Automatic Near Real-Time Web-based Flood Monitoring System with Multitask Learned Water Detection Deep Learning Model

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Abstract *Extreme rainfall events, characterized by substantial precipitation in a short period, have increased in frequency and intensity as climate change intensifies. Disaster response capabilities have become more crucial due to the increasing rate of unpredicted flood events. These extreme rainfall patterns necessitate the (near) real-time identification of affected areas to support decision-making and minimize damages. Synthetic Aperture Radar (SAR), unaffected by cloud cover and lighting conditions, is an optimized remote sensor for detecting flood occurrences and their extent. However, for real-time analysis of satellite images and support for disaster response, an automated flood monitoring system is required. In this study, we employed Amazon Web Services(AWS) to automatically acquire and preprocess Sentinel-1 satellite images of South Korea, followed by the use of AI deep learning models to detect water bodies in (near) real-time. Considering that flood-prone area of Korea typically occur along small streams, we adopted Multitask learning in medium-resolution (20m) Sentinel-1 images to detect fine rivers. By assigning two tasks (water body detection and the extraction of river embankment centerlines) to two decoders sharing a single encoder, we enhance the detection rate of small streams. The detected water bodies are compared against geographic information databases, such as those for river embankments and reservoir areas, to classify flood-affected regions. The satellite images and analyzed results are automatically transmitted to the web-based visualization system (Satellite Current View; SCV). SCV also provides additional spatial data, including roads, bridges, urban planning maps, and land use maps, to offer further information on disaster-affected areas. We have analyzed and provided Sentinel-1 images of actual flood events in Korea, especially 2020 and 2023 flood events. Additionally, high-resolution SAR images captured by ICEYE and Umbra are also used to analyze flood-affected areas in Korea and are visualized through SCV.*

Keywords: Sentinel-1, Flood Monitoring, Automatic Disaster Monitoring, Water detection

Introduction

Human-induced climate change is increasingly exacerbating extreme weather events, notably episodes of intense rainfall. These rainfall events are marked by substantial precipitation over a short period, often surpassing the environment's natural capacity to absorb or manage the resulting influx of water. The disaster management cycle is composed of four stages: mitigation, preparedness, response and recovery(Altay & Green III, 2006). With the growing frequency and unpredictability of extreme rainfall events, the response and recovery stages within the disaster management cycle are becoming increasingly critical. These extreme rainfall patterns necessitate the (near) real-time identification of affected areas to support decision-making and minimize damages.

As an active microwave sensor, Synthetic Aperture Radar (SAR) penetrates clouds with its own energy and detects the reflected signals. This capability allows SAR to operate under all weather conditions, making it highly suitable for continuous disaster monitoring, particularly in adverse weather and cloud-covered environments. SAR is highly sensitive to the roughness of surfaces. Flat surface reflects radar signals away from the sensor, resulting in low backscatter. In contrast, rough surface has higher backscatter and appears brighter in SAR imagery. As the inland water has usually smooth surfaces, we can monitoring detect flood occurrences and their extent.

However, for real-time analysis of satellite images and effective disaster response, the manual interpretation of SAR data is not feasible due to the need for immediate decision-making. As a result, the development of an automated SAR-based flood monitoring system is essential to support disaster management agencies. The automated flood monitoring system includes acquiring and preprocessing SAR images, detection of water areas, and providing near-instantaneous updates on flood extent with geospatial data.

In this study, we employed Amazon Web Services (AWS) to construct the automated end-to-end real time web-based flood monitoring system. AWS provides flexible high-performance computing capabilities for processing massive satellite images through the deployment of cloud-based virtual machines, which enables a robust technological foundation for rapid image acquisition and analysis.

Given that flood-prone areas in Korea are typically located along smaller rivers, we adopted a multitask learning-based AI model to automate water detection. The model aims to both water area detection and the river embankment centerline extraction with two decoders sharing one encoder, which enhances the accuracy of small river detection. After water area analysis, the result automatically visualized in web-based visualization system (Satellite Current view; SCV[1]). As SCV provides additional geospatial data including land use maps, roads, we could extract extra information on disaster-affected areas. We analyzed Sentinel-1 images captured in Korea during heavy rain season. Additionally, high-resolution SAR images by Umbra is also analyzed and visualized through SCV.

