Utilization of satellite imagery and artificial intelligence for disaster management: Approaches and case studies

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The advent of advanced satellite observations and the rapid evolution of Artificial Intelligence (AI) technologies have led to a fundamental shift in disaster management. These technologies enhance precise prediction, closer monitoring, and more efficient and effective responses to natural disasters. This study introduces AI-based satellite image analysis solutions throughout the disaster management cycle: prevention, preparedness, response, and recovery. Satellite imagery, captured through various channels, resolutions, and orbits, plays a crucial role throughout the entire disaster management cycle. This is because satellites have the advantage of capturing broad areas and can also image disaster regions that are inaccessible to humans due to secondary risks. We utilize high-resolution geostationary satellite imagery for real-time hazard monitoring and forecasting and synthetic Electro-Optical (EO) satellite imagery derived from Synthetic Aperture Radar (SAR) observations for monitoring flooded areas under cloudy conditions. EO satellite imagery is photographic-like images of Earth's surface using visible and infrared sensors, enabling detailed observation and analysis for applications such as mapping, surveillance, and disaster monitoring. And SAR gives high-resolution images using radar signals, capable of operating in all weather conditions and through cloud cover or darkness, making it ideal for monitoring and mapping. Additionally, AI-based damage assessment solutions facilitate the rapid detection and classification of building damage, enabling a quick response and reconstruction. Considering these technologies by government agencies, NGOs, and other stakeholders is essential, particularly in developing countries with limited surface observation capabilities and specialists. With these advanced technologies, AI-based disaster management solutions are expected to contribute significantly to the Early Warning for All initiative.

Keywords – Damage detection, deep learning, disaster response, satellite imagery, weather forecasting

1. INTRODUCTION

The field of disaster management has experienced a major transformation due to the latest advancements in satellite observation and artificial intelligence technologies. These technological advancements improve each phase of the disaster management cycle, prevention, preparedness, response, and recovery, by creating opportunities for more precise prediction, more detailed monitoring, and more efficient and effective responses to natural disasters.

Recent studies [1, 2, 3] have introduced the application of AI techniques in analyzing data related to disasters to enhance disaster management throughout its cycle. These AI techniques enable rapid analysis of big data, effectively speeding up the decision-making process. For example, real-time monitoring using AI helps make data-driven decisions about resource allocation and operational strategies. In addition, AI's capability to quickly assess disaster damage accelerates the onset of recovery [8, 9, 10]. Furthermore, it also leads to the development of AI-driven models [4, 5, 6, 7] that can predict disasters using various observational data.

The effectiveness and precision of AI approaches in disaster management rely significantly on the type and quality of data. Satellites, with their unique ability to capture extensive areas in a single image and access regions that are otherwise inaccessible to humans, particularly during disasters, are indispensable for effectively monitoring and forecasting catastrophic events. Moreover, observations across diverse spectral ranges yield scientifically meaningful insights relevant to conditions before and after disasters.

In recent years, the development in the field of satellites and image-analysis techniques has significantly enhanced the capability to manage major disasters and humanitarian crises. The International Charter Space and Major Disasters [11] and Copernicus Emergency Management Service [12] have crucial roles in providing timely and effective satellite-based disaster response. However, despite worldwide collaboration, there is still room for improvement in delivering ready-to-use information products, speeding up data delivery, and enhancing coordination among stakeholders due to the increasing number of satellite images and the specialized expertise required to analyze data from various sensors.

In this context, utilizing AI techniques to analyze satellite imagery becomes crucial. AI can effectively process and analyze these vast datasets, making it easier for users to gain rapid and accurate insights from satellite imagery. This ensures faster and more efficient disaster preparedness and response, making critical information accessible to all, regardless of their technical expertise.

This study will explore how satellites can be utilized at different stages of the disaster management cycle and identify which satellites are most suitable for these purposes. Additionally, we will examine which deep learning techniques (a subset of AI) can be employed at each stage, with a particular focus on reducing the impact of heavy rainfall-related floods and tropical cyclones. By integrating satellite technology with advanced AI methods, this study aims to develop a comprehensive framework, present case studies, and offer practical recommendations for future applications. This approach enhances disaster management efficiency, responsiveness, and resilience, contributing to ongoing global efforts in this field.

2. DATA AND METHODS

Disaster management aims to reduce potential losses from hazards and prepare for rapid recovery after a disaster (Fig.1). It is divided into a total of four stages: pre-disaster stages, prevention and preparedness, and post-disaster stages, response and recovery [13]. Prevention aims to minimize the impact of disasters through measures such as vulnerability analyses and public education. Preparedness involves the government's planning, implementing warning systems, and conducting emergency training. Response efforts focus on reducing the hazards a disaster creates with activities like search and rescue operations. Finally, recovery seeks to return the community to normalcy, utilizing grants and medical care to aid the process. All stages are repeated for each disaster, ensuring that preparation helps respond appropriately to the next disaster.

