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Rapid web-based crisis information through automation of processes: enhancing first responders' access to critical geodata

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ABSTRACT

Rapid and straightforward dissemination of information to emergency services is critical for informed decision-making during crises. Earth observation data is a valuable source for obtaining a widespread situational overview, e.g. by delineating the water extent during flood events. In this study, we present a prototype process chain for the rapid delivery of web-based crisis information derived from very high-resolution (VHR) optical imagery, introducing more automation across the stages of satellite-based emergency mapping. Initiated by a monitoring system of relevant warning sources, we leverage the time benefits of pre-tasking VHR satellites by employing a programmatic ordering of satellite data. The water extent is segmented based on a deep learning trained model from which further geodata are derived. The relevant information is disseminated via a web application that enables interactive exploration and rapid updates. Testing the process chain for a simulated flood event demonstrated that the crisis information could be provided within hours after the warned flood event and was positively evaluated by first responders. While automation improves the timeliness of crisis product delivery, we conclude that semi-automation is preferable to full automation, as each crisis is unique and requires expert decisions at critical stages.

RÉSUMÉ

La dissémination rapide et directe d'informations aux services d'urgence est une étape critique pour la prise de décision pendant les crises. Les données d'observation de la terre sont des sources précieuses pour obtenir une vue d'ensemble à disposition de la situation, par exemple en délimitant l'étendue de la surface d'eau pendant une inondation. Dans cette recherche, nous présentons un prototype de chaîne de processus de mise à disposition rapide sur le web d'informations utiles pour la gestion de crise, dérivées d'images optiques de très haute résolution (VHR), et introduisant plus d'automatisation dans les

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étapes de cartographie de crise à base d'images satellites. Grâce à un système de surveillance des sources d'alerte pertinentes, nous tirons parti des gains de temps offerts par la programmation préalable des missions des satellites VHR en mettant en place un ordre de traitement systématique des données satellitaires. L'extension de la surface d'eau est segmentée grâce à un modèle entraîné par apprentissage profond, à partir de laquelle d'autres données géographiques sont dérivées. L'information pertinente est disséminée via une application web qui permet une exploration interactive et des mises à jour rapides. Un test réalisé sur la chaîne du processus pour une inondation simulée montre que l'information relative à la crise pouvait être communiquée dans les heures qui suivaient l'alerte de l'inondation. Le test a reçu un avis positif par les premières personnes consultées. Alors que l'automatisation améliore la rapidité de la communication de l'information, nous optons plutôt pour une automatisation partielle, dans la mesure où chaque crise est unique et requiert des décisions d'experts lors des étapes critiques.

1. Introduction

Natural hazards such as floods, droughts, wildfires, and heatwaves are globally increasing in frequency and severity, underscoring the need for rapid and reliable remote sensing-based crisis information to support effective emergency response (Kaku, 2019; Rolla et al., 2025; Voigt et al., 2016). In Europe, floods in particular represent a major risk, as demonstrated by the impacts of the Ahr Valley flood 2021 and subsequent widespread flooding in 2024, resulting in fatalities and substantial material damage (Mohr et al., 2024). Climate change is projected to increase the frequency and intensity of such events, with Central Europe particularly vulnerable to floods and wildfires in view of changing precipitation patterns and rising temperatures (European Environment Agency, 2024; Fang et al., 2024; Intergovernmental Panel on Climate Change, 2021).

In these crisis situations, the rapid and straightforward dissemination of information to emergency services is crucial for effective response and decision-making. Beyond timeliness, the information must be comprehensive and intuitive, since first responders and decision makers often need to interpret heterogeneous information sources under time pressure (Voigt et al., 2016). Integrating Earth Observation (EO) data into accessible, web-based product formats has therefore emerged as a practical solution for delivering geospatial crisis information (Barth et al., 2022; Gstaiger et al., 2022; Roll et al., 2025). Complementing the continued use of printable static maps in field operations, software platforms such as Esri (n.d.a) or Mapbox (n.d.) increasingly support the dynamic cartographic visualisation enabling both interactive analysis and rapid updates.

The rapid provision of crisis products – whether static maps, web applications, or situation reports – ensures that critical information reaches coordinators and first responders promptly. This is the objective of satellite-based emergency mapping (SEM) services such as the Copernicus Emergency Management Service (CEMS), the UNOSAT Rapid Mapping Service or the International Charter on Space and Major Disasters. The increasing availability of very high-resolution (VHR) satellites allows for detailed damage assessments, particularly for infrastructure or buildings (Gähler,

2016). Optical EO, synthetic aperture radar (SAR), infrared and hyperspectral EO constellations rank among the most prominent applications of planned and launched systems (Kulu, 2024). While freely available medium-resolution data (e.g. Copernicus Sentinel) supports large-scale monitoring, VHR data – mainly operated by commercial providers such as Vantor (Vantor, n.d.a), Airbus (Airbus, n.d.), or Planet (Planet, n.d.a) – enhances spatial detail for SEM but remains constrained by data access, acquisition, analysis, and product dissemination bottlenecks. Pre-tasking of VHR satellites has already improved the timeliness of crisis information delivery (Wania et al., 2021). However, comparable automation to established medium-resolution workflows such as the Global Flood Monitoring (GFM) (Wagner et al., 2025) is still lacking, although advances have been made in the machine learning-based rapid analysis of VHR imagery (Wieland et al., 2023b; Yuan et al., 2021).

This study presents a proof-of-concept semi-automated process chain for the rapid provision of crisis information based on VHR satellite imagery for flood events. The approach introduces more automation across all stages of SEM while maintaining expert validation at critical stages and culminates in a web-based application to support decision-making. The developed process chain was tested for a simulated flood event and evaluated by first responders, with potential applicability to other hazards.