Literature Review

[1] https://scv.snu.ac.kr/

In recent years, advancements in remote sensing technology have significantly enhanced disaster mapping capabilities, allowing for more efficient monitoring and management of natural disasters. NASA's Disasters Mapping Portal[2](Lucey et al., 2021) is a prominent system that integrates remote sensing data from sources such as NASA, NOAA, and the US Geological Survey, offering near real-time tracking and analysis of environmental conditions, particularly during events such as hurricanes, floods, and wildfires. The platform's GIS-based functionality enables users to visualize disaster impacts and track recovery efforts. Additionally, the United Nations Platform for Space-based Information for Disaster Management and Emergency Response(UN-SPIDER) [3] (Zollner, 2018) platform has made strides in providing space-based information for disaster management, especially in aiding developing countries with disaster risk reduction and emergency response. This platform facilitates access to satellite data for hazard mapping, risk assessments, and ongoing monitoring, making space-based technologies more accessible to governments and relief organizations globally.

If we limits the disaster to flood, there are several interactive web maps for flood monitoring. Dartmouth Flood Observatory provides the Dartmouth Flood Observatory inundation maps(https://floodobservatory.colorado.edu/index.html)(Kettner et al., 2021) based on optical satellite imagery(MODIS) with event-based Sentinel-1.This map shows active floods comparing with historic flood record. Similarly, NASA also map MODIS NRT Global Flood Product(MCDWD)[4](Policelli et al., 2017), which automatically produces floodwater extent of active floods for near-real time based on MODIS optical imagery.

However, global flood monitoring systems often overlook floods in Korea, as the country's river systems and flood-prone areas are relatively smaller in scale compared to other regions. Also, the topography of Korea makes the detection more difficult. Therefore, there is a need for flood monitoring that optimized in Korea regions.

Convolutional Neural Networks(CNN) has demonstrated its powerful feature extraction capabilities in SAR water detection(Guo et al., 2022). Many image segmentation AI models, including Fully Convolutional Networks(FCN)(Long et al., 2015), U-Net(Ronneberger et al., 2015), HRnet(Wang et al., 2020), are applied in SAR water detection and exhibit the

[2] https://disasters-nasa.hub.arcgis.com/

[3] https://www.un-spider.org/

[4] https://go.nasa.gov/3OiKtYB

accuracy(Kang et al., 2018; Kim et al., 2021). Especially U-Net, which has U-shaped symmetrical architecture, is widely used(Denbina, 2020 #9)(Lalchhanhima et al., 2021; Pai et al., 2019; Verma et al., 2021). The encoder path progressively captures high-level features through a series of convolutional and pooling layers, while the decoder path performs up-sampling to recover spatial details and produce pixel-wise segmentation maps. The skip connections between corresponding layers of the encoder and decoder paths allow the network to retain fine-grained spatial information that would otherwise be lost during the down-sampling process.

Despite significant progress in water segmentation, detecting smaller streams remains a challenge, primarily due to scale imbalances in the segmentation process. To mitigate this issue, we propose a multitask learning framework that simultaneously performs water segmentation and embankment centerline extraction. Multitask learning involves training a single neural network to handle multiple related tasks concurrently, rather than training individual models for each task(Zhang & Yang, 2018). This approach enables the network to leverage shared information across tasks, which can enhance the overall performance.

In the field of remote sensing image segmentation, multitask learning is still in its early stages. Limited research has been conducted, particularly in areas such as road and centerline extraction from optical imagery(Alshaikhli et al., 2021; Lu et al., 2022) and Synthetic Aperture Radar (SAR) images(Wei et al., 2021). Previous studies have demonstrated the potential of multitask learning in improving segmentation outcomes. For example, (Alshaikhli et al., 2021) compared different multitask learning models for road and centerline extraction, showing that a one-encoder-two-decoder architecture with an attention gate yielded improved predictions. The attention gate helped transfer essential features between the encoder and each decoder, contributing to more accurate results. (Lu et al., 2022) utilized a cascade multitask framework to simultaneously extract roads, centerlines, and edges from optical satellite images. By combining multiscale features with the road branch output, and employing topology-aware learning alongside hard example mining loss, the model achieved state-of-the-art performance, particularly in complex urban environments. Additionally, centerline extraction from SAR images using ordinal regression and a novel road-topology loss function demonstrated enhanced network connectivity and segmentation completeness by predicting discrete distance labels for centerlines(Wei et al., 2021).

These studies underline the potential of multitask learning in remote sensing, especially for complex segmentation tasks that require more than just boundary delineation, such as extracting intricate topological features like centerlines.