Each stage requires different satellite imagery specifications and applications for effective disaster management. In the prevention stage, disaster risk maps can be achieved using satellite imagery across various spectral bands. For instance, multispectral and hyperspectral images, using non-visible wavelengths, can be used to assess flood risks, identify landslide-prone areas, and map hazard zones. During the preparedness stage, satellite imagery is essential for optimizing evacuation solutions. High-resolution images can be used to map out evacuation routes, identify suitable locations for shelters, and assess the structural integrity of buildings and other critical infrastructure. In the response stage, real-time monitoring and rapid damage assessment are crucial. High-resolution satellite imagery provides detailed information on the extent of damage, helping to organize response efforts and allocate resources efficiently. In the recovery stage, satellite imagery is used to monitor and assess the progress of recovery efforts. It helps evaluate the effectiveness of reconstruction activities and ensure that rebuilding efforts are on track.

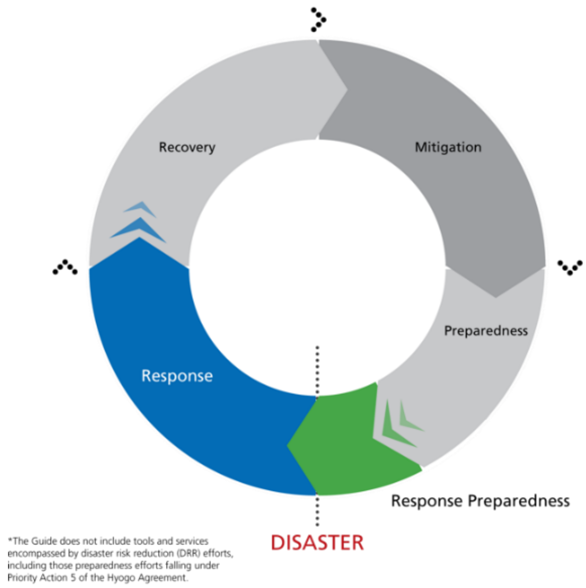

Figure 1– Disaster management cycle (source: UNOCHA)

2.1 Types of satellites

2.1.1 GEO and LEO

Among the satellites that observe the Earth, meteorological satellites can be divided into Geostationary Orbits (GEOs) and Low Earth Orbits (LEOs), including polar orbits.

Geostationary orbit satellites are located at relatively high altitudes of approximately 36 000 km. Therefore, they can observe almost half of the Earth's surface at any given time. This extensive coverage allows these satellites to provide continuous monitoring and valuable data for applications such as weather forecasting, environmental monitoring, and disaster management. Currently, operating meteorological satellites include GK2A (South Korea), GOES-17, 18 (USA), Himawari-9 (Japan), Meteosat-11 (EU), and FY-2H (China). They have a spatial resolution of 0.5 to 2 km and mainly use visible and infrared wavelength bands. Various bands allow for the observation of water vapor, clouds, atmospheric motion, extreme weather, etc.

LEO satellites typically orbit at altitudes between 160 to 1 000 km, according to the definition by the European Space Agency (ESA). These satellites are capable of capturing very high-resolution (1 km – 3 m) images due to their lower altitudes, which allow for more detailed observation of the Earth's surface. This capability makes them valuable in various fields, particularly in disaster detection and management. Sentinel-1, operated by the ESA, uses radar sensors to monitor changes on the Earth's surface regardless of weather conditions, making it useful for tracking the trail of floods, earthquakes, and landslides. The Landsat series, managed jointly by the US Geological Survey (USGS) and NASA, provides multispectral images to detect and analyze disasters such as wildfires, floods, and droughts. Terra and Aqua, part of NASA's Earth Observing System (EOS), utilize the MODIS sensor for global disaster monitoring, covering events like fires, floods, and hurricanes. PlanetScope, operated by Planet Labs, is a constellation of small satellites providing frequent and detailed imagery for disaster assessment and response.

Polar-orbiting satellites, a particular type of LEO satellite, cross over the South and North Poles and rotate around the Earth. This movement allows them to scan the entire surface of the planet as the Earth rotates beneath them. An example of such a satellite is NOAA-20 (JPSS-1), operated by the National Oceanic and Atmospheric Administration (NOAA) as part of the Joint Polar Satellite System (JPSS). NOAA-20 offers global coverage twice daily, which is essential for monitoring weather patterns, environmental changes, and natural disasters. Sentinel-3, operated by the ESA as part of the Copernicus Programme, is another example of a polar-orbiting satellite. Sentinel-3 focuses on ocean and land monitoring, providing data on sea surface topography, sea and land surface temperature, and ocean and land color.

2.1.2 EO and SAR

Electro-Optical (EO) satellites and Synthetic Aperture Radar (SAR) satellites are essential for monitoring and studying the Earth's surface. EO satellites use optical sensors to capture high-resolution images (less than 1 km) in various wavelengths of light, including visible and infrared, which are similar to photographs and intuitive to interpret. However, EO sensors are limited by weather conditions (e.g., cloud cover and fog) and daylight. In contrast, SAR satellites are active sensors that emit their signals and then measure the reflected signals bouncing back from the Earth's surface. These satellites use microwaves to penetrate clouds, allowing them to capture detailed images regardless of weather conditions or the time of day.

Examples of EO satellites include Sentinel-2 and Landsat-8. Sentinel-2, part of the ESA's Copernicus Programme, contains multispectral instruments that capture high-resolution optical images across 13 spectral bands. These images are used for land monitoring, vegetation, soil, and water cover, as well as urban areas. Landsat-8, a joint mission by NASA and the USGS, provides multispectral and thermal imagery widely used for environmental monitoring, agriculture, forestry, and disaster response.