2. Background and related work

2.1. Satellite-based emergency mapping (SEM)

SEM mechanisms support disaster response by providing rapid situational awareness from EO data. Typically, SEM is initiated by an authorised user request following a crisis event, triggering several consecutive processing stages: (i) the EO data request, (ii) the satellite image acquisition, (iii) the image delivery and analysis, (iv) and the (cartographic) product generation for the end users (Mühlbauer et al., 2024).

One of the most widely used operational SEM services is the CEMS, operated by the European Commission, which provides publicly available standardised cartographic products within hours to days, but is activated only by authorised civil protection entities (Copernicus Emergency Management Service [CEMS], 2024, n.d.). Additionally, UNOSAT provides 24/7 satellite-based analysis and mapping products to support humanitarian response worldwide (United Nations Satellite Centre, 2024). Global access to EO data during crises is offered by the International Charter on Space and Major Disasters through a global collaboration of space agencies and satellite operators, with varying product formats and delivery times depending on the contributing agency and situation (Martinis et al., 2017). These international mechanisms are complemented by national capacities, such as the Satellite Based Crisis and Situation Service (BKG) (Federal Agency for Cartography and Geodesy, n.d.) or the Center for Satellite Based Crisis Information (ZKI) in Germany. The ZKI at the German Aerospace Center (DLR) provides support on request using standardised procedures and develops EO-based crisis information products, with a strong focus on transferring scientific results into user-oriented applications (Center for Satellite Based Crisis Information [ZKI], 2024).

The timeliness of all SEM crisis information products depends on satellite data availability. Medium-resolution satellites (e.g. Sentinel or Landsat) continuously acquire EO

data, while VHR satellites (e.g. Vantor WorldView or Airbus Pléiades Neo), with a geometric resolution up to 30 cm, require tasking for specific Area of Interest (AOI) and time window. The acquisition of tasked VHR imagery depends on orbit paths and possible competing requests, but is strongly influenced by the tasking order timing, leading to delays in the SEM process when initiated only after the disaster onset. In this context, Early Warnings Systems (EWS) and forecasting information are essential, since the time lag between the first warnings, event onset, and event peak influences the emergency response (Wania et al., 2021). For example, during the Ahr Valley flood 2021, the European Flood Awareness System (EFAS) and German Meteorological Service (DWD) issued warnings up to four days before the activation of CEMS, which then coincided with the flood onset (Mühlbauer et al., 2024). While the effect of an earlier use of this information cannot be assessed, this case highlights the importance of systematically considering EWS. Accordingly, to mitigate potential delays, the CEMS has employed anticipatory mechanisms that enable pre-tasking based on EFAS forecasts, which improves the timely availability of EO imagery in flood events (Wania et al., 2021).

At the same time, both the availability and accessibility of commercial VHR imagery have improved in recent years and are expected to further increase (Kulu, 2024). This is also reflected in the provision of dedicated Application Programming Interfaces (APIs) that enable programmatic ordering of VHR acquisitions for specific AOIs and time windows, e.g. from commercial providers such as Vantor, EUSI (European Space Imaging [EUSI], 2025, n.d.a, n.d.b), Airbus (Airbus, n.d.) or Planet (Planet, n.d.a). These streamlining developments reduce manual order labour and open up opportunities for automation in the SEM process. Despite these advances, costs of VHR data remain a relevant factor, as pricing depends on several factors such as spatial resolution, order size, priority tasking, or licensing. Publicly available records show, for example, costs of ~ 40 USD/SQKM for priority tasking optical VHR imagery from SkySat (Planet, n.d.b). These costs, however, can be reduced through national framework agreements or institutional licenses. The CEMS or the International Charter on Space and Major Disasters can also be activated by authorised users.

2.2. Image analysis for flood detection

To provide first responders with reliable geodata in the event of flooding, it is essential to first accurately identify inundated areas using EO data. In contrast to traditional rapid mapping approaches, existing monitoring systems are based on individual satellite missions and rely on sensor-specific, complex rule-based methods (Pekel et al., 2016; Salamon et al., 2021). Although effective for large-scale overviews, approaches such as the GFM remain constrained by limited generalisation ability across sensors and difficulties in capturing small-scale features as provided by VHR imagery (Wieland et al., 2023b).

Optical VHR satellite data offer significant advantages for a detailed feature analysis, particularly for smaller-scale monitoring. While medium-resolution data, such as those from Sentinel-2, provide a larger spatial footprint and are well-suited for large-scale monitoring, VHR imagery serves a complementary role in enhancing the detail of the crisis-related geospatial information. The footprint size of VHR data acquisitions requires a precise definition of the AOI, which can be achieved by considering auxiliary data

sources such as EFAS (Wania et al., 2021). Despite footprint limitations, the increasing number from recently launched VHR satellite constellations improves the potential spatial and temporal coverage (up to 15 overpasses per day), although operational constraints such as competing tasking requests may reduce actual acquisition frequency. Prominent optical satellite missions include Vantor Legion (multispectral, 30 cm) (Vantor, n.d.b) or Planet SkySat (multispectral, 50 cm) (Planet, n.d.c).

In parallel with these new data sources, the methodological developments in recent years are expanding the possibilities for rapid crisis mapping. VHR sensors are often restricted in their spectral resolution and can limit the application of traditional water extraction methods for optical imagery, i.e. the Normalised Difference Water Index, which depends on the short-wave infrared (SWIR) band in the modified formula by Xu (2006) for a better delineation of open water in urban areas. Since not all VHR sensors contain the SWIR band, machine learning-based approaches are better suited for automating rapid mapping analysis from heterogeneous sensor data.

