Improved Satellite-Based Emergency Mapping through Automated Triggering of Processes

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ABSTRACT

For more than two decades, satellite-based emergency mapping (SEM) supports authorities and responders in the rapid assessment of disaster situations. Although automation has been advanced, particularly in the field of satellite image analysis, the standard SEM workflow of the Copernicus Emergency Mapping Service (CEMS) is mostly user-driven at crucial steps. The 2021 flood events in western Germany show, as an example, the strong influence of manual interaction on the timely provision of satellite-based crisis products to emergency managers. We examine where latencies occur in the CEMS workflow and show a concept for the automation of processes and the usage of primarily open web data for process triggering to overcome delays. Our assumption is that a combination of both components is key for a faster SEM workflow, which we discuss along further benefits and challenges. A prototypical information system demonstrates the practical applicability of the concept.

Keywords

Earth observation, disaster management, satellite-based emergency mapping, web data analysis.

INTRODUCTION

Large-scale natural disasters such as the severe floods in western Germany in 2021 (e.g. Ahr valley) or Pakistan in 2022, the extensive wildfires in Portugal in 2017, Spain in 2022, Chile in 2023 and 2024 or the devastating earthquake in the bordering region of Turkey and Syria in 2023 require an effective, fast and coordinated disaster management (DM). When a disaster strikes, rapid, timely situation assessment is key for an adequate operational planning, so that available resources can be used effectively, shown by the example of the Ahr valley flood (Holzheimer et al., 2022). Earth observation (EO) data products have proven highly valuable in providing an up-to-date overview of an affected region and valuable information on the extent and distribution of damage (Gstaiger et al., 2022). Satellite-based emergency mapping (SEM) services such as the Copernicus Emergency Management Service (CEMS) rapid mapping service (RMS) (CEMS, 2024) provide geospatial information on demand and fast in support of DM activities before, during or immediately following a disaster (Voigt et al., 2016).

In contrast to sudden-onset disasters like earthquakes, the availability of early warnings, e.g. for meteorological events, may enlarge the time window for an improved DM support with EO data. Recent undertakings to accelerate SEM in terms of delivery timeliness of the crisis information by utilizing early warning systems have proven effective (Wania et al., 2021), however the process remains user-driven at crucial steps. In this paper, we investigate possible enhancements for the SEM process and propose a concept for automation of manual steps to improve both, timely provision and accuracy of EO-based crisis information. Afterwards, we show how our approach is applied in a prototypical implementation as a proof-of-concept.

Our work is based on design science research (Hevner et al., 2004). The presented artifacts, an improved SEM process and an information system prototype, are the first results of an ongoing development process with practice and state-of-the-art research in mind. This is made possible in particular by the authors' position as employees of an RMS (Center for Satellite-Based Crisis Information (ZKI)) based at a research organization (German Aerospace Center (DLR)). Both the relevance and rigor of the artifacts can thus be iteratively ensured.

RELATED WORK

Since 2003, ZKI has established one of the first rapid mapping mechanisms that continued to evolve with concurrent advances in satellite technology to provide users with precise EO-based crisis information (Gähler, 2016). Among other RMS providers, DLR has contributed to the predecessor of the CEMS (Schneiderhan et al., 2010). Today, the standard SEM process of the CEMS starts with a user-driven activation, which on average is requested 20h after the user-defined event time. Upon activation, the state-of-the-art process follows the steps 1) satellite tasking (optional, see chapter “Satellite Acquisitions”) 2) image acquisition, 3) image delivery and 4) map product delivery including image analysis (Wania et al., 2021) (Figure 1).

The timeline for the severe Ahr valley flooding was reconstructed to illustrate this SEM process. Figure 2 shows early warnings by the European Flood Awareness System (EFAS, https://www.efas.eu) and the German National Meteorological Service (DWD, 2021a, 2021b) four, respectively, one day before the CEMS activation by the German Joint Information and Situation Centre (GMLZ). Upon the activation, cloud cover prevented the use of optical satellite imagery for damage assessment during the initial flooding days. The ZKI became active at request of the Bavarian Red Cross given the DWD warnings and by chance was able to provide timely aerial imagery (Holzheimer et al., 2022). An automatic flood detection based on Sentinel-1 radar satellite images was also published (ZKI, 2021). This case exemplifies the time delays in the current SEM workflow due to manual activation responsibilities and handover procedures. It is important to note that the disaster response cannot be reconstructed for a theoretical case in which the SEM would have been activated at an earlier stage.