Examples of SAR satellites include Sentinel-1 and RADARSAT-2. Sentinel-1, also part of ESA's Copernicus Programme, carries C-band synthetic aperture radar instruments, providing all-weather, day-and-night radar imagery for applications such as land deformation monitoring, flood mapping, and maritime surveillance. RADARSAT-2, operated by the Canadian Space Agency (CSA), carries a C-band SAR instrument used for ice monitoring, agriculture, disaster management, and defense.

Table 1 – Satellite details (source: WMO OSCAR)

Satellite Name	Orbit/ Type	Resolution	Cycle	Providing Agency
Sentinel-1	LEO/SAR	4–80 m	5 days	ESA
Sentinel-2	LEO/EO	10–60 m	10 days	ESA
Sentinel-3	LEO/ multi-instrument	0.3–2 km	1-2 days	ESA
Terra/ Aqua	LEO/EO	0.25–1 km	Twice/ day	NASA
PlanetScope	LEO/EO	3–5 m	daily	Planet Labs
Landsat-8	LEO/EO	15-30 m	16 days	NASA
RadarSat-2	LEO/SAR	3–100 m	1 week	CSA
GK2A	GEO/Multi-spectral	0.5-2 km	Every 10 min	KMA
Himawari-9	GEO/Multi-spectral	0.5–2 km	Every 10 min	JMA
GOES-17,18	GEO/Multi-spectral	0.5–2 km	Every 15 min	NOAA
Meteosat-11	GEO/Multi-spectral	1-4.8 km	Every 15 min	EUMETSAT
FY-2H	GEO/Multi-spectral	1.25–5 km	Every 30 min	CMA

2.2 Early warning system and disaster risk reduction

2.2.1 Prevention and preparedness

2.2.1.1 Necessity of early warning systems

According to the WMO, about 30% of people in the world are still not covered by early warning systems. An 'Early Warning System (EWS)' is an integrated system of hazard monitoring, forecasting, communication, and preparedness activities to take timely action to reduce disaster risks [14]. EWS is known as the most effective tool to mitigate damage from climate change-related disasters. If an early warning is issued within 24 hours, damage can be reduced by 30%[1] .

However, most people who are vulnerable to disasters and do not receive early warnings live in Small Island Developing States (SIDS), Least Developed Countries (LDCs), and Africa. In those countries, the coverage of EWS is minimal, and the availability of weather observation systems is also severely limited. Traditional disaster forecasting relies on radio, television, sirens, etc., which are likely to not work properly in disaster situations or be transmitted immediately after a disaster. These countries have few meteorological observation facilities and trained personnel, making it difficult to make timely and accurate forecasts. Extreme weather events and related disasters, such as heat waves, floods, and storms, are increasing around the world, exacerbated by climate change [15]. Unmitigated

[1] WMO EWS (https://wmo.int/topics/early-warning-system)

climate change is estimated to reduce global GDP by more than 20% by 2100 [16]. Damage can occur more immediately and significantly, especially in countries where EWS are unavailable.

In response to this necessity, the UN announced the Early Warning for ALL (EW4ALL) initiative to improve the end-to-end and Multi-Hazard EWS (MHEWS) across the four essential pillars (Fig. 2) at COP27 (2022)[2] : disaster risk knowledge, observations and forecasting, dissemination and communication, and preparedness to respond. The final goal of this initiative is to cover everyone everywhere by 2027. They also encourage the use of technologies like AI and 5G networks to support the attainment of the initiative

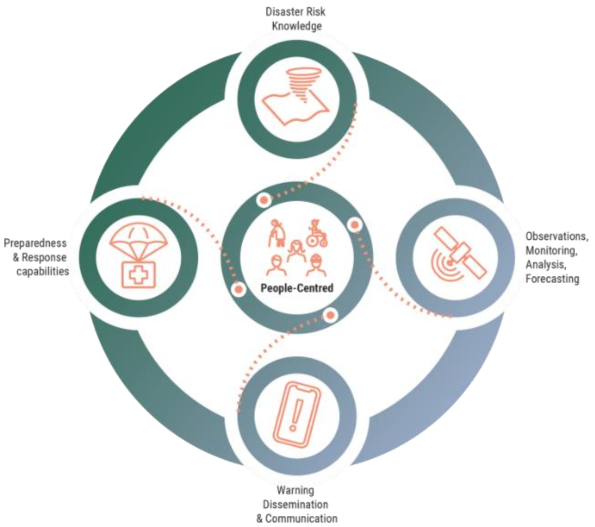

Figure 2 – Early Warning for ALL value chain diagram (source: WMO)

2.2.1.2 Real-time monitoring and forecasting of hazards

The primary advantage of using AI-based models in early warning tasks is that they significantly reduce computational time while maintaining higher accuracy. These models can analyze data from various sources, such as satellite imagery, weather station data, and social media feeds, providing a comprehensive and data-driven approach to early warning and disaster prediction. This capability is particularly important because disasters can arise from complex and interrelated causes. Utilizing diverse data sources allows for a more holistic understanding and better prediction of such events, enhancing the ability to respond effectively to various disaster scenarios. Satellites were traditionally used solely to monitor real-time conditions and to improve the accuracy of the initial conditions for numerical weather prediction models. However, with the advancement of artificial intelligence, technologies have been developed that enable the prediction of future events using satellite data itself. To leverage these advantages, we have developed high-resolution AI analytics services for disaster monitoring and forecasting: WeatheO_Rain, WeatheO_Cloud, and WeatheO_Typhoon.