Methodology

a. Sentinel-1 acquisition and preprocessing

The acquisition of new Sentinel-1 data is available through the Sentinel-1 Registry of open data(https://registry.opendata.aws/sentinel-1) on AWS. Sentinel-1 data are updated regularly within few hours after they are available on Copernicus OpenHub. When the new Sentinel-1 of Korea peninsula are noticed, the GRDH SAR images are automatically downloaded and transferred to Amazon Simple Storage Service (Amazon S3) and a trigger for analysis is generated.

b. Multitask learned SAR water detection AI model

We utilized Synthetic Aperture Radar (SAR) imagery from the freely accessible Sentinel-1 satellite, in Interferometric Wide (IW) mode High-Resolution Ground Range Detected (GRD-H). To minimize the impact of topographic variations, we applied radiometrically terrain-corrected Gamma naught VH, VV polarizations, and local incidence angles, which served as input layers. The label dataset was derived from the Landcover Map provided by the Ministry of Environment of South Korea and was synchronized with the corresponding aerial orthophotos to ensure accurate ground-truth data. In total, 93 Sentinel-1 images were used to construct 4,056 patches training dataset. For centerline label we obtained shapefiles of river embankments and reservoirs from the National Geographic Information Institute. A Geographic Information System (GIS) tool was employed to extract the centerlines. Figure 1 depicts the three components of the training dataset: SAR input images, segmented water labels, and river embankment centerlines.

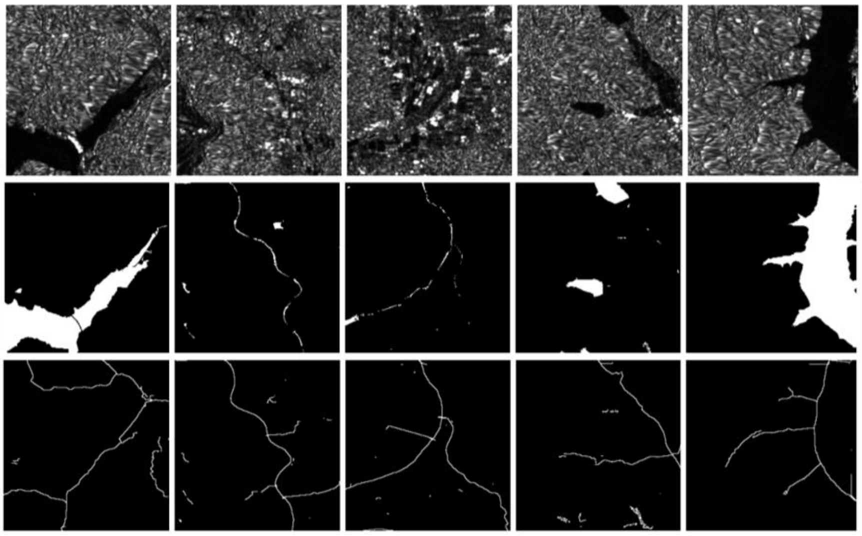

Figure 1: The examples of training dataset: (from top to down) SAR, water label, centerline label.

For water detection, we propose a dual-decoder U-Net architecture capable of performing both centerline extraction and waterbody segmentation using satellite imagery. The model is composed of an encoder and dual decoders, enabling simultaneous boundary and area prediction with enhanced precision. The encoder extracts multi-scale feature maps from the input image by progressively downsampling the spatial dimensions while increasing the feature representation. It consists of five convolutional blocks, each followed by max pooling. Each convolutional block comprises two 3x3 convolution layers, batch normalization, and ReLU activation. As we move deeper into the encoder, the number of channels increases, allowing the network to capture more complex and abstract features. The proposed U-Net model includes two separate decoders: a "centerline decoder" for water centerline extraction and a "segmentation decoder" for waterbody area segmentation. Both decoders employ a U-Net-like upsampling structure, utilizing skip connections to restore spatial resolution while combining low- and high-level feature maps from the encoder. The Centerline Decoder performs a series of upsampling and concatenation steps, with each stage consisting of two 3x3 convolution layers, to progressively reconstruct the spatial details. The output layer applies a 1x1 convolution followed by a sigmoid activation function to produce the binary centerline map. The Segmentation Decoder, while similar in structure to the centerline decoder, introduces an attention mechanism that leverages the centerline information from the centerline decoder to guide the segmentation process. Specifically, the feature maps from the encoder are multiplied with the output of the centerline decoder to refine the segmentation prediction. The final output of the segmentation decoder is generated using a 1x1 convolution followed by a sigmoid activation function, producing the segmented water area.

