Rapid identification of disaster hotspots by means of a geospatial information fusion from remote sensing and social media

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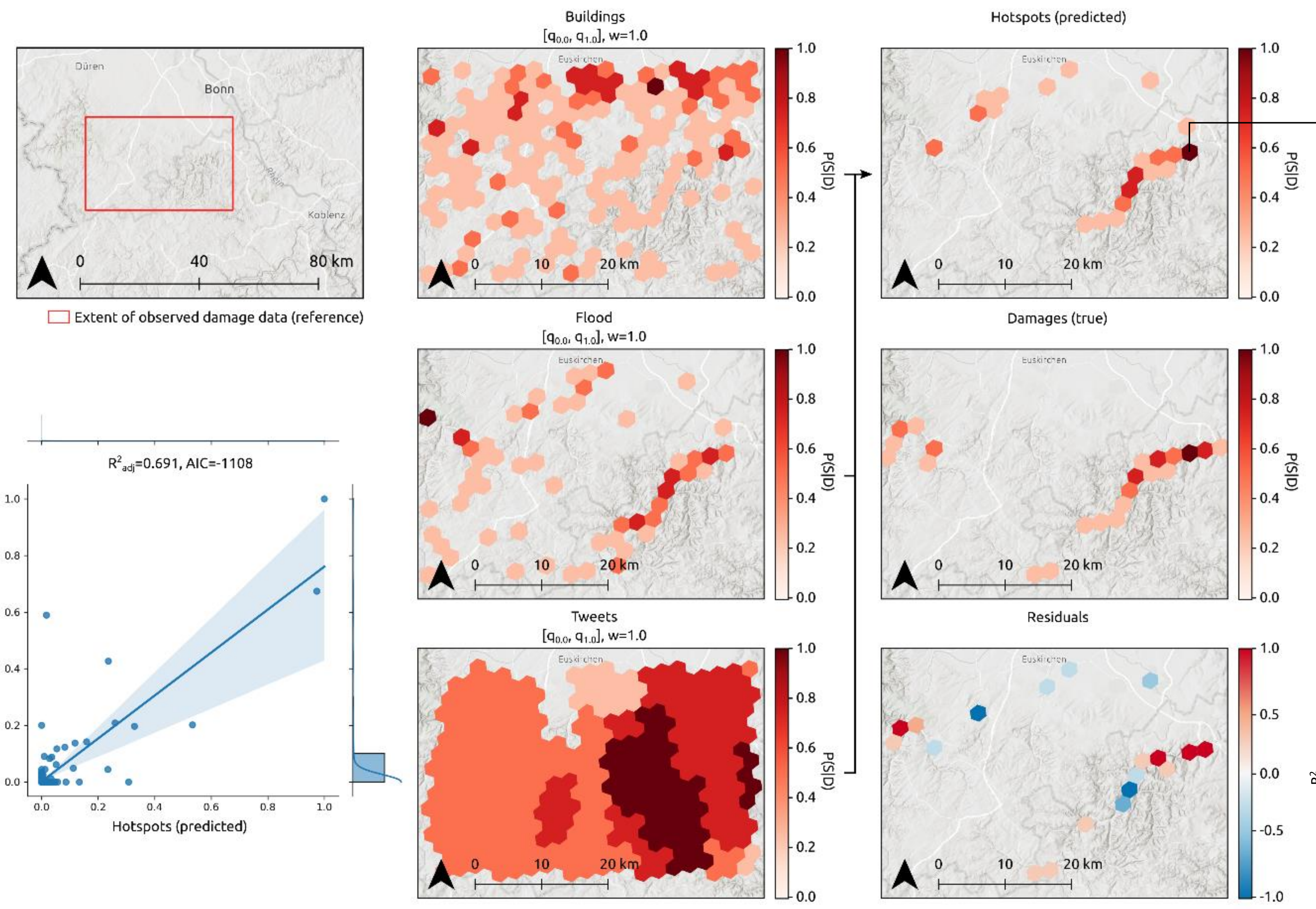
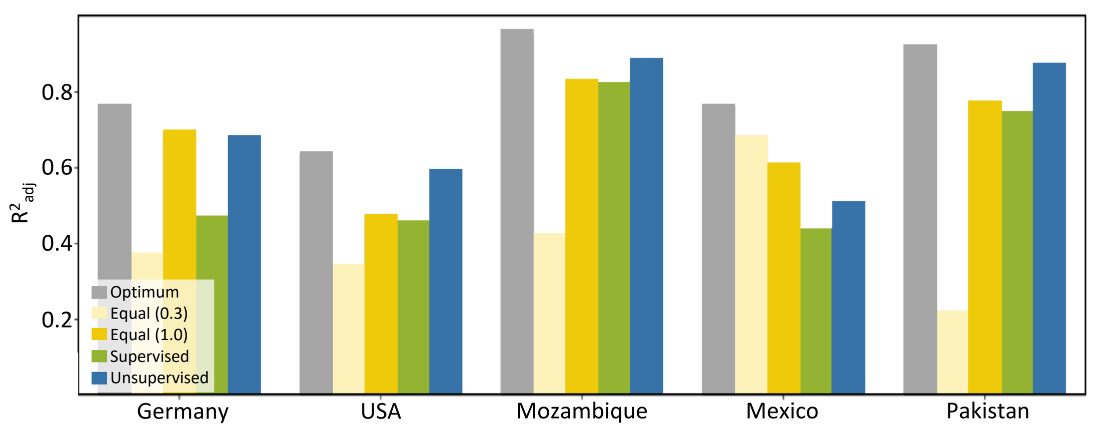


