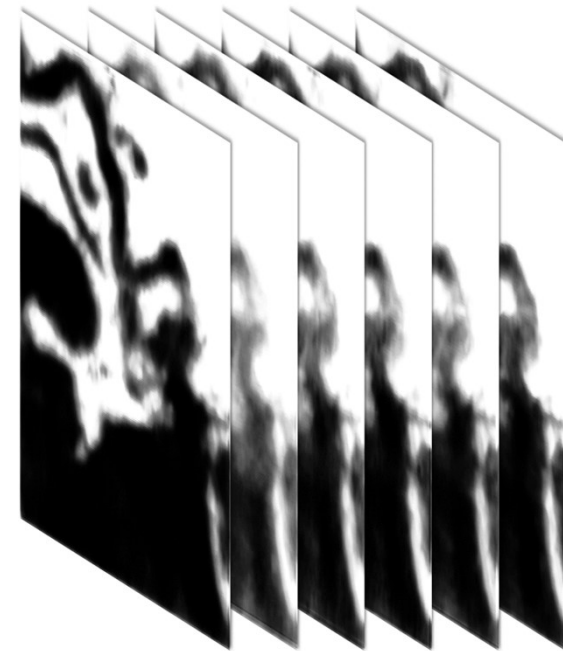


b) Bayesian CNN: Distribution over weights

# Deterministic vs probabilistic model outputs

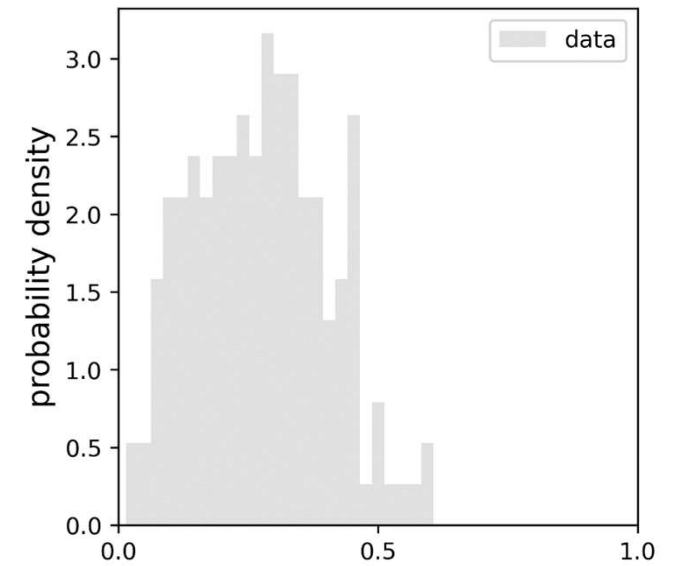
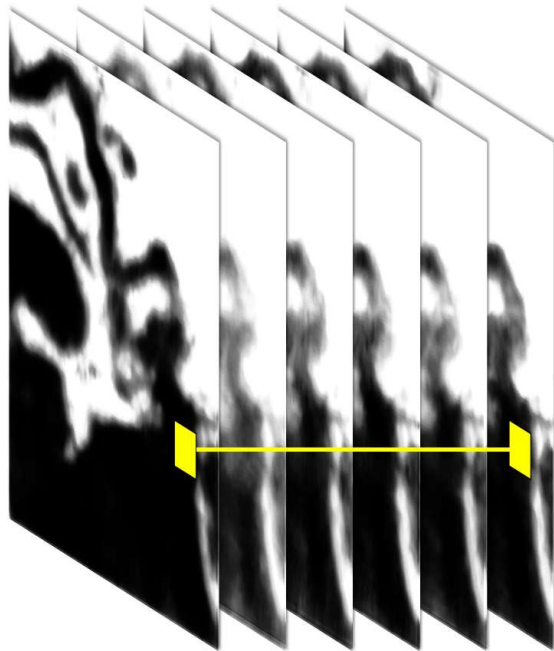