Potentially more accurate and flexible deep learning (DL) methods have only been explored in experimental studies (Bentivoglio et al., 2022). While Convolutional Neural Networks represent the standard in image-based segmentation (Bereczky et al., 2022), Transformer architectures are also gaining importance (Chamatidis et al., 2024). An often-overlooked challenge in floodwater segmentation research is the ability of trained models to generalise to out-of-domain settings, as encountered in real-world applications with unseen sensors, acquisition geometries, or environmental conditions (Wieland et al., 2023b). A growing number of publicly available benchmark datasets based on heterogeneous sensor data (Bountos et al., 2023; Wieland et al., 2023a) are emerging, enabling further research into multimodal flood segmentation. Following the segmentation of the water extent, the analysis can be further leveraged for informed crisis information by a fusion with additional geospatial datasets, such as population data (Wieland et al., 2025).

2.3. Product dissemination

The usability of the information generated for first responders ultimately depends on meaningful product generation and dissemination. Crisis information products are usually provided as static maps, geodata layers, or interactive web applications, each serving different operational needs. Static maps remain useful in environments with poor internet connectivity and serve as a reliable record for field operations. In parallel, geodata layers can be integrated into existing GIS systems where they can be updated automatically as new results become available (CEMS, 2024).

Increasingly, interactive web applications are being employed as they allow users to explore multiple datasets, such as satellite-derived flood extents, population exposure, and infrastructure data, in a single browser-based platform. Systems such as CEMS (CEMS, 2024), UNOSAT Live Web Maps (UNOSAT, n.d.), or the ZKI web viewers (ZKI, n.d., 2024) demonstrate how such platforms can support situational awareness and support coordination among diverse stakeholders. The presentation of geographic information depends on the web application software used (Zejdlík & Vozenilek, 2025).

The degree of automation between these systems varies. While many products require manual interpretation, automated workflows developed by services such as the GFM and

DLR developed automated workflows can generate and update crisis layers within hours (Bereczky et al., 2022; Wieland & Martinis, 2019).

3. Semi-automated workflow for crisis geodata provision

The following section outlines the developed semi-automated workflow for the rapid provision of crisis information in the event of flooding initiated by the monitoring and programmatic triggering of VHR optical data (Figure 1). The area of focus for this workflow is Germany. We present the products derived automatically from the satellite data to determine the flood extent and estimated impact on the population, before describing our approach to web-based visualisation of crisis information.

3.1 Monitoring and triggering

The process chain is initiated by continuously downloading public warnings from the World Wide Web, implemented through an automated backend system managing the data retrieval via available interfaces, thus replacing the need for manual observation. We rely on official authorities as sources to ensure the credibility of the warnings. To provide automatic notifications before a potential flood situation, the warnings must be harmonised and processed accordingly. The monitoring and triggering component relies on internet-based (early) warnings of catastrophic events (Mühlbauer et al., 2024). Data on flooding in Europe is particularly diverse. For instance, authorities publish warnings based on simulations that can predict catastrophic events. Additionally, current water level measurements, obtained through water gauges, are available for many rivers. Precipitation warnings from meteorological services can also indicate impending

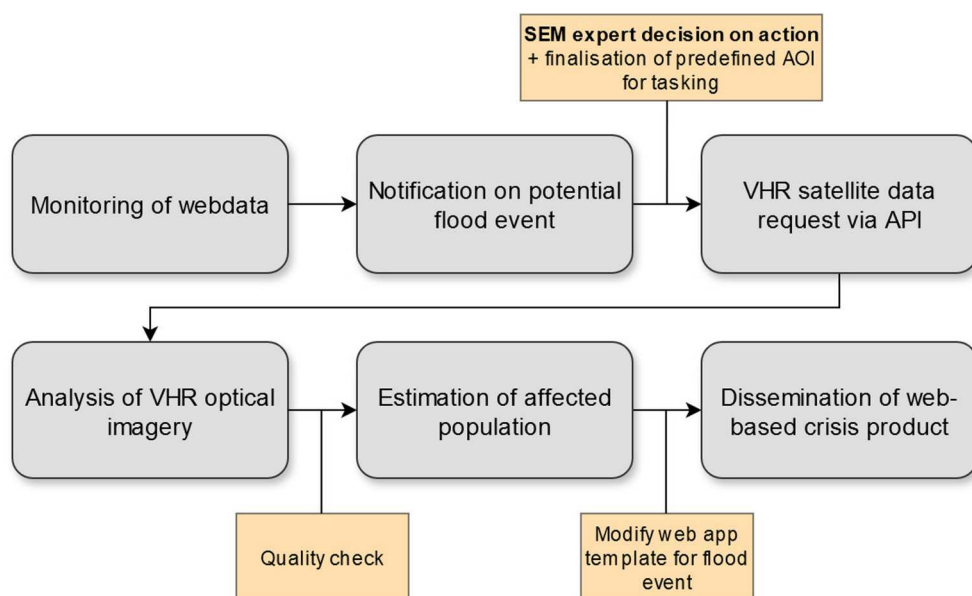


Figure 1. Workflow of the semi-automated process chain indicating relevant manual actions.

flooding if more accurate sources are unavailable. These sources have at least two attributes in common: a location and a timestamp of the expected event.