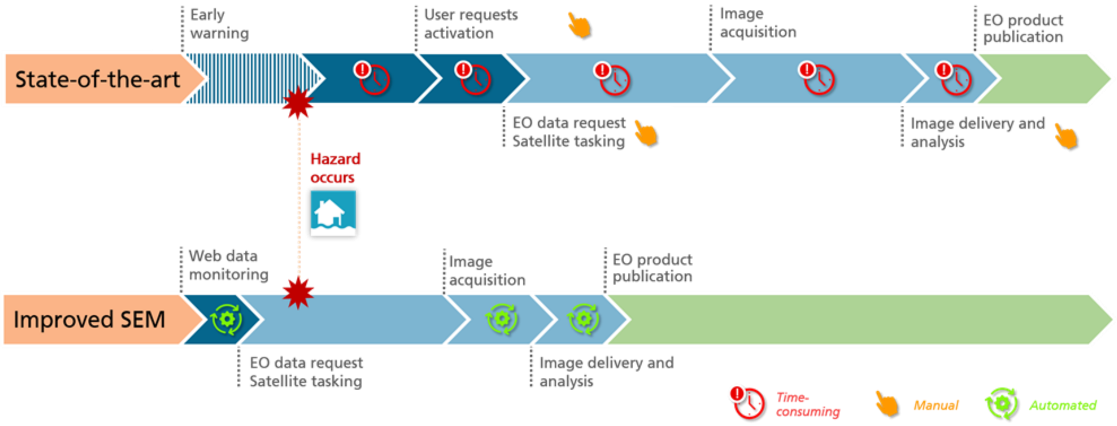


Figure 1. Comparison between state-of-the-art and proposed automated SEM workflow

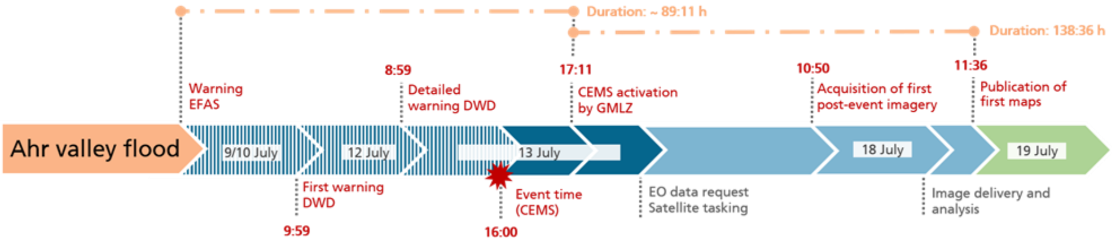


Figure 2. Condensed timeline of the RMS activation EMSR517 for Bad Neuenahr-Ahrweiler with time in UTC (based on CEMS, 2021a, 2021b; Weidinger, 2022)

Overall, we can identify several significant gaps in time delay 1) between the initial early warning and the SEM activation, being manually performed by an authorized user, and 2) between the activation and satellite tasking. Furthermore, 3) the latency between satellite sensing and image delivery (e.g. on Copernicus Open Access Hub, https://scihub.copernicus.eu) and 4) the time- and labor-intense manual and semi-automatic visual image interpretation delay the SEM process at later steps. Most attention has been given to optimizing the latter gap, which remains an area for ongoing improvements, such as fully automated flood detection (Wieland & Martinis, 2019; Bereczky et al., 2022), and burnt area derivation (Nolde et al., 2020; Knopp et al., 2020).

Considering the first two gaps, mental workload and initial uncertainties affect both users and SEM providers during disasters. Authorities must be aware of the event location to define the area of interest (AOI) for a SEM activation. End users are often unaware of possible and upcoming satellite data acquisitions, including Copernicus and very high-resolution (VHR) satellites, and the time until map product availability. SEM service providers are engaged in a time-consuming search and coordination for suitable satellite data sources. Reducing manual activation time delay is crucial given past delays in RMS activation of, for instance, 36h after disasters in Bosnia and Herzegovina (CEMS, 2014). Since 2016, EFAS has been linked to the CEMS SEM process to anticipate satellite tasking for riverine floods. Wania et al. (2021) found that EFAS pre-tasking reduced delivery time for the first map product from 28:47 h to 16:05 h on average considering 14 flood events in Europe from 2016 to 2020. Similarly, Ajmar et al. (2019) proposed to include early warning alerts like those of the Global Disaster Alert and Coordination System (GDACS, https://www.gdacs.org), which also integrates tsunami models to reduce acquisition times by up to one day (GDACS, n.d.).

THE PROPOSED CONCEPT

The SEM workflow described above reveals that manual interaction and latency are the main reasons for a delayed provision of EO-based data products for DM, particularly the triggering step and the search for suitable satellite data sources. There are already approaches in place that shorten the time for triggering, but these are limited to specific natural events, and in some cases are not commonly accessible. Thus, we propose an approach that substitutes manual interaction and latency with a) the automation of processes and b) the usage of primarily open data from the WWW. Our assumption is that combining both components is key for an accelerated and therefore substantially improved SEM workflow.