WeatheO_Rain uses high-resolution (2 km) geostationary satellite imagery[3] to generate AI-based radar rain products, enabling effective precipitation monitoring in areas lacking weather radar coverage. Weather radars are crucial for monitoring disasters related to heavy rainfall, but they are expensive to install and operate, require experts for data processing, and can only be installed on land. Due to these limitations, attempts have been made to monitor heavy rainfall using geostationary satellites, but their accuracy has been low, limiting their utility. However, the deep learning approach [17] used for WeatheO_Rain has significantly improved the accuracy of satellite-derived rainfall data, demonstrating approximately twice the accuracy performance compared to the level 2 products currently provided by operational geostationary satellites, allowing for more effective and continuous monitoring of rainfall-related disasters over large areas. Additionally, it is free from the geographical constraints of ground-based weather observation systems, making it possible to estimate rainfall in ocean and mountain regions.

Fig. 3 shows the comparison of observation and AI-generated results. Fig. 3(a) shows the rain rate from radar observation, (b) from a geostationary satellite product, and (c) generated by the WeatheO_Rain model. The figures indicate that radar observations are considered ground truth but have a limited observation area. In contrast, satellite-derived products can cover larger areas but tend to overestimate rainfall. Our product combines the advantages of both radar and satellite data. The results of WeatheO_Rain show a high correlation with radar data in terms of rain patterns and intensity, even in areas where radar coverage is limited.

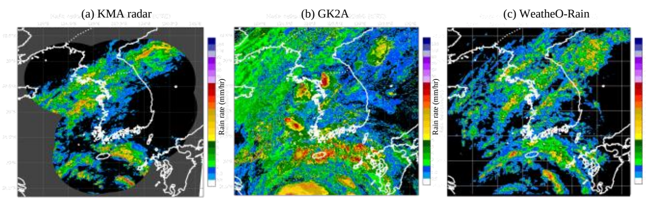

Figure 3 – Rain rate (mm/hr) at 2022-09-05 00:00 UTC, Typhoon Hinnamnor case. (a) is the radar product from a ground-based weather radar system, (b) is the satellite- level 2 product from the Korean geostationary satellite, GK2A, and (c) is our result from WeatheO_Rain.

[2] WMO EW4ALL (https://earlywarningsforall.org/site/early-warnings-all)

[3] GK2A/AMI data used in this study is available on https://datasvc.nmsc.kma.go.kr/datasvc/html/main/main.do?lang=en (accessed on 2 January 2025).

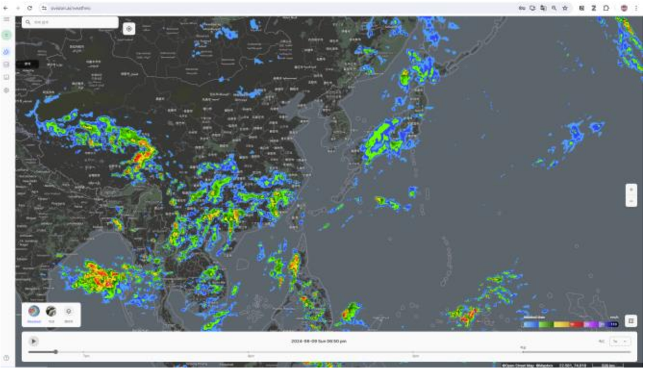

Figure 4 – A screenshot of the WeatheO_Rain demo

Fig. 4 is a screenshot of the WeatheO_Rain interface for the Asia-Pacific region. WeatheO_Rain demonstrates the ability to provide radar-like information seamlessly, even in areas without radar coverage, without any spatial discontinuities. WeatheO_Rain was initially developed for East Asia but has since been extended and validated in Africa and South America. Fig. 5 shows the result in Africa with the European geostationary satellite, Meteosat Second Generation (MSG). In September 2023, when the heaviest flooding in a decade occurred in Libya, the region lacked adequate weather radar systems to observe the approaching rain systems. However, with WeatheO_Rain, we were able to generate reliable monitoring maps of rain rate and storm location.

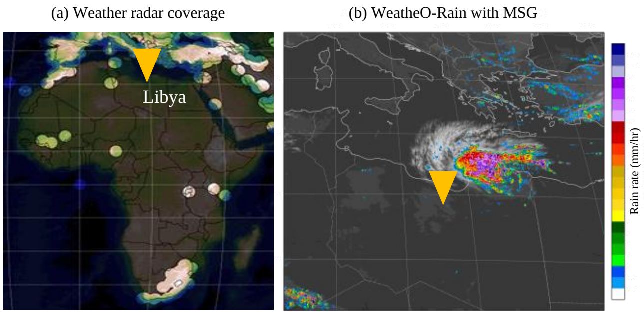

Figure 5 – (a) weather radar coverage (bright area) in Africa[4] , and (b) rain rate at 2023-09-11 00:29 UTC, Mediterranean Storm Daniel case, at Libya region. WetheO-Rain can generate radar-like rain products without radar observation systems.