Different data sources relevant to flood events are currently integrated in the semi-automated workflow presented here, among those, the cross-state flood portal consolidating official warnings and water gauge data from the federal states in Germany (Länderübergreifendes Hochwasserportal, [n.d.](#)) and the DWD providing meteorological warnings which inform on precipitation dynamics (German Meteorological Service, [n.d.](#)). The developed monitoring system automatically retrieves all relevant data from the internet at configurable intervals, harmonises it, and stores it in a database (Mühlbauer et al., [2024](#)). During the harmonisation step, the original data is mapped to an internal data schema based on the Common Alerting Protocol (CAP) for a standardisation of warning messages (OASIS, [2010](#)). Accordingly, key warning information – such as title, description, severity, urgency, sent time, onset, and expiry – is retrieved hourly. The data is assigned to an event by analysing location, time, and type of natural hazard, followed by the aggregation of relevant input data (e.g. population and riverine data) into a flood incident defining the expected affected region and preliminary AOI for potential VHR tasking ([Figure 2](#)). For this purpose, the discrete global grid system H3 is used to facilitate the spatial aggregation (Roll et al., [2024](#); Wieland et al., [2025](#)). The H3 grid system is characterised by a hierarchical structure with 16 spatial resolutions, in which each hexagonal cell is uniquely identified by a 64-bit index (Brodsky, [2018](#); Sahr, [2011](#)). Identifying detailed AOIs is crucial for ordering high-resolution data, which has smaller coverage (e.g. WorldView-3 with a 13 km swath (European Space Agency [ESA], [n.d.a](#))) in comparison to medium-resolution satellite sensors like Sentinel (e.g. Sentinel-2 with a 290 km swath (ESA, [n.d.b](#))). It is assumed that in most flood event cases, tasking a satellite is mainly relevant for populated areas near river regions. In addition, the monitoring system integrates satellite overpass schedules, e.g. of the Sentinel or WorldView Series, to estimate the acquisition potential over the affected regions (Mühlbauer et al., [2024](#)).

Once a certain threshold is reached (e.g. level of severity) a notification service provides subscribed users with a quick email overview of current disaster events. Following this automated alerting phase, responsibility shifts to SEM coordination experts, who manually assess the necessity of initiating VHR satellite data acquisitions for the specific event.

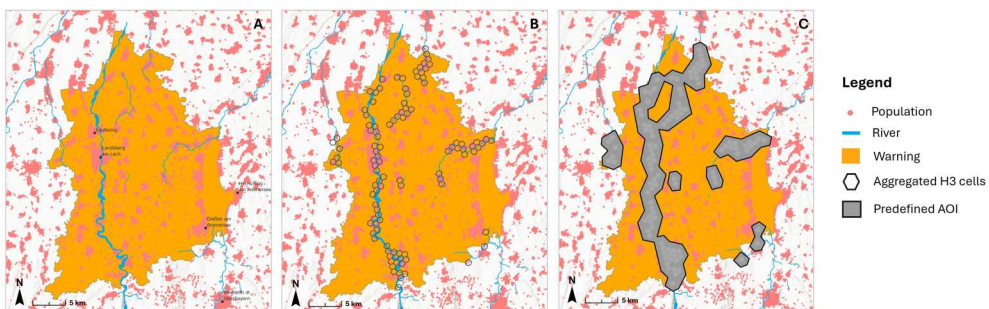


Figure 2. Automatic predefinition of a flood-relevant area of interest for VHR imagery. (A) Warning, population, and river datasets are combined. (B) After normalisation and aggregation with the H3 grid, only overlapping areas are retained. (C) The selected H3 cells are converted into simplified geometries for manual processing.

3.2. VHR satellite data tasking and acquisition

The second phase of the semi-automated process chain focuses on the meaningful automation for VHR satellite data tasking and acquisition. It also considers the automatic search for suitable archive images to allow for a visual comparison and change detection of post and pre-event imagery. While the initial establishment of the process chain relies on optical VHR imagery, integrating SAR data will become crucial for flood mapping under cloud-covered conditions. In this study, satellite data provision was realised in collaboration with EUSI enabling streamlined tasking and data access, with reduced latency due to the ground station proximity of DLR's ZKI and priority tasking. However, this approach for increasing automation in SEM is not limited to a specific provider but rather depends on the access to APIs for direct tasking and archive ordering.

In the process chain presented here, the Tasking Archive API (TARA) of EUSI was integrated into the SEM process. TARA is an application programming interface following the design principles of the representational state transfer (REST) paradigm that enables both the programmatic searching and ordering from the entire image archive of EUSI and Vantor, as well as the tasking request of new acquisitions via HTTP requests (EUSI, 2025).

The use of TARA replaces the manual ordering process, which was previously done via an order form, enabling seamless integration of EO data ordering into the SEM workflow. All relevant search and production parameters (e.g. sensors, radiometric and geometric resolution, maximum cloud coverage, and acquisition angle) were predefined to meet the requirements for subsequent image analysis for the water segmentation analysis, which, however, must always be reviewed and adjusted during ongoing events. The AOI and time window for acquiring satellite images have to be set individually for each crisis and are automatically predefined based on the spatial extent and event onset of the monitored data sources.

Once the required parameters have been specified via the API, the user can either request a feasibility study to evaluate the likelihood of successful acquisition given the user's criteria and factors, such as weather, or proceed directly with tasking. If the ordering conditions are not met within the specified time window, no satellite image will be captured or delivered. After a successful acquisition, the satellite imagery can be delivered immediately or up to 15 min after the image collection (EUSI, n.d.a).

In addition to new acquisitions, ordering archive data as a pre-event image is crucial for water extent change detection. The archival search, which is usually carried out manually using a web browser interface, was automated with TARA by predefined relevant filters such as the AOI coverage, cloud cover (e.g. below 30%), or temporal filter. The temporal search is based on the event date of the warning and considers images taken during the same months of the event date within the past four years. After the data has been ordered via the API and processed by EUSI, it is delivered to an S3 bucket for both the tasking and archival search. Upon completion of delivery, the data is automatically retrieved by the processing pipeline.