Comparison of predicted hotspot map and prior distribution from observed damage data of the Germany floods 2021 with severely affected Ahr valley in the center. Input layers were prepared at H3 resolution 7 and normalized without truncation



Comparison of methods to choose log-linear pooling weights for the input layers grouped by study area

From remote sensing and social media proxies to disaster hotspots

Effective management of complex disaster scenarios relies on achieving comprehensive situational awareness. During the response phase, it is vital to rapidly identify the most affected areas to guide emergency actions and allocate limited resources effectively. Initial estimates, often based on incomplete or imprecise data, play a crucial role in forming an early situational overview before detailed damage assessments are conducted. Early-stage proxies, such as population distribution and hazard zones, can support planning data collection efforts, enhancing situational understanding and focusing response efforts.

Let D_i be the set of proxies that are relevant for the prioritization of disaster hotspots and that are geographically aligned at H3 grid cells. The conditional probability of sampling given a single proxy $P(S|D_i)$ can be defined by a simple normalization of its values to the range [0,1], where larger values indicate higher relevance of a location for the disaster under consideration. To approximate the joint probability of sampling given more than one D_i, a log-linear pooling operator is used:

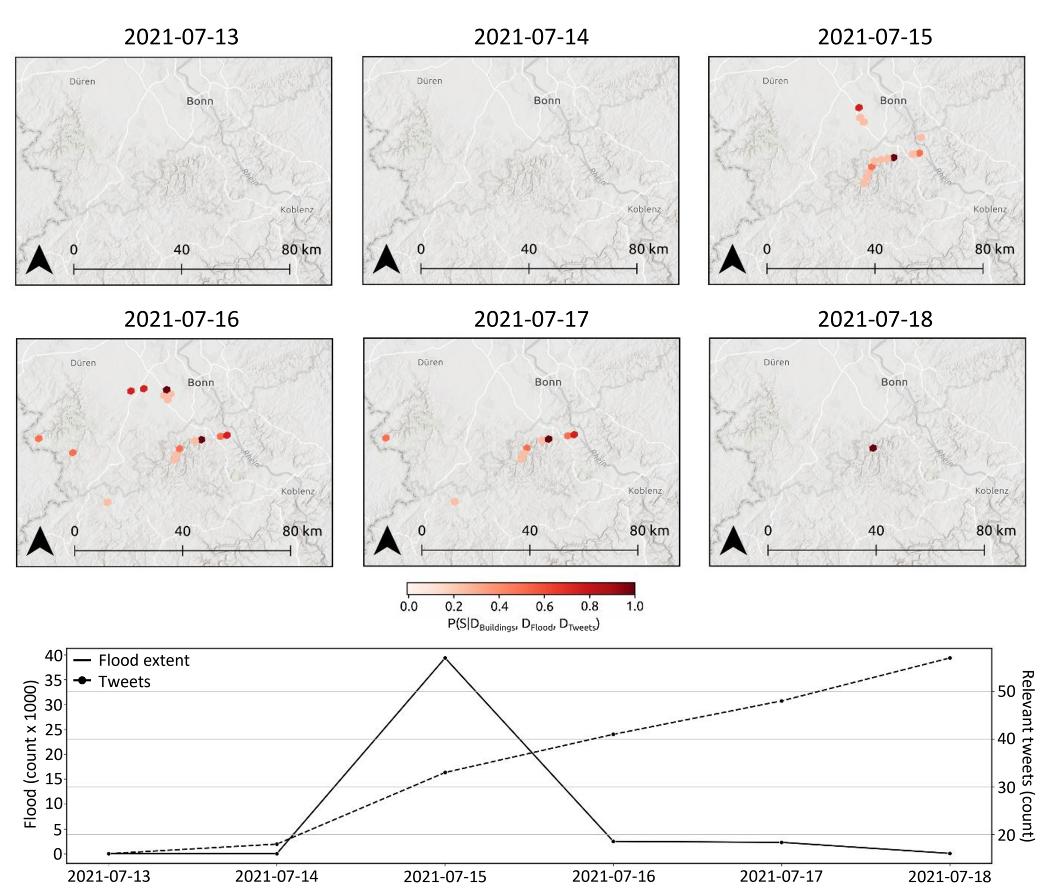
$$P(S|D_1, D_2, \dots, D_n) = \ln Z + \sum_{i=1}^{n} w_i \ln P(S|D_i)$$