AOI Definition

Figure 1 shows our proposed workflow for automating the initial steps of a SEM activation, which requires two types of input data: a) data that allows us to determine an AOI and b) data that contains information on future satellite data acquisitions. In our approach, the AOI is defined as an automatically derived area in which an event is likely to happen in the near future or has just happened. An event can be anything that might require an observation with remote sensing technologies, such as a natural or man-made disaster. While the AOI is currently determined manually by the entity that requests the satellite data, we propose a process that automatically retrieves the AOI by monitoring crisis-related data from the WWW. Monitoring involves continuously analyzing heterogeneous data to detect spatiotemporal anomalies in a given context.

Sometimes web data contain such anomalies implicitly. In case of natural disasters, for example, numerous national and international entities issue official alert messages already including an AOI (e.g. MeteoAlarm, https://www.meteoalarm.org). For predictable events, such as storms, these alerts can be early warnings. For sudden-onset disasters, such as earthquakes, these alerts are usually published in a short time frame after the event.

Another example of publicly available spatiotemporal anomalies are event databases like the Global Database of Events, Language, and Tone (https://www.gdeltproject.org). These databases may contain conflict-related events, such as air raids. Technically, we can directly use the spatiotemporal information from alerts and event databases for building an AOI. Yet, trustworthiness of the sources must be considered. Warnings issued by widely accepted institutions such as GDACS can be regarded as very reliable. We can trust the expertise of the specialists and integrate the provided AOIs into our process. However, sometimes there are no official warnings or up-to-date event databases for the region or the event type we are interested in. As an example, quickly emerging refugee camps or natural disasters in countries without warning infrastructure can be mentioned. In such cases, or when the information derived from alerts and event databases is not satisfactory, other data sources should be considered, for example media monitors (e.g. Europe Media Monitor, https://emm.newsbrief.eu) and social media platforms. Here, the challenges are data access, data reliability and the fact that the spatiotemporal anomaly detection has to be performed by ourselves. An automated event detection approach (see Li et al. (2022) for examples) can be applied to turn unstructured textual data into well-structured events that describe the location, the time and the type of a disaster (Resch et al., 2018; Havas & Resch, 2021).

In summary, we can assume that in certain situations only one data source might be sufficient for the definition of an AOI. Even more, this applies to situations where a) the size of the footprint of the satellite is much bigger than the AOI, b) the satellite data are available free of charge and c) the satellite data will be analyzed automatically. In other situations, we cannot rely on only one data source. For instance, an official alert might cover a vast administrative entity. However, an RMS provider is primarily interested in the situation in populated areas. In such cases, we propose the fusion of as many data sources as necessary to determine a sensible AOI. In this scenario, together with the official alert(s), we could use a population distribution dataset and social media analysis for refinement (Lorini et al., 2019). The efforts pay off particularly when a) the size of the footprint of the satellite is smaller or approximately of the same size as the AOI, b) the satellite data are only available commercially at a high price and c) the satellite data will be analyzed manually.

Satellite Acquisitions

Besides the definition of AOIs for specific events, information on satellite acquisitions is essential in our approach. We have to distinguish three different satellite categories depending on the availability of satellite data. 1) Some EO satellites collect data permanently. The data are made available free of charge on platforms on the WWW. Besides the actual imagery, acquisition planning data are sometimes published on the WWW. Hence, we know when and where a satellite will acquire data in the coming days. Examples for this category are the Copernicus Sentinel (e.g. Sentinel-2, see European Space Agency, n.d.) or Landsat missions. 2) Some EO satellites offer a direct data broadcast. These satellites still collect data permanently. However, ground stations can directly receive the data when the satellite passes over and before the data is published on official platforms. Alongside the sometimes publicly available acquisition planning data, information from and about ground stations is required to assess data availability. Examples of this category are Sentinel-1, Aqua, Terra and Suomi NPP. 3) Some EO satellites do not collect data on a permanent basis. Instead, these satellites have to be tasked by an authorized entity. For acquisition planning, a ground station has to uplink information to the satellite, such as where and when data have to be acquired. Examples of this category are commercial VHR optical satellites (e.g. WorldView-3) and radar satellites (e.g. TerraSAR-X).