3.3. Information extraction and analysis from VHR data

To efficiently analyse relevant geodata, we developed a preliminary automated method to determine the water extent based on VHR optical imagery. Then, secondary information layers are derived to further analyse the impact and context of the event.

3.3.1. Segmentation of water areas

The analysis module of the process chain builds on a previous study that systematically evaluated DL models for water segmentation in VHR satellite and aerial images under varying imaging conditions (Wieland et al., 2023b). In this study, we investigated the effects of network architecture, encoder backbone, spectral input configuration, data augmentation, pre-training strategies, and transfer learning between satellite and aerial imagery. Across all experiments, the U-Net architecture consistently outperformed DeepLabV3+ in both accuracy and inference speed, with MobileNet-V3 being the most efficient encoder in terms of accuracy and inference speed trade-offs. The experiments further showed that including additional spectral information substantially improved performance. When near-infrared (NIR) data were available, models trained on R-G-B-NIR inputs achieved the highest accuracy, and the combination of R-G-B-NIR with slope information offered the best cross-sensor generalisation. In cases where NIR spectral band was not available, R-G-B combined with slope data provided the most robust alternative. The study also demonstrated that train-time data augmentation through random changes in contrast, brightness, scale, and rotation consistently improved segmentation results. Pre-training on ImageNet weights, moreover, resulted in better generalisation to unseen sensors than domain-specific pre-training on Sentinel-2 imagery. Pre-processing images with contrast enhancement further improved transferability, and combining high-quality and noisy datasets during training increased robustness to variations in sensor type and acquisition platform. Finally, inference using a tile-based strategy with overlapping predictions and tapered cosine blending reduced border artifacts and preserved segmentation quality (Wieland & Martinis, 2019).

Based on these findings, we adopt the best-performing pre-trained U-Net model with a MobileNet-V3 encoder, initialised with ImageNet weights for R-G-B-NIR spectral bands plus slope information, trained with contrast-enhanced inputs and data augmentation. We integrate this model into an automated image processing pipeline that comprises four main modules (Figure 3). A data ingestion module takes care of reading provider specific metadata and image formats and feeds the relevant data to a preprocessing module. In this module, imagery is geometrically and radiometrically corrected, contrast-enhanced and complemented with slope information derived from digital elevation models. The Copernicus GLO-30 (Copernicus Data Space, n.d.) is used to ensure global consistency and applicability of the method, since higher resolved elevation data such as from LIDAR are only sparsely available and of varying quality. A custom Python module has been developed to parse sensor metadata and apply coefficients and

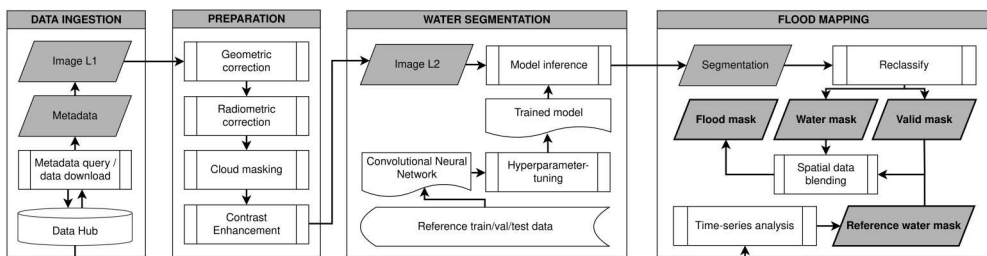


Figure 3. Image processing pipeline for water segmentation in VHR optical satellite images.

functions for radiometric calibration of the satellite images based on DG-calibration (EOatDHI, [n.d.](#)). Optionally, cloud masking is performed using the freely available UKIS Cloud Shadow MASK tool (Wieland, 2021; Wieland et al., 2019). In the analysis module, the pre-trained U-Net MobileNet-V3 DL network performs semantic segmentation of water bodies on input tiles. In the postprocessing module, predictions are merged into seamless scene-wide masks using mirror-padding, overlapping tiles, and tapered cosine blending to minimise border artifacts. Binary water masks are derived based on the prediction probability and identified optimal threshold. If a reference water mask is available (e.g. from time-series analysis of pre-flood satellite-derived water masks (Martinis et al., 2022)), spatial data blending separates permanent from temporary flooded areas. This integration enables fully automated, sensor-agnostic detection of (flood) water bodies in VHR optical satellite images, with the possibility of occasional quality checks to ensure reliability.

These methods for water segmentation were applied during different flood events in Germany, such as on September 18, 2024, in Dresden and on June 4, 2024, in Deggendorf ([Figure 4](#)).