Unsupervised pooling weights optimization is performed by minimizing the sum of the Kullback-Leibler divergences from each input layer distribution to the pooled distribution:

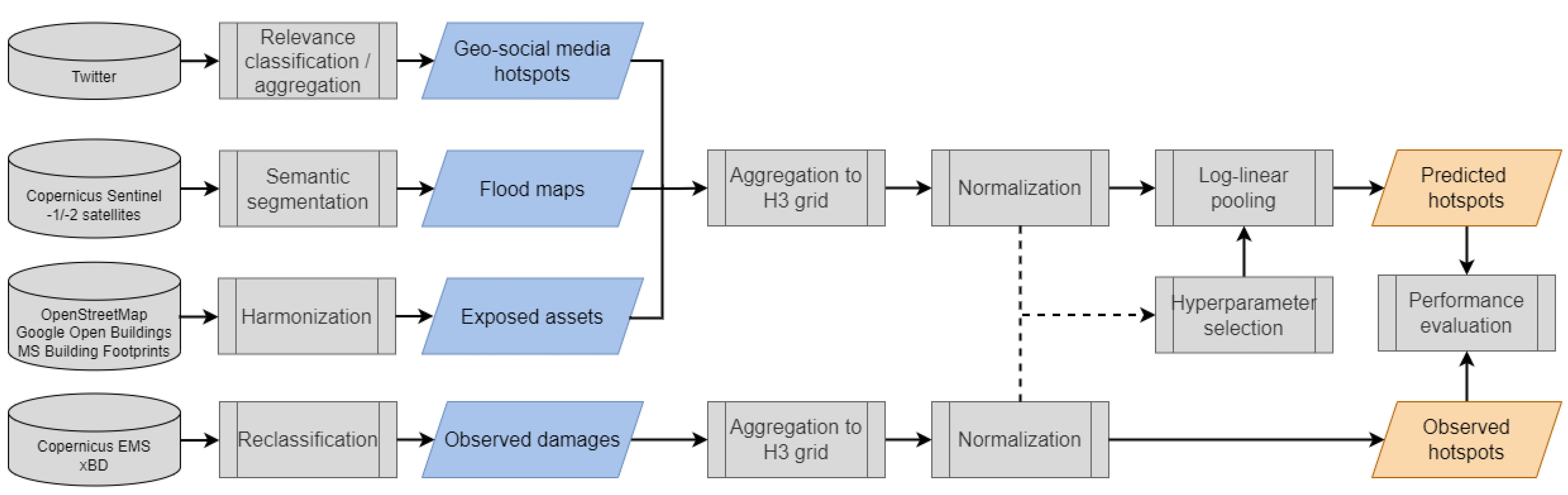
$$\min_{w} \sum_{i=1}^{n} \sum_{x \in X} P(S \mid D_i)(x) \log\left(\frac{P(S \mid D_i)(x)}{P(S \mid D_1, D_2, \dots, D_n)(x)}\right)$$

An extensive hyperparameter analysis revealed that while equal-weight methods offer simplicity and effectiveness, optimized pooling weights generally yield superior results. Context-specific tuning was critical for optimal performance in log-linear pooling. An unsupervised method minimizing the Kullback-Leibler divergence between input distributions and predictions outperformed supervised approaches, overcoming the limitations of training data. This method's transparency and adaptability allow it to incorporate geospatial layers with varying resolutions and semantic relevance, making it particularly flexible to other hazards or categories of exposed assets.

Time series of predicted hotspot maps at H3 resolution 7



Flowchart of the methodological framework



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H3H Python package: Disaster hotspot analysis with H3. https://github.com/MWieland/h3h

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