Data Intersection

For satellites from category one, as defined in chapter “Satellite Acquisitions”, each of the derived AOIs can be intersected with the potential sensing areas. No manual interaction is required and all the necessary data can be downloaded from the WWW. For satellites from category two, we additionally have to consider the direct acquisition capacities of ground stations. For satellites from category three an interface with commercial satellite operators has to be established in order to ensure that the requested AOIs can be considered in acquisition planning. The overall goal remains the same in all three cases: We want to know which satellite data will be available for our AOIs at what time. This information is of great value to decision makers in crisis situations based on experience gathered from previous ZKI activations and research projects, e.g. EU FP7 PHAROS (Community Research and Development Information Service (CORDIS), 2023) and EU H2020 HEIMDALL (CORDIS, 2022). At this point of the workflow, users can quickly be informed by means of decision proposals, for instance short email notifications, about their options for their customized satellite-based product. Thus, decision proposals are a further means to strengthen situational awareness (Endsley, 1995). While our system is intended to function fully automatically until this step, the relevance of decision proposals becomes evident if the acquisition of possibly expensive commercial data is proposed.

When EO analyses are based on publicly available data, further automation is possible and intended. In our approach, as soon as the EO data for the derived AOI are available, automatic thematic processors would instantly start analyzing these data. After a manual expert-based quality control, the EO product can be delivered to users. Besides the important EO product validation, we envisage an equally important step of AOI validation. Above we have shown that AOI derivation might be based on our own spatiotemporal anomaly detections. In such cases, we have to ensure that thresholds are calibrated correctly in order to constantly improve the quality of derived AOIs.

PROTOTYPE AND EXAMPLE

In order to demonstrate the feasibility of our concept we have implemented an experimental application based on disaster alerts from various official international (e.g. GDACS) and national (e.g. German DWD) sources as well as acquisition data of Sentinel-1A, Sentinel-2A, Sentinel-2B und Landsat-8. The prototype automatically collects the alerts from the WWW and calculates when the potential sensing area of a satellite intersects with an AOI. The results are saved in a database that can be queried by a graphical user interface for visualization purposes. Additionally, a dissemination service automatically generates textual notifications with current disaster events and matching satellite acquisition options.

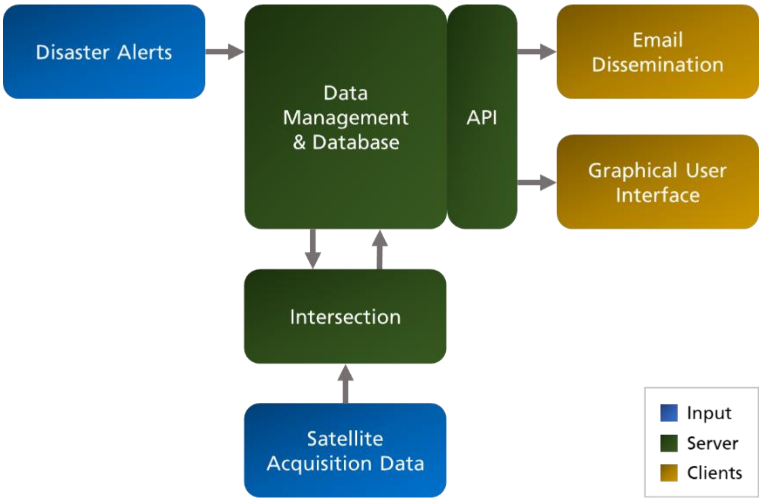
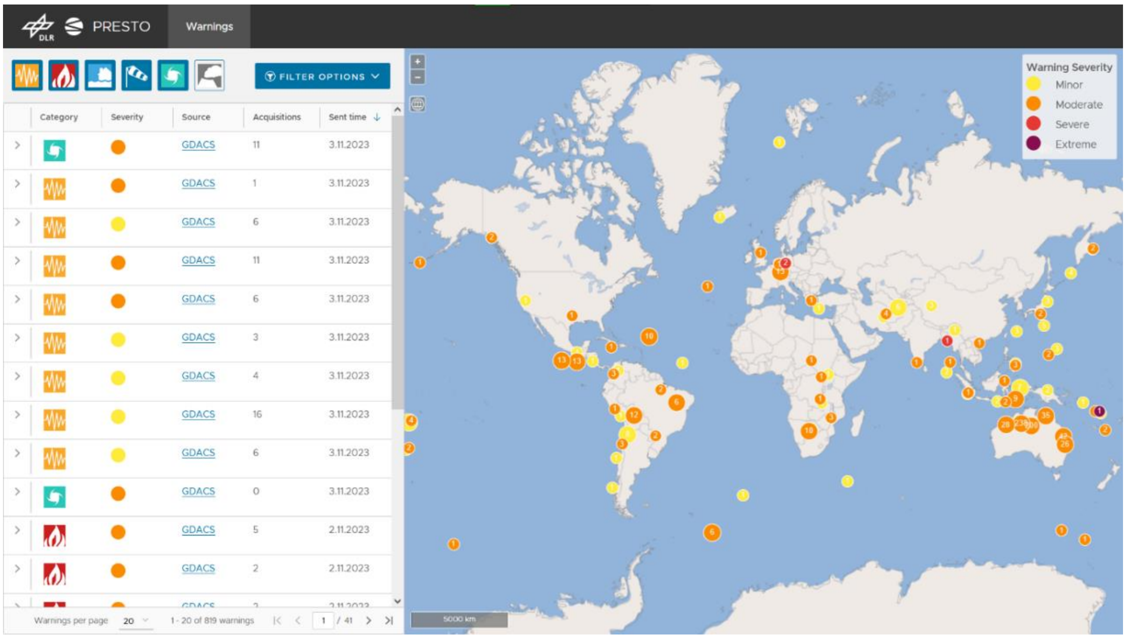


Figure 3. Major components of the prototype. The arrows indicate the direction of the data flow.