WeatheO_Cloud predicts the future frames of geostationary satellite imagery up to 20 hours in advance. The deep learning approach enables predictions of future atmospheric states using only past observation data. This product employs the Deterministic Guidance Diffusion Model (DGDM) [18], which combines AI-based deterministic and probabilistic forecasting methods. The model's results effectively demonstrate its ability to capture cloud movements, formations, and dissipation. Meanwhile, traditional methods, such as extrapolation techniques, are useful for short-term cloud movement predictions but have limitations in forecasting cloud development or dissipation.

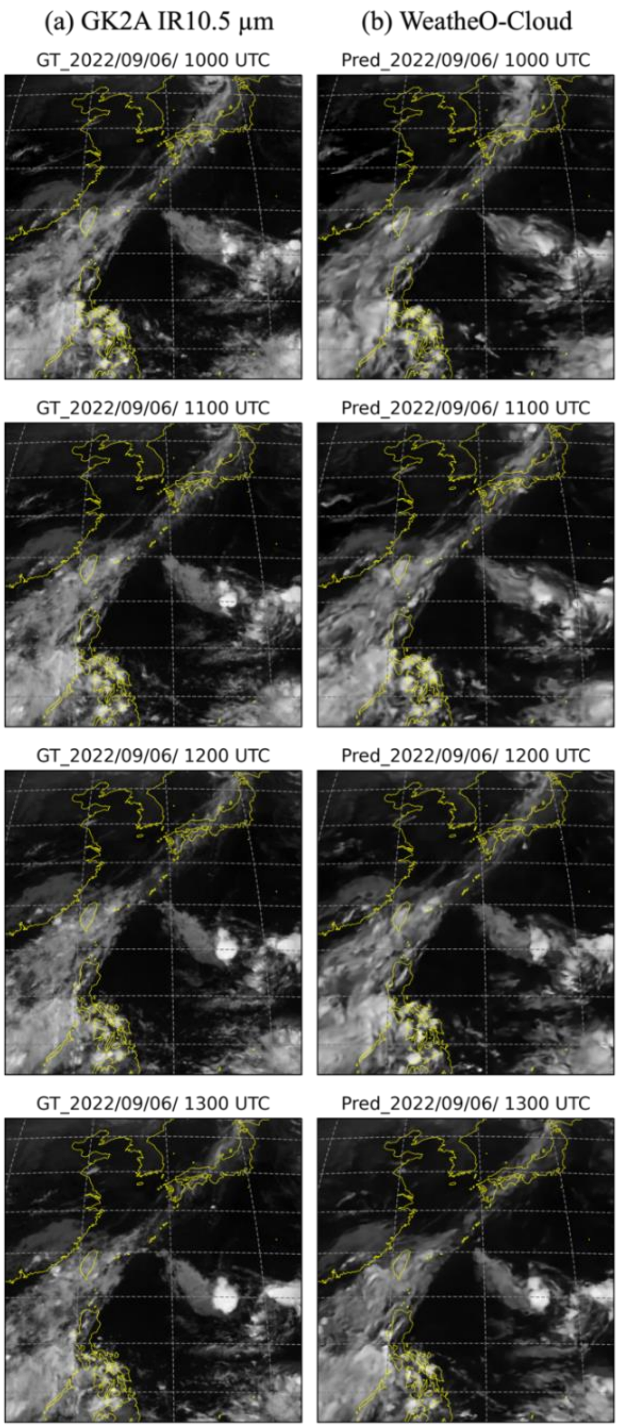

Figure 6 – Comparison of satellite imagery and WeatheO_Cloud results. (a) is infrared 10.5 µm channel images from GK2A, and (b) is WeatheO_Cloud predicted results. We input ten satellite images (2022-09-06 00-09 UTC) and predict 20 satellite images (2022-09-06 10 UTC - 2022-09-07 05 UTC). Bright and gray areas mean diverse types of clouds.

Similarly, physics-based models simulate atmospheric processes but cannot resolve clouds at the necessary scale, leading to parameterization, which limits detailed cloud information. However, with deep learning technology, it is

[4] Image is cropped from Saltikoff, Elena, et al. (2019)

possible to observe detailed cloud development and movement using high-resolution satellite imagery at 2 km. Recently, geostationary satellites with resolutions up to 250 m have been utilized, raising expectations that learning from high-resolution cloud information will enhance our understanding of cloud physics. Additionally, because deep learning can integrate and learn from diverse datasets, incorporating various cloud observations is expected to further improve accuracy.

WeatheO_Cloud can provide timely warnings, enabling better preparedness and response strategies to mitigate the impacts of severe weather events, including rapidly developing convective clouds and intense thunderstorms. This improvement ensures more accurate and effective early warning systems, enhancing overall disaster response capabilities.

Fig. 6 shows the forecasting results from the WeatheO_Cloud model. Compared with (a) GK2A satellite imagery, (b) WeatheO_Cloud results show similar cloud movements to the ground truth. Previous video prediction models [19, 20] could predict future imagery to some extent but struggled to capture the generating or dissipating processes of cloud cells. Consequently, the total amount of cloud predicted by previous models decreased as prediction time increased. Our model alleviates this limitation, successfully predicting the development process of cloud cells in the middle of the Philippine Sea in terms of location, size, and intensity.