a) CNN: Single prediction



b) Bayesian CNN: Prediction ensemble

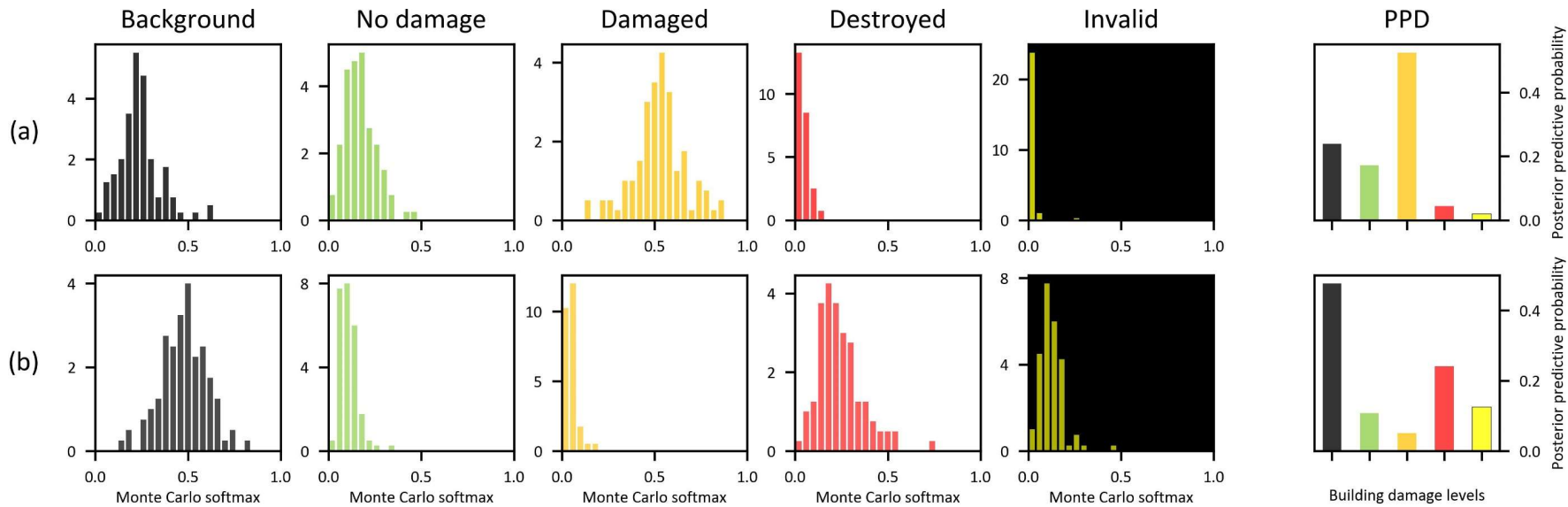
# Pixel-level uncertainty quantification