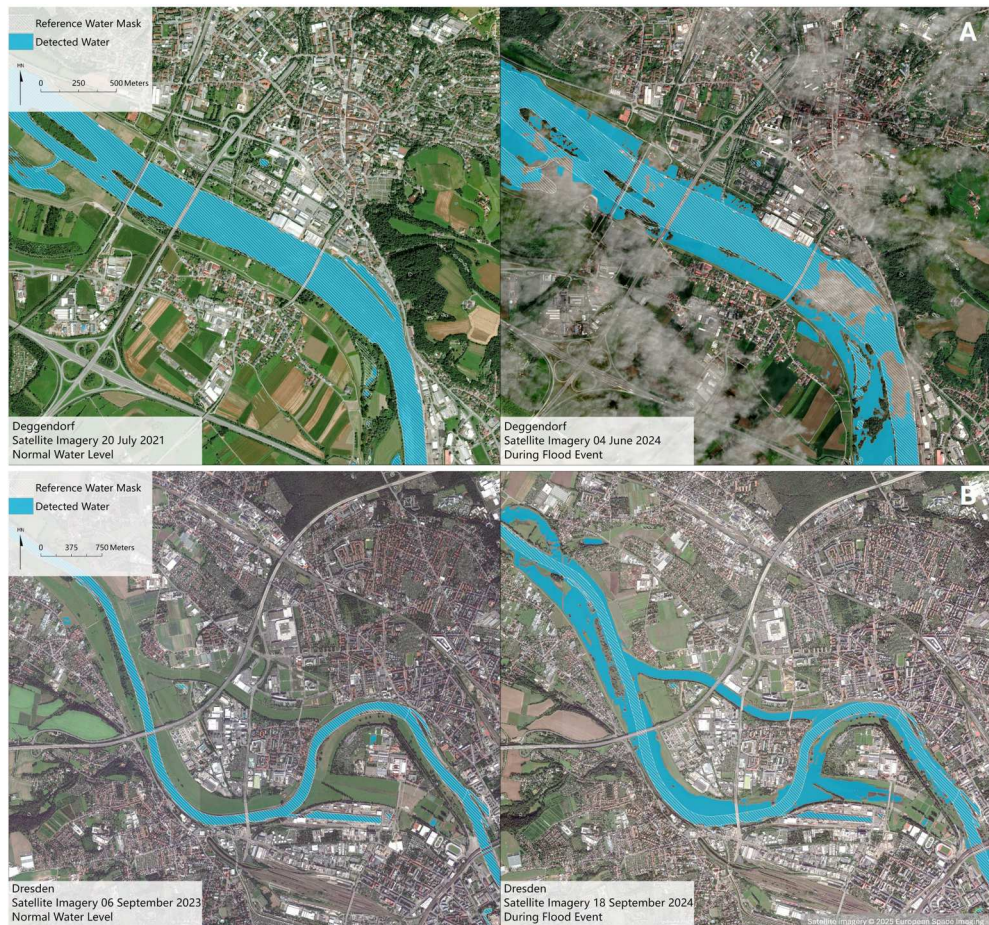


Figure 4. Results of water segmentation from VHR optical imagery. (A) Deggendorf and (B) Dresden, each showing water extent under normal conditions (left) and during a flood event (right).

3.3.2. Derivation of secondary information layer

The segmented water areas are intersected with geodata, such as population data, critical infrastructure layers, and other relevant information for the rapid identification of affected areas and prioritisation of response efforts (Armenakis & Nirupama, 2013; Wieland et al., 2025). Further information and analysis data can be derived by intersecting the water mask e.g. with critical infrastructure layers, which may include hospitals, emergency services, or transportation networks.

Consequently, the derived water masks are automatically intersected with high-resolution population datasets from BKG to estimate the population affected by the flood event. The H3 grid system was implemented to enhance the scalability and flexibility of the data visualisation. This allows for different levels of detail in analysis: resolution 7 (cell diameter ~13 km) is suitable for municipal or district-level assessments, resolution 8 (cell diameter ~4.7 km) for detecting local clusters or hotspots of affected areas, and resolution 9 (cell diameter ~1.7 km) for providing detailed analysis within urban areas or specific locations of interest.

3.4. Web-based visualisation

Effective communication of crisis information is crucial for disaster response. A web-based platform encompasses the geodata derived from the VHR satellite data resulting from the process chain, as well as ancillary data such as transportation, critical infrastructure, or statistical flood layers.

The ZKI web-based visualisation environment is built on Esri's ArcGIS Online Experience Builder, which offers a comprehensive set of tools for geodata visualisation and management (Esri, n.d.b). The system was integrated in the analysis workflow and supports a variety of map layers and interactive functions, presenting complex datasets clearly and intuitively. By connecting directly to the outputs of our semi-automated processing chain, crisis information can be made available to users shortly after data acquisition.

ZKI templates are designed using the Experience Builder and can be quickly adapted and deployed in the event of a disaster. These include pre-defined configurations such as standardised layouts and pre-positioned core layers (e.g. rivers, population datasets, and critical infrastructure), as well as a consistent arrangement of tools and widgets. The templates retain the flexibility to accommodate event-specific requirements, such as localised hazard data or unique geographic extents, ensuring both efficiency and operational relevance. The design concept for the web interface is guided by principles of clarity, accessibility, and operational effectiveness. The visualisation emphasises focus areas that are most relevant to first responders, including densely populated zones, critical infrastructure, and flood-prone regions. Upon accessing the platform, users are presented with a default view that immediately displays key information such as the flood extent and the estimated number of people affected, providing instant situational awareness. From this starting point, predefined bookmarks allow quick navigation to priority locations, while interactive tools enable users to toggle layers, compare datasets using swipe functionality, and extract coordinates for field operations (Figure 5).

In our process chain, new satellite imagery and geospatial products are made accessible to users via the web application as soon as they are generated, with minimal human intervention. Automating these updates reduces the delay between data acquisition and



Figure 5. Web-based application providing a situational overview. The map illustrates a simulated flood event in Deggendorf, showing segmented water extent, affected population, statistical flood zones, and relevant critical infrastructure.

field deployment. To support a more detailed analysis, the platform also allows the integration of external datasets and user-generated content. Responders can upload their own files, such as geotagged photographs from the field, which are then positioned on the map to enhance situational awareness and enrich the shared operational picture. Visual aids, including annotations, legends, and tooltips, are integrated to help users interpret the data quickly.

The dissemination of satellite data is subject to licensing and usage restrictions, especially for commercial VHR imagery, which may limit redistribution and public access. While open-access data can be shared freely, the ZKI ensures compliance by restricting access to authorised users and, where necessary, provides only derived products such as flood masks. Accordingly, the web platform is not publicly accessible but available to registered users from public authorities and disaster relief organisations. Role-based access is managed via ArcGIS Online to ensure secure data sharing and efficient collaboration during crisis situations.