Figure 3 illustrates the major components of the developed prototype and their interactions. The prototype is designed as a client-server web application (Gallaugher & Ramanathan, 1996). The server comprises a data management component, an intersection component, a database and an API. The data management component is built with Python. Its tasks are, for instance, the download of alerts and the triggering of the intersection component. The spatiotemporal intersection component is a Java-based extension of the operational PSM (Processing System Management) (Böttcher, 2001) deployed at DLR's ground station for satellite data reception in Neustrelitz, Germany. It selects those satellite acquisitions within the next 7 days that spatially and temporally overlap with the AOIs from the alerts and returns the results to the data management. The communication between data management and intersection runs via gRPC (gRPC Remote Procedure Calls) (https://grpc.io). Next, the results are stored in a PostgreSQL database. A GraphQL API (https://graphql.org) built with Hasura (https://hasura.io) delivers the requested results to clients. The server part runs automatically at regular intervals, e.g. once per hour. A dissemination service written in Python generates brief email notifications based on the intersection results. For a more detailed insight into the collected and generated data, there's a web-based graphical user interface with an interactive map and various sorting and filter options. The graphical user interface is implemented with DLR's open source software for geoscientific web applications UKIS (Environmental and Crisis Information Systems) (Muehlbauer, n.d.; https://github.com/dlr-eoc/ukis-frontend-libraries).

The following screenshots of the prototype's graphical user interface show exemplarily how our system worked in the context of a predicted flood in northern Germany in November 2023. The "Warnings" view in Figure 4 gives an overview on all disaster alerts currently registered in the system. After selecting one particular alert, the system displays the AOI together with the matching satellite acquisitions. See "Detail" view in Figure 5.

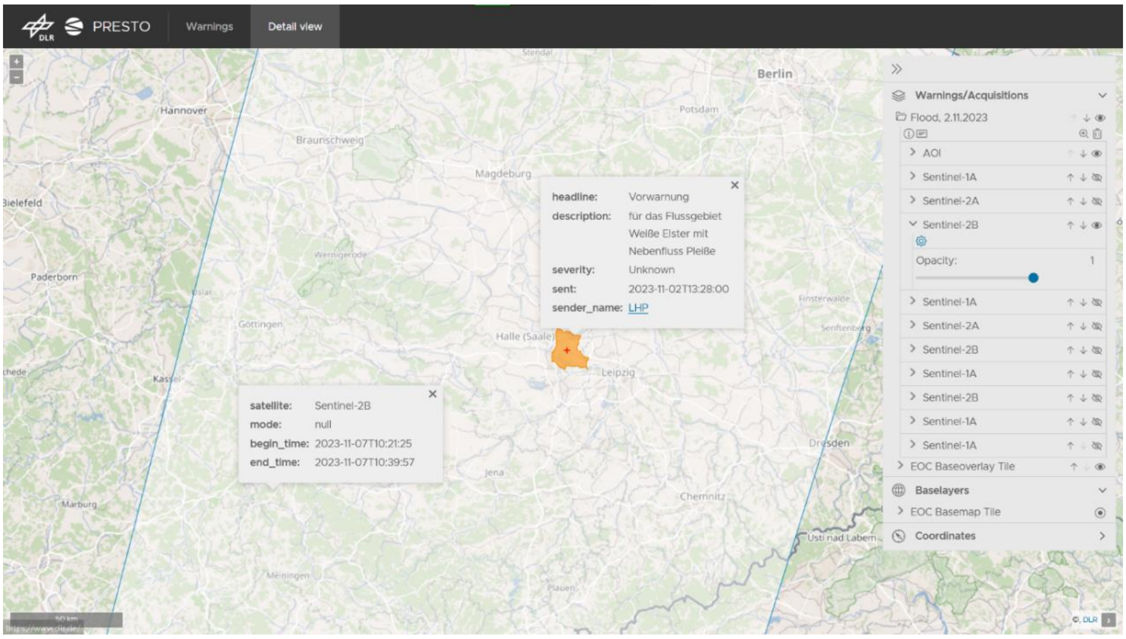
Due to automation, the prototype was able to generate these results within minutes after the official warning was issued. As the underlying alert was an early warning, we could predict which satellite data would be available at what point of time before the actual event had happened.