b) Bayesian CNN: Prediction ensemble

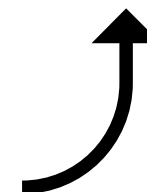
Monte Carlo sigmoid output

# Pixel-level uncertainty quantification



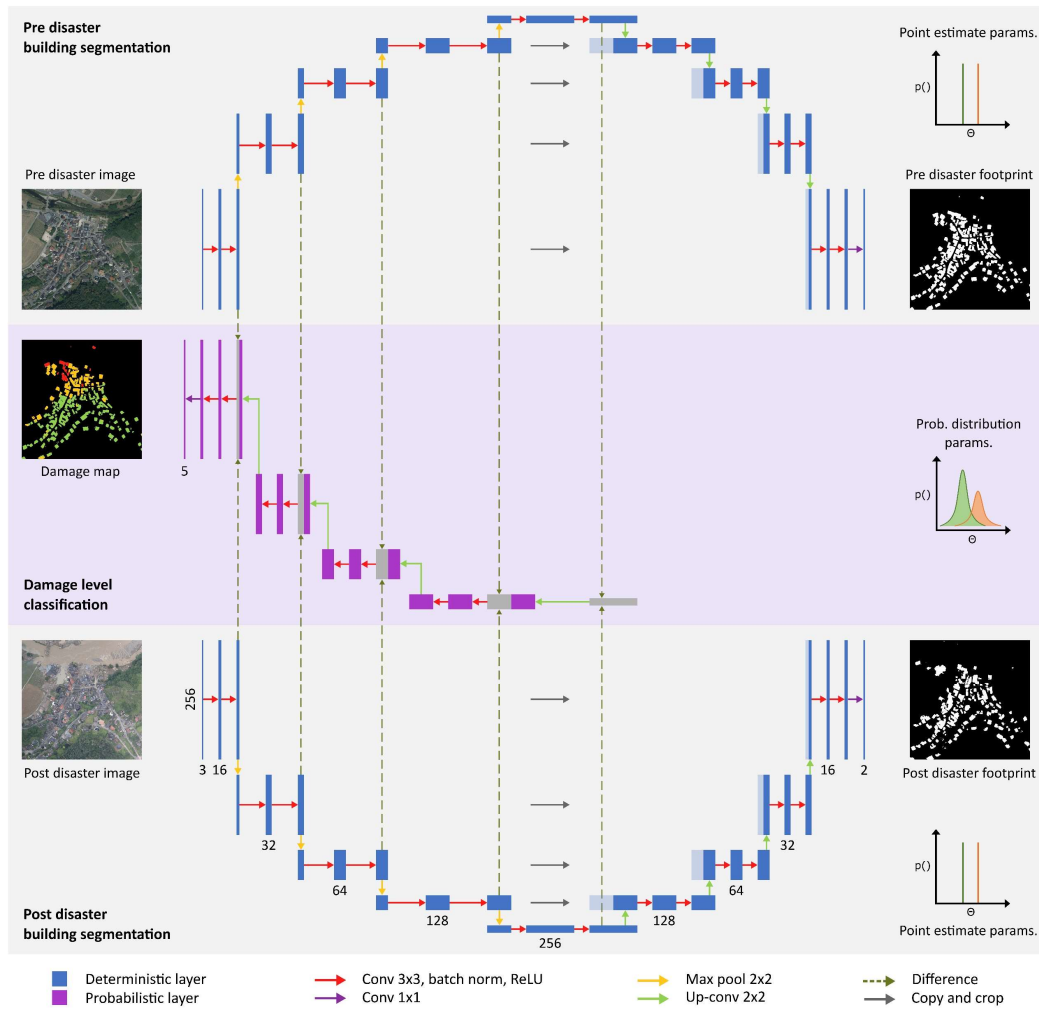
$$p(\tilde{x}|\mathbf{X}) = \int_{\theta} p(\tilde{x}|\theta) p(\theta|\mathbf{X}) d\theta$$

$\mathbf{X} = \{x_1, \dots, x_N\}$ :  $N$  i.i.d. observations  
 $\tilde{x}$ : Future data  
 $\theta \in \Theta$ : Model parameter