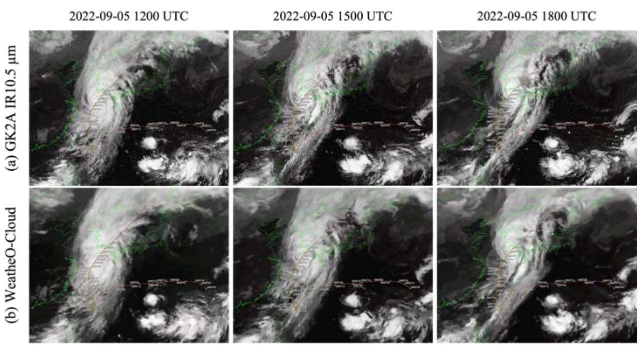

Figure 7 – Satellite imagery prediction results by WeatheO_Cloud (b) compared with GK2A's infrared images (a). The case is Typhoon Hinnamnor. The results show satellite images from 2022-09-05, 1200 – 1800 UTC, predicted at 3-hour intervals based on GK2A IR 10.5 µm data from 0200 – 1100 UTC. The red line indicates the typhoon track according to IBTrACS .

We also leveraged WeatheO_Cloud to track the typhoon trajectory shown in Fig. 7. In the satellite imagery predicted for up to 20 hours, the center of the typhoon appears to be correctly aligned with the red line, which represents the best typhoon track. In other words, we can determine the typhoon's path and development up to 10 hours in advance. This capability could provide a basis for decision-makers to support quick and informed decisions. The quantitative performance results of this prediction model can be found in [18].

WeatheO_Typhoon provides future typhoon track forecasts for up to 72 hours. This service uses the LT3P model [7], which introduces a novel approach by utilizing real-time Unified Model (UM) data instead of relying on reanalysis data (ERA5), which is not available in real time. It features a physics-conditioned encoder to accurately capture atmospheric dynamics and a bias correction mechanism to improve the accuracy of UM data. This model uses prediction results from numerical weather prediction models as 2D map-type image inputs while simultaneously integrating 1D best track information (longitude and latitude) of typhoons. This approach demonstrates the advantage of deep learning in effectively combining and leveraging two distinct types of data, a capability that was not feasible with previous physics-based models.

Fig. 8 shows the prediction results of the LT3P model for four typhoon cases (Kalmaegi, Lingling, Danas, and Faxai) occurring in the Asia-Pacific region. Our model's prediction (pink line) shows a similar direction and speed to the best track data (green line) over a 72-hour typhoon trajectory. As seen in Fig. 8, the LT3P model does not follow the errors commonly observed in most data-driven methodologies and produces results similar to numerical weather prediction model outcomes by constraining physical characteristics based on meteorological background fields. Moreover, in the stochastic figures, the spread of the predictions is narrow, which means that the results are consistent and reliable.

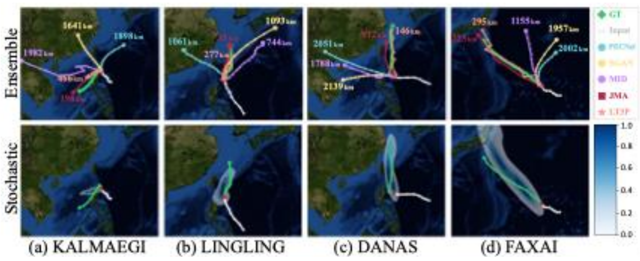

Figure 8 – Typhoon trajectory prediction results by the LT3P model. The ensemble figure shows each model's trajectory prediction and the difference in final distance with ground truth (green). The stochastic figure maps the prediction probabilities generated by the LT3P model [7].

The WeatheO series is based on deep learning methods and requires minimal computational capacity and time, making it highly efficient and accessible. Each model in the series can be used independently, but when combined, they significantly enhance their usability and effectiveness. These models can predict precipitation by utilizing future satellite imagery, enabling precise forecasting of rainfall patterns. Furthermore, they can identify areas prone to typhoon damage, providing crucial information for disaster preparedness and response. Since geostationary satellites offer continuous and wide-reaching coverage, this capability is particularly valuable for monitoring dynamic weather systems and providing real-time data essential for accurate prediction. In addition, geostationary satellites are expected to ensure comprehensive Earth observation, effectively eliminating spatial constraints in weather forecasting and bolstering the EW4ALL initiative.

2.2.2 Response and recovery

Through the WeatheO series and weather satellite data, we can predict various disasters in advance and mitigate their impact. For instance, WeatheO_Rain and WeatheO_Typhoon play vital roles in forecasting and preparing for disasters. Additionally, high-resolution satellite imagery is crucial for effective disaster response and recovery, providing detailed insights that are essential for assessing post-disaster conditions.

While optical EO satellites are highly valuable, their use can be limited under certain conditions, such as cloudy weather or at night time. In these scenarios, SAR satellites are indispensable due to their ability to penetrate clouds and function even without sunlight. However, analyzing SAR data can be complex, and AI-based methodologies like SAR2EO offer significant advantages by simplifying data interpretation and extracting actionable insights.

To enhance disaster management at all stages, we are integrating high-resolution satellite imagery from SAR and EO sensors with AI capabilities into the WeatheO platform. This comprehensive approach enables rapid and effective responses during and after disasters, minimizing damage and improving recovery efforts.