Category	Severity	Source	Acquisitions	Sent time ↓
	🟠	GDACS	11	3.11.2023
	🟠	GDACS	1	3.11.2023
	🟡	GDACS	6	3.11.2023
	🟠	GDACS	11	3.11.2023
	🟠	GDACS	6	3.11.2023
	🟡	GDACS	3	3.11.2023
	🟡	GDACS	4	3.11.2023
	🟡	GDACS	16	3.11.2023
	🟡	GDACS	6	3.11.2023
	🟠	GDACS	0	3.11.2023
	🟠	GDACS	5	2.11.2023
	🟠	GDACS	2	2.11.2023

Warnings per page 20 1 - 20 of 819 warnings 1 / 41

Figure 4. "Warnings" view of the prototype: The list at the left shows alerts for natural disasters with some of their attributes. The column "Acquisitions" contains the number of possible satellite data acquisitions for the respective AOI. The list can be filtered (here: source equals "GDACS") and ordered (here: time stamp descending) by the user. The map at the right shows the locations of the alerts, with colors indicating the severity of an alert.



headline: Vorwarnung
description: für das Flussgebiet Weiße Elster mit Nebenfluss Pleiße
severity: Unknown
sent: 2023-11-02T13:28:00
sender_name: LHP

satellite: Sentinel-2B
mode: null
begin_time: 2023-11-07T10:21:25
end_time: 2023-11-07T10:39:57

Figure 5. "Details" view of the prototype: The layer control element at the right contains entries for the AOI as well as all matching satellite acquisitions. A click on the AOI displays information such as the source of the alert and the original alert description. A click on an acquisition segment shows attributes such as the satellite name or the sensing time(s).

DISCUSSION

We consider our approach as a possible advancement of well-established SEM workflows addressing different kinds of natural or man-made disasters. Proven SEM process steps are combined with automation and primarily open data in order to satisfy the prevalent requirement of users of SEM products: faster information and product availability. The main objective is to improve the timeliness, but we also anticipate improved quality in the final EO products. If data interpretation cannot be fully automated, an EO expert will have additional time for analysis. Also, alerts, media articles etc. used to trigger the workflow can enrich the final product. Our approach improves the user's situational awareness by automatically generating decision proposals regarding EO data and product availability. This can also comprise crucial information such as the expected cloud coverage. Besides the user's benefits, there are advantages on the RMS provider's side. The monitoring of trigger data on a continental or global scale can lead to useful products that would not have been possible with human triggers alone. Cost is another factor. As long as no commercial data acquisition is involved, the workflow is based on free input data. Of course, we acknowledge the significant challenges associated with automation and open data. We heavily rely on trusted data sources such as official alerts. Yet, even official alerts might contain errors. Other possible data sources for the AOI generation, particularly media and social media, must be treated even more carefully. We try to eliminate as many inaccuracies as possible with a fusion of a reasonable amount of data sources in the respective use case. To achieve this fusion, the heterogeneous data sources first could be aggregated geometrically e.g. by incorporating the discrete global grid system H3 (https://h3geo.org). Afterwards, rule-based criteria can be applied to further validate and refine the AOI as much as possible (Roll, 2024). Moreover, a manual validation step for the AOI generation should be in place. The fusion approach also tries to absorb the loss of web data sources in course of time. Given that, for example, official alerts, events from online news and events from social media were used to define AOIs, the system would continue to function if social media were removed. Certainly, we cannot eliminate an inherent problem of satellite-based EO: the satellite most likely is not at the position over a disaster event or has just passed by. Latency is the result. Also, cloud coverage might further delay the assessment of optical imagery.

An automatic trigger can generate the decisive advantage in time, for example, by allowing data reception via direct broadcast. While automatically intersecting publicly available AOIs and acquisition plans is straightforward, including ground stations and commercial data providers may appear technically and administratively obstructive. However, an interface with DLR's ground station for satellite data reception in Neustrelitz, Germany could be established for our prototype. Finally, we want to emphasize the importance of the human factor in our approach. Crucial decisions will still – and have to – be made by humans based on their experience and transparent decision proposals. Expert knowledge from specialists at the disaster site is, once available, of utmost significance and we treat it as yet another – but very trustworthy – data source of the system.