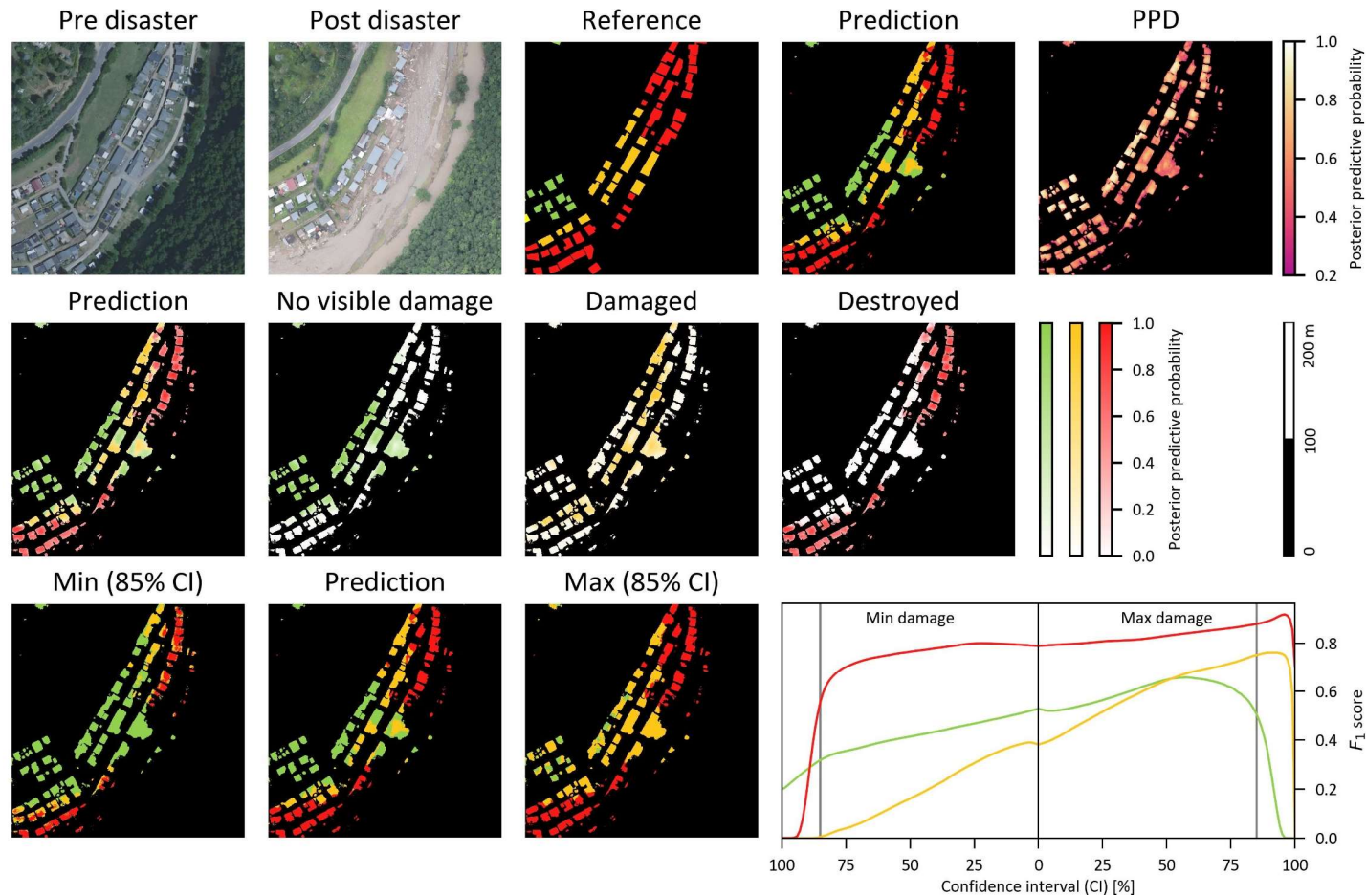
Probabilistic model output with the respective posterior predictive distribution (PPD): (a) shows a correctly classified 'Damaged' pixel. (b) shows a 'Destroyed' pixel incorrectly classified as 'Background'.

# Bayesian Siamese multitask learning architecture



Bayesian Siamese multitask learning architecture (BayeSiamMTL). The two weight-shared UNets with point estimate model parameters (highlighted in grey) simultaneously segment building footprints from pre- and post-disaster imagery. The Bayesian Siamese difference-based decoder with probability distributions as model parameters (highlighted in purple) classifies damage levels probabilistically based on the segmented patches.

# Uncertainty visualization



Confidence-informed damage maps: (a) input data, reference mask, model prediction, and probabilistic certainty mask. (b) integrated prediction-certainty map with disaggregated and stratified probabilities of damage clusters. (c) minimum and maximum damage extent delineated from confidence intervals.

## References



- Victor Hertel, Omar Wani, Christian Geiß, Marc Wieland, Hannes Taubenböck, BayeSiamMTL: Uncertainty-aware multitask learning for post-disaster building damage assessment, International Journal of Applied Earth Observation and Geoinformation, Volume 143, 2025, 104759, ISSN 1569-8432, <https://doi.org/10.1016/j.jag.2025.104759>.
- Victor Hertel, Christian Geiß, Marc Wieland, Hannes Taubenböck, Rapid domain adaptation for disaster impact assessment: Remote sensing of building damage after the 2021 Germany floods, Science of Remote Sensing, Volume 12, 2025, 100287, ISSN 2666-0172, <https://doi.org/10.1016/j.srs.2025.100287>.