Each decoder is optimized with a distinct loss function. For the centerline decoder, we employ Binary Focal Cross-Entropy loss, while Binary Cross-Entropy loss is applied to the segmentation decoder. The loss of segmentation decoder are three-times weighted to balance the contributions with stable training.

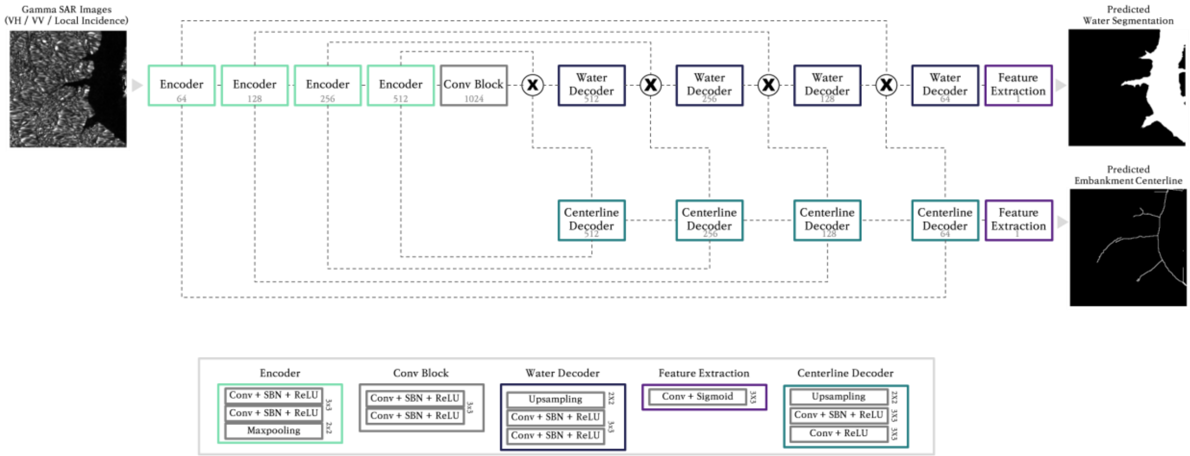

Figure 2: The architecture of multitask water segmentation framework, which is composed of the water segmentation decoder and the embankment centerline extraction decoder.

c. Visualization of Flood monitoring with web-based Satellite Current View(SCV)

After the trigger of new Sentinel-1 images acquisition generated, end-to-end Flood monitoring function is activated through AWS Lambda. AWS Lambda is a serverless computing service with event-driven execution. New Sentinel-1 images are radiometrically calibrated and geometric corrected and produced radiometrically terrain-corrected Gamma naught VH, VV, and the local incidence angle. The water detection using AI model described in section b is activated on the preprocessed Sentinel-1 images. The output of water detection model is changed into integer RGB format and automatically delivered to the SCV server, where the event images are visualized and could be compared with geospatial data.