SUMMARY AND FUTURE WORK

In this paper, we presented our vision of an enhanced SEM workflow as well as a first proof-of-concept implementation. We believe that our workflow can help to narrow down some gaps in the current state-of-the-art SEM. An accelerated process, better transparency, and more high-quality EO products can be achieved by automated processes and the combination of existing data. First experiments based on publicly available alerts and satellite acquisition data from DLR's ground station have demonstrated promising results: The prototype shows that satellite data availabilities can automatically be determined for areas potentially affected by a crisis. Our future work will focus on the transformation of our vision into a stable software that reliably supports future SEM activities. This includes a logic that considers the suitability of each satellite for each disaster type. Also, we aim at automatically generating more refined AOIs by aggregating available warning sources and filtering relevant attributes. Eventually, we plan to link our system to processing chains for satellite data in order to automate a further process step. Not only the 2021 Ahr valley flood in Germany has shown that an improvement of existing processes is relevant and possible.

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REFERENCES

Ajmar, A., Annunziato, A., Boccardo, P., Tonolo, F.G., & Wania, A. (2019). Tsunami Modeling and Satellite-Based Emergency Mapping: Workflow Integration Opportunities. *Geosciences*, 9(7), 314. https://doi.org/10.3390/geosciences9070314

Bereczky, M., Wieland, M., Krullikowski, C., Martinis, S. & Plank, S. (2022). Sentinel-1-Based Water and Flood Mapping: Benchmarking Convolutional Neural Networks Against an Operational Rule-Based Processing Chain. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 15, 2023-2036. https://doi.org/10.1109/JSTARS.2022.3152127

Böttcher, M., Reißig, R., Mikusch, E. & Reck, C. (2001). Processing Management Tools for Earth Observation Products at DLR-DFD. *Procedings of DASIA*, France.

Community Research and Development Information Service. (2022). *Project on a multi-hazard open platform for satellite based downstream services*. European Union, CORDIS EU research results. https://cordis.europa.eu/project/id/606982

Community Research and Development Information Service. (2023). *Heimdall – Multi-hazard cooperative management tool for data exchange, response planning and scenario building*. European Union, CORDIS EU research results. https://cordis.europa.eu/project/id/740689

Copernicus Emergency Management Service. (2024). *Copernicus Emergency Management Service – Mapping*. https://emergency.copernicus.eu/mapping

Copernicus Emergency Management Service. (2021a). *EMSR517: Flood in Western Germany*. European Union. https://emergency.copernicus.eu/mapping/list-of-components/EMSR517

Copernicus Emergency Management Service. (2021b, 16 July). *The Copernicus Emergency Management Service forecasts, notifies, and monitors devastating floods in Germany, Netherlands, Belgium and Switzerland*. https://emergency.copernicus.eu/mapping/ems/copernicus-emergency-management-service-forecasts-notifies-and-monitors-devastating-floods

Copernicus Emergency Management Service. (2014). *EMSR087: Floods in Bosnia and Herzegovina*. European Union. https://emergency.copernicus.eu/mapping/list-of-components/EMSR087

Deutscher Wetterdienst [@DWD_presse]. (2021a, 13 July). *#Update zur #Starkregen-/#Dauerregen-Lage: Im Umfeld der Eifel ist mit den höchsten Niederschlagsmengen zu rechnen, daher wurden die #Warnungen in* [Post]. X. https://twitter.com/DWD_presse/status/1414872018005241857

Deutscher Wetterdienst [@DWD_presse]. (2021b, 12 July). *Besonders Teilen des Westens drohen in den nächsten Tagen große Regenmengen. Im Südwesten muss man sich mancherorts bereits in der* [Image attached] [Post]. X. https://twitter.com/DWD_presse/status/1414524803273400323

Endsley, M. R. (1995). Toward a Theory of Situation Awareness in Dynamic Systems. *Human Factors*, 37(1), 32-64. http://dx.doi.org/10.1518/001872095779049543

European Space Agency. (n.d.). *Acquisition Plans.* https://sentinel.esa.int/web/sentinel/copernicus/sentinel-2/acquisition-plans

Gähler, M. (2016). Remote sensing for natural or man-made disasters and environmental changes. *Environmental applications of remote sensing*, 309-338.

Gallaugher, J. M. & Ramanathan, S. C. (1996). Choosing a Client/Server Architecture. *Information Systems Management*, 13(2), 7-13. https://doi.org/10.1080/10580539608906981

Global Disaster Alert and Coordination System. (n.d.). *Models – Earthquake*. Retrieved February 12, 2024, from https://www.gdacs.org/Knowledge/models_eq.aspx.

Gstaiger, V., Merkle, N., Rosenbaum, D., Wieland, M., Lechner, K., & Kippnich, U. (2022). Aus dem All und aus der Luft frisch auf den (Lage-)Tisch: Der Nutzen von Luft- und Satellitendaten für die Lageerfassung. *Im Einsatz*, 56-61.

Havas, C., & Resch, B. (2021). Portability of semantic and spatial–temporal machine learning methods to analyse social media for near-real-time disaster monitoring. *Natural Hazards*, *108*(3), 2939-2969. https://doi.org/10.1007/s11069-021-04808-4

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS quarterly*, 75-105.

Holzheimer, E., Kippnich, U., Kippnich, M., Lechner, K., & Wieland, M. (2022). Erkundung im Ahrtal mit Unterstützung von Verfahren der Künstlichen Intelligenz. *Die Flut im Juli 2021. Erfahrungen und Perspektiven aus dem Rettungsingenieurwesen und Katastrophenrisikomanagement*, 1, 22-26.

Knopp, L., Wieland, M., Rättich, M., & Martinis, S. (2020). A Deep Learning Approach for Burned Area Segmentation with Sentinel-2 Data. *Remote Sensing*, 12(15), 2422. https://doi.org/10.3390/rs12152422

Li, Q., Chao, Y., Li, D., Lu, Y., & Zhang, C. (2022). Event Detection from Social Media Stream: Methods, Datasets and Opportunities. *2022 IEEE International Conference on Big Data (Big Data)*, Osaka, Japan, 3509-3516. https://doi.org/10.1109/BigData55660.2022.10020411

Lorini, V., Castillo, C., Peterson, S., Rufolo, P., Purohit, H., Pajarito, D., De Albuquerque, J.P., & Buntain, C. (2021). Social media for emergency management: Opportunities and challenges at the intersection of research and practice. *Proceedings of the 18th International Conference on Information Systems for Crisis Response and Management*, USA, 772-777.

Muehlbauer, M. (n.d.*). UKIS – Environmental and Crisis Information Systems*. German Aerospace Center, Earth Observation Center. Retrieved May 14, 2024, from https://www.dlr.de/de/eoc/ueber-uns/deutsches_fernerkundungsdatenzentrum/georisiken-und-zivile-sicherheit/informationssysteme-und-geomatik/ukis-umwelt-und-kriseninformationssysteme

Nolde, M., Plank, S., & Riedlinger, T. (2020). An Adaptive and Extensible System for Satellite-Based, Large Scale Burnt Area Monitoring in Near-Real Time. *Remote Sensing*, 12(13), 2162. https://doi.org/10.3390/rs12132162

Resch, B., Usländer, F., & Havas, C. (2018). Combining machine-learning topic models and spatiotemporal analysis of social media data for disaster footprint and damage assessment. *Cartography and geographic information science*, *45*(4), 362-376. https://doi.org/10.1080/15230406.2017.1356242

Roll, J., Schneibel, A., Mühlbauer, M. & Gähler, M. (2024, March 7-8). *Aggregation of heterogeneous data sources for the early acquisition of satellite images in case of flood events* [Book of abstracts]. Discussing Geographic Method(ologie)s: Integration, Experimentation, and Innovation, Innsbruck, Austria. https://fileshare.uibk.ac.at/f/ebef338271b44ca59816

Schneiderhan, T., Gähler, M., Kranz, O., & Voigt, S. (2010). Insights to the Emergency Mapping Service within the GMES project SAFER-Highlights, main achievements and challenges. *Conference Proceedings of the Living Planet Symposium*, Bergen, Norway, 1-5.

Voigt, S., Giulio-Tonolo, F., Lyons, J., Kučera, J., Jones, B., Schneiderhan, T., Platzeck, G., Kaku, KK., Hazarika, M.K., Czaran, L., Li, S., Pedersen, W., James, G.K., Proy, C., Muthike, D.M., Bequignon, J., & Guha-Sapir, D. (2016). Global trends in satellite-based emergency mapping. *Science*, 353(6296), 247-252. https://doi.org/10.1126/science.aad8728

Wania, A., Joubert-Boitat, I., Dottori, F., Kalas, M., & Salamon, P. (2021). Increasing Timeliness of Satellite-Based Flood Mapping Using Early Warning Systems in the Copernicus Emergency Management Service. *Remote Sensing*, 13(11), 2114. https://doi.org/10.3390/rs13112114

Weidinger, A. (2023, June 6). *Was ist in der Flutnacht passiert? – Ein Protokoll*. Südwestrundfunk SWR. https://www.swr.de/swraktuell/rheinland-pfalz/flut-rekonstruktion-ahrtal-protokoll-100.html

Wieland, M. & Martinis, S. (2019). A Modular Processing Chain for Automated Flood Monitoring from Multi-Spectral Satellite Data. *Remote Sensing*, 11(19), 2330. https://doi.org/10.3390/rs11192330

Zentrum für satellitengestützte Kriseninformation. (2021, July 15). *Unwetter in Nordrhein-Westfalen und Rheinland-Pfalz, Deutschland*. German Aerospace Center (DLR), Earth Observation Center. Retrieved February 14, 2024, from https://activations.zki.dlr.de/en/activations/items/ACT152.html