4. Case study: simulated flood scenario in Bavaria

The presented process chain was tested during a simulated flood event under realistic conditions in collaboration with first responders from the Bavarian Red Cross (BRK), who then evaluated the timeliness and provided crisis products.

4.1. Scenario setup

As no significant flood events occurred in Germany during the demonstration period (October–November 2024), a scenario combining past flood data and simulated flood areas was prepared and implemented for testing purposes. This approach ensured that the system’s performance was evaluated under both real and hypothetical conditions.

The demonstration involved selecting suitable, high-resolution, optical satellite data from the June 2024 flood in Bavaria, as well as preparing simulated flood areas. The water extent derived from this combination of real and simulated flood data was then compared to newly tasked satellite scenes. This allowed for the testing of the tasking functionalities, the automation of processes related to ordering, acquiring, and analysing satellite imagery, and deriving further secondary information layers, culminating in the rapid provision of crisis information on the web-based platform.

Due to the anticipated cloud cover during the demonstration period, new satellite scenes were ordered to test the tasking process, while water detection methods were primarily tested using archive data. Flood warnings were also generated based on historical alert data and integrated into the monitoring system to trigger notifications.

4.2. Execution and workflow performance

The test study was initiated with the sending of automated email notifications (based on the prepared alerts). The BRK was then informed of the activation, and the following steps in the process chain were initiated. Figure 6 shows the detailed timeline of the semi-automated process chain executed for this flood scenario.

For testing the tasking capabilities via the API, the cut-off time for the tasking order was reduced to one hour (default: 24 h), and the tasking priority was set to high, allowing for immediate acquisition opportunities. Following the notification about the expected extreme flood event (07:10 h) and the decision to acquire new optical VHR imagery, the AOIs for the tasking were finalised and requested for tasking via the API at 07:40 h. For the AOIs an immediate overpass was available at 10:33 h and the imagery could be delivered directly one hour later.

Following the download from the S3 bucket, the water segmentation was executed. Depending on the size of the area, the extraction of water areas based on the trained DL model and the subsequent processing (i.e. vectorisation) took 15–40 min. Following, the vectorised water mask and derived affected population proxy layer were uploaded to ArcGIS Online and integrated into the prepared web application template. The processing and uploading of the original satellite data to the web application showed to be more time-consuming, taking an average of approximately 2 h. The web application with the relevant geodata was completed at 5:20 pm and made available to the BRK.

4.3. Feedback

Following the demonstration, a semi-structured feedback session was conducted with first responders, including representatives from the BRK. The feedback on both the

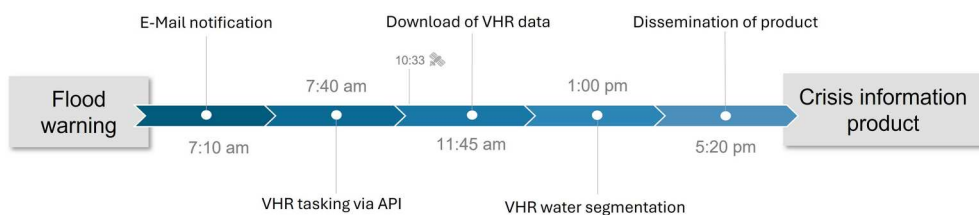


Figure 6. Timeline of the semi-automated SEM process chain applied in the case study.

demonstration and the developed methods was predominantly positive and highlighted the good timeliness of data delivery and the relevance of the content presented in the web application. Statistical flood extents, the overlay of georeferenced data with water masks, and complementary derived products were considered operationally useful. It was noted, that while the analysis on VHR imagery offers detailed insights, broader spatial coverage e.g. from Sentinel sensors provides a first valuable overview during crises.

Suggestions for future improvements included the integration of responsibility areas for warning districts, the provision of forecasts and modelled flood development, access to real-time statistical data during flood events (e.g. information on evacuations), broader accessibility of the web application, and explicit communication regarding the expected data availability. The first responders also emphasised the importance of user training to ensure effective use of the system.

Beyond user feedback, systematically assessing the reliability of the derived products is a key aspect. EO based crisis information is subject to uncertainties arising from sensor limitations, acquisition conditions, and processing methods, which are communicated through product-specific disclaimers. The feedback from first responders has shown that timely information is often prioritised over full validation in crisis situations. In this context, prediction probabilities for the derived water mask can be included as an auxiliary layer to provide contextual information (Hertel et al., 2023). Increasing automation, however, makes the validation of underlying products essential in subsequent work.

5. Discussion

5.1. Data sources for triggering

For the presented process chain, we predominantly considered web-based warning information which can be fetched directly and contains the attributes required for the CAP protocol. These warnings provided valuable information on the onset of flood events and were therefore used to pre-define the tasking window for VHR satellite acquisitions. Forecasting systems such as EFAS and the Global Flood Awareness System (GloFAS) add significant value by providing predictions of flood peaks and impacts (Wania et al., 2021), offering a more informed basis for tasking. In the presented approach, warnings containing information on the flood onset rather than the expected peak are used to pre-define the VHR tasking window. While projected peak information could improve the initialisation, onset-based tasking may in turn increase the likelihood of timely image acquisition for first responders. The automatic pre-definition of AOIs was achieved by implementing the H3 system to spatially aggregate heterogeneous data sources (Roll et al., 2025). The temporal aggregation, however, proved challenging given warning updates with varying onset dates; considering sources that include the estimated event peak can facilitate this step.