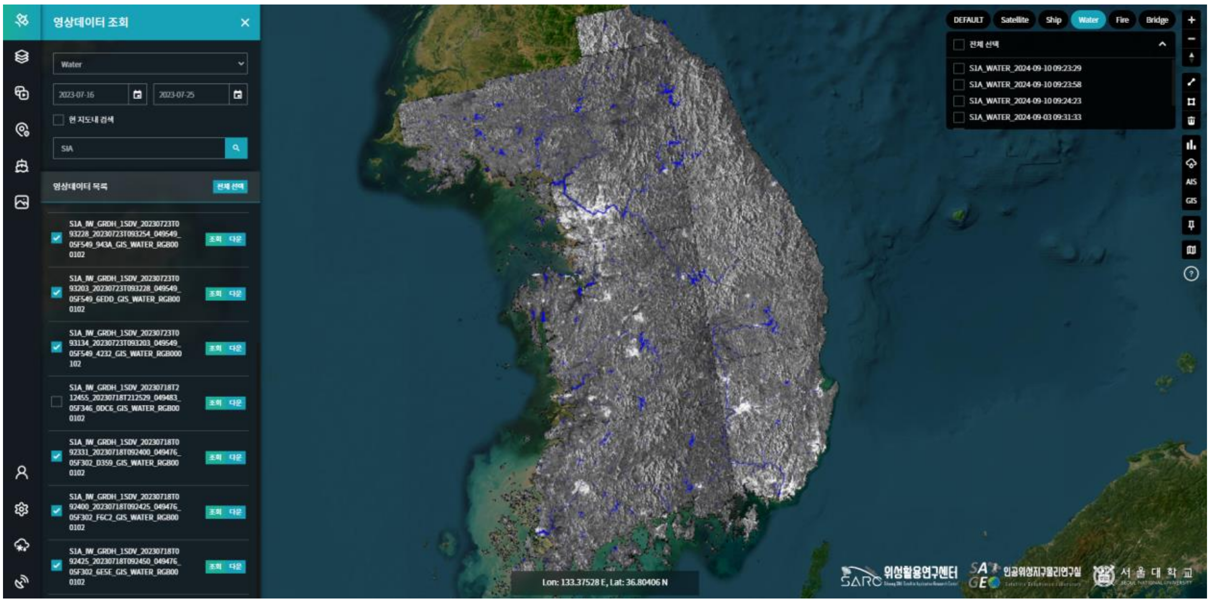

Figure 3. The automatic water detection results visualized through Satellite Current View(SCV) of Sentinel-1 SAR images acquired during July, 18 – 23, 2023.

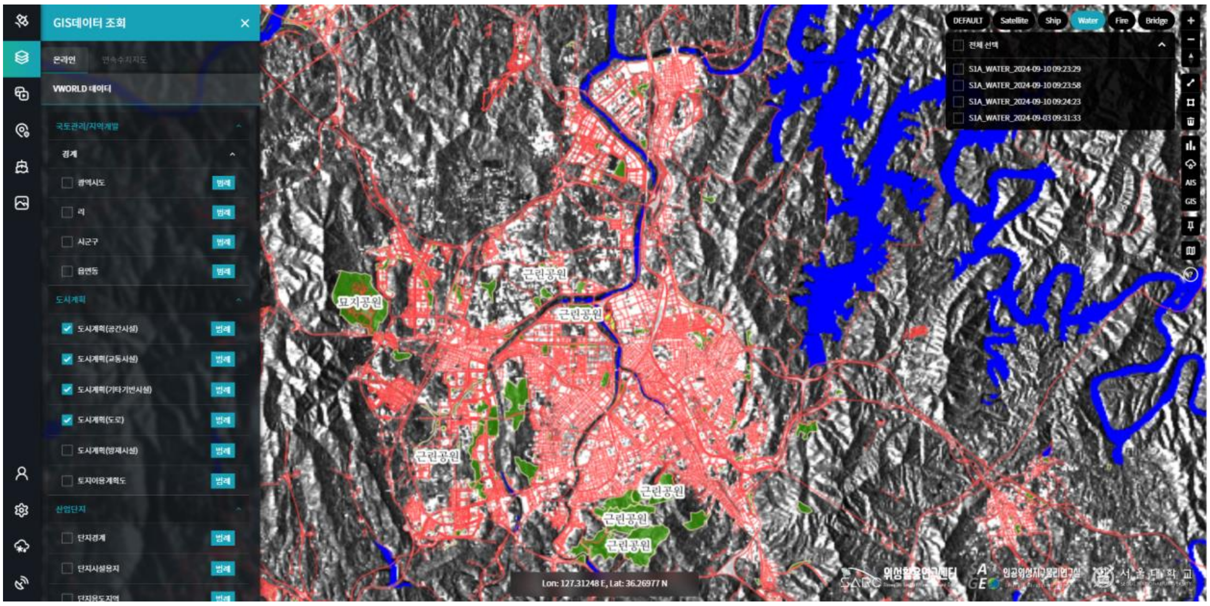

Figure 4. The example of geospatial layers(e.g.urban plan map) with the result of water detection result.

Results and Discussion

To validate the multitask learning model, we compared the dual decoder U-Net with the original U-Net model. The training dataset, consisting of 4,056 patches which are cropped to a resolution of 256x256 pixels, is split into training, validation, and test sets using a ratio of 81:9:10. For each Gamma naught VH and Gamma naught VV, we constrained the amplitude value from 0 to 0.5 and normalized them in to [0, 1]. The local incidence angle band is also constrained into [0, 90].

The model is trained using the Adam optimizer with a learning rate schedule based on Cosine Decay Restarts. The initial learning