2.2.2.1 Enhancing satellite imagery utilization for timely damage detection

Following a disaster, swift responses are crucial to minimize damage. The response process aims to promptly and effectively deploy resources such as medical aid, equipment, and shelters. A critical initial step involves the timely detection of disaster-affected areas. Satellites are highly useful for this purpose, assessing damage over large areas at a national or city scale, but not all satellites provide high-resolution images down to tens of centimeters, which is typically provided by companies such as MAXAR or Planet (in the private sector). This level of detail is essential for thorough assessments but can be costly to acquire.

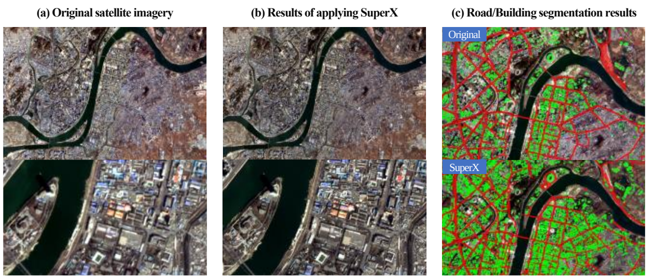

Figure 9 – SuperX result.: On the left is the original satellite image, the middle shows the result after applying SuperX, and the two images on the far right depict extracted roads and buildings; the upper image is based on the original image, while the lower one is derived from the SuperX-enhanced image.

An economical alternative involves leveraging publicly-available satellite data, such as from Sentinel satellites. The main limitation of Sentinel data is its 10-meter resolution, which lacks detail. In such cases, AI-based super-resolution techniques can be invaluable. We started our SuperX service to provide enhanced satellite images with high quality. Enhanced resolution allows for finer details to distinguish the level of damage and for better edge detection to accurately assess the extent of the damage. As shown in Fig. 9, we can detect more roads and buildings through the image processed by SuperX. This is well-suited for comparing conditions before and after a disaster.

Furthermore, a significant portion of the Earth's surface is obscured by thick clouds, which can make it difficult to detect damage such as floods and landslides that occur in such conditions. In this situation, SAR imagery, which is available in all weather and time conditions, is utilized. However, SAR imagery often contains impediments to interpretation, like speckle noise, which significantly extends the time required to interpret the data without additional EO imagery. To solve this problem, we propose a SAR2EO model based on generative AI, which can effectively convert SAR into EO imagery [21]. This method, which is intended to easily and quickly detect inundated areas during flood events, generates photographic-like EO images (Synthetic EO) from SAR noise using a diffusion model. The results can then be passed on to governments or NGOs, which can be used to prioritize and make decisions. SAR2EO technology can be similarly utilized to identify damages such as landslides and typhoons as well as floods caused by thick cloud cover accompanying heavy rain.

Fig. 10 shows the input pair of EO and SAR imagery, as well as the synthetic EO imagery generated by our SAR2EO model. The water system area is clearly visible in the SAR imagery (b), but it is obscured by clouds in the EO imagery (a). Using EO imagery alone makes it difficult to identify a flooded area until the clouds clear. Therefore, the synthetic EO (SynEO) image generated with the SAR2EO model (c) can help decision-makers understand disaster situations more rapidly and accurately.

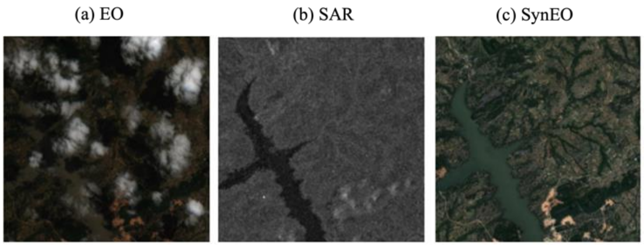

Figure 10 – SAR2EO result. (a) EO satellite imagery, (b) SAR satellite imagery, and (c) SynEO (Synthetic EO) image generated from the SAR image in (b). The SAR image in (b) has been preprocessed to denoise from the original SAR imagery [21].

While SAR2EO facilitates large-scale detection of disaster impacts, a more detailed assessment is often required to understand the specific damage to individual structures. This is where the Building Damage Assessment (BDA) model plays a critical role. SAR2EO identifies regions impacted by disasters, such as floods or landslides, while BDA provides granular insights into the structural damage of buildings within those regions. Together, these technologies offer a comprehensive disaster response framework, enabling governments and NGOs to allocate resources efficiently and prioritize recovery efforts. By integrating outputs from SAR2EO and BDA, decision-makers can achieve a more holistic understanding of both the broader disaster impacts and localized damage, ensuring a more effective and timely disaster response.

2.2.2.2 Rapid damage detection methods using AI

Landslides, tropical cyclones, and earthquakes can lead to the collapse of buildings and roads, including major infrastructure such as schools, hospitals, government offices, and major roads like highways. In disaster situations, accessing affected areas can be challenging due to additional risks and the destruction or inaccessibility of major roads. In these cases, satellites can effectively capture images of the disaster regions. Moreover, satellites are highly effective in covering wide areas impacted by disasters in a single shot, offering various resolutions ranging from 30 cm to several meters. This capability makes them an invaluable tool for comprehensive disaster assessment and response.

For the analysis and assessment of the impact of disasters with satellite imagery, AI can be utilized to rapidly process and analyze the data, significantly speeding up the evaluation process. Until now, damage assessment results typically took several days to weeks to obtain, mainly relying on surveys, reports from residents in the affected areas, and manual assessments by insurance companies. These traditional methods involve on-site investigations of damage and casualties, which can lead to secondary risks and they are time-consuming. Devoid of associated risk after a disaster, using satellite imagery and AI for rapid damage assessments will enable quick reconstruction and mitigation in disaster-affected areas. From disaster alerts to satellite image capture, AI-based analysis, and result dissemination, the entire process can be automated without human intervention, thereby enhancing the efficiency and effectiveness of the response.

In these contexts, recent studies suggest AI-based Building Damage Assessment (BDA) methods for detecting buildings damaged by disasters and classifying them according to the degree of damage [22, 23, 24]. Fig. 11 shows the result of our BDA model [22], applied to the aftermath of a tornado in the USA using high-resolution optical imagery. In [22], we exploit transfer learning with a simple bagging method to solve the data imbalance problem. Using this model, we can detect the most damaged places in near-real time and, in combination with a road segmentation and change detection algorithm [22, 23], obtain information on the most effective evacuation routes. We have also tested this model for wildfires and earthquakes and confirmed that as long as imagery of the damaged buildings is available, the analysis results can be obtained within minutes. This information can be used by local governments, NGOs, and relief teams for rapid decision-making.

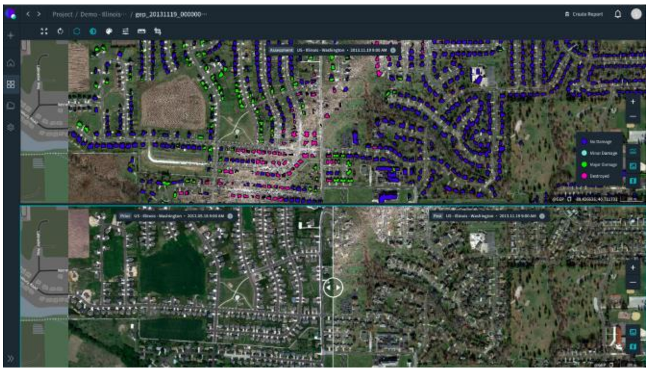

Figure 11 – Detection results of the BDA model. Each color mark shows the degree of building damage: blue – no damage, cyan – minor damage, green – major damage, and pink – destroyed. The image in the upper section results from applying the BDA model after the hurricane. The left column below shows satellite images before the hurricane, and the right column shows post-disaster images.

3. FUTURE RESEARCH AND CONCLUSIONS

We have introduced solutions that leverage satellite data and AI methods across the entire disaster management cycle: prevention, preparedness, response, and recovery. Each stage utilizes different satellite types with various channels, resolutions, and orbits. With the abundance of satellite imagery, AI-based models significantly enhance disaster management by reducing computational time and improving accuracy. Our AI analytics services, including WeatheO_Rain, WeatheO_Cloud, and WeatheO_Typhoon, utilize high-resolution geostationary satellite imagery for real-time monitoring and forecasting of hazards, ensuring timely and accurate early warning systems. Additionally, our SAR2EO model converts SAR imagery into synthetic EO images, providing clear views of flooded areas even under cloud cover. AI-based Building Damage Assessment (BDA) models can detect and classify building damage in near-real time, facilitating quick reconstruction and mitigation. We have validated these services for various disasters, confirming that analysis results can be obtained within minutes. These solutions have the potential to significantly enhance the efficiency of disaster responses by reducing information gaps and saving critical time.

For even faster analysis, there is a need to develop processes that enable the rapid analysis of satellite imagery directly on board the satellite, with results promptly transmitted to ground stations. This would significantly reduce the time lag between image capture and data utilization, further enhancing the efficiency of disaster response. Subsequently, it is imperative to verify the explainability and reliability of AI-based model predictions. Given that disaster prediction is directly related to the potential for loss of life and property, these models should not be used in isolation but should be developed to support the decision-making process of skilled experts such as weather forecasters and rescue teams. To this end, we employ generative AI models to evaluate various scenarios, thereby providing probability maps that enable experts to focus solely on reliable prediction outcomes

[7, 18]. This approach ensures that AI-generated insights are integrated with expert knowledge, leading to more robust and trustworthy disaster management strategies.

Traditionally, disaster alerts to remote areas have been achieved using community radio stations. However, with the recent increase in mobile device penetration, warnings can now be transmitted rapidly through mobile applications. Integrating AI-based disaster management solutions with app-based alerting systems can significantly enhance the effectiveness of disaster response. This app-based approach not only facilitates timely disaster notifications but also provides critical information on response procedures, evacuation routes, first aid stations, and other essential services. Also, by incorporating features that allow users to share and report their situations, mobile applications can become interactive platforms for collecting user information. This user-generated data can be invaluable for verifying and improving the accuracy of satellite analysis.

Finally, while technological advancements are crucial, these solutions must be actively adopted by government agencies, local governments, NGOs, and other stakeholders involved in disaster prevention. AI and satellite-based solutions can address the gaps in human resources and observational equipment that are particularly prevalent in developing countries. By cooperating with various international funds (e.g., Green Climate Fund and World Bank), international organizations (World Meteorological Organization and International Telecommunication Union), and advanced solutions, the Early Warning System for All initiative can be successfully achieved.

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