5.2. Flood mapping with optical VHR imagery

In our process chain, we considered VHR optical imagery for the derivation of crisis information. While the use of optical sensor data for flood analysis is limited due to the usually

associated cloud coverage, it can still provide valuable insights (Robinson et al., 2019). The advantages and limitations of using VHR optical imagery for flood detection need to be considered in relation to the specific flood context. During long-lasting or slowly evolving flood events, optical data provide effective monitoring capabilities, with VHR imagery enabling precise water segmentation and accurate delineation of small water bodies and fragmented flood patches (Wieland et al., 2023b). Also, the methodical pipeline applied here could be adapted for complementary purposes, such as damage assessment, if optical imagery is maintained as the primary data source (Yuan et al., 2021). Validation of remote sensing products must be continuously updated as an integral part of all subsequent development steps.

Nevertheless, for comprehensive flood mapping, the integration of additional data sources, in particular, SAR imagery, is essential, given the robust sensor capabilities under unfavourable atmospheric conditions and during nighttime (Li et al., 2019). Combining optical imagery and SAR provides complementary perspectives, improving both flood detection capacity and impact assessment quality (Foroughnia et al., 2022). Integrating SAR APIs (e.g. Umbra (Umbra, n.d.a)) and utilising doubleshot opportunities (EUSI, n.d.b) can further improve the data basis, but requires robust flood detection methods for different SAR sensors (Dasgupta et al., 2018), such as those developed for TerraSAR-X data (Martinis et al., 2015). Given limited annotated VHR SAR data for flood mapping, adapting pretrained Sentinel-1 models (Bereczky et al., 2022) to higher-resolution SAR data and leveraging self-supervised learning on unlabelled data from VHR sources such as Capella Space (Capella Space, n.d.), Umbra (Umbra, n.d.b), and TerraSAR-X can serve as an effective intermediate step prior to supervised fine-tuning, facilitating efficient domain adaptation without the need for training models from scratch.

5.3. Estimation of the affected population

For the approximation of the affected population, a dataset from the BKG was utilised. Regardless of their spatial detail and accessibility, a limitation of these datasets is their static nature as they do not account for temporal changes. The estimated population from the dataset may therefore not accurately reflect the number of people present during the event in question. To overcome this, GPS traces from mobile phones and social media data can be used to provide a real-time assessment of affected population hotspots (Detera et al., 2023).

5.4. Crisis information dissemination

The integration and dissemination of crisis information via a web application proved highly valuable, as it provides an interactive and continuously updatable situational overview. Compared to static products, web interfaces support the dynamic exploration of the data, allowing users to focus on operationally relevant information. However, cartographic design must be chosen purposefully to ensure user orientation (Zejdlik & Vozenilek, 2025). The use of predefined templates accelerated product delivery, and further automation through standardised upload scripts is possible, although this requires regular maintenance to ensure reliability.

5.5. Transferability of the approach

The presented approach is particularly relevant for institutions providing satellite-based crisis information to coordinators and first responders. Its transferability depends on the availability of triggering data, access to and processing of VHR data, and the choice of visualisation. Suitable triggering data must be available and should include event location, time, and type, while the automatic AOI pre-definition must be adapted to the respective data sources. In addition to EFAS/GLOFAS, high-quality warnings from regional or national authorities are preferable; if unavailable, international sources such as the Global Disaster Alert and Coordination System (GDACS, 2026), or events extracted automatically from online media can be used (Schmidt et al., 2025). The technical transferability further relies on access to satellite tasking APIs and priority acquisition. Where direct access is limited due to financial constraints, national framework agreements, international mechanisms (e.g. International Charter) or freely available data (e.g. Sentinel) can be used. Following the delivery of the VHR data, the DL based analysis workflow is adaptable to available data sources and models, while the performance and scalability depends on the computational infrastructure. The derived flood maps can be intersected with auxiliary data (e.g. population or infrastructure) as required, and adapted to suit the intended end users. While the web viewer in this study was built using Esri ArcGIS Experience Builder, the choice of visualisation platform depends on operational requirements, desired flexibility and available resources. Commercial solutions such as Esri enable rapid deployment, with licensing and infrastructure managed by the provider, allowing end users to access the platform without additional cost. The widespread use of Esri within government and public protection organisations further facilitates interoperability, data exchange, and user familiarity. Alternatives such as open-source frameworks (e.g. Leaflet (Cheng et al., 2025) or OpenLayers (OpenLayers Contributors, 2026)) or deploying fully custom platforms, offer greater flexibility, but usually require increased development effort.

6. Conclusion

This study presented a proof-of-concept process chain that included more automation at different stages of SEM to quickly provide relevant crisis information in a comprehensive manner to first responders. The method was applied to flood events since the already high risk will be further aggravated, driven by climate change. Tested for a simulated flood event in Bavaria, which combined historical and statistical flood extents, the approach proved valid as it provided various web-based crisis information within hours after the warned flood event and was positively evaluated by the first responders.

We recognise that for a fully operational SEM chain with a high degree of automation, further improvement of the individual components and validation of the remote sensing-based products is required. At the same time, as each crisis evolves differently and human decisions have to be made at crucial stages, meaningful semi-automation is aimed at rather than full automation. The approach is particularly relevant for institutions delivering satellite-based crisis information to coordinators and first responders, while its application depends on the availability of suitable data for triggering, access to satellite imagery, and adaptation of the components to the operational capacities.

Close cooperation and exchange with first responders and decision-makers is crucial to ensure that crisis information is usable. This includes coordinating standardised formats (e.g. WMS or WFS) and commonly used interfaces (e.g. STAC, APIs) for information exchange. Providing multiple dissemination options is important, as users also aim to integrate the derived data into their existing and familiar systems. This shows the relevance of a user-demand-driven approach when developing situational crisis information products.

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Author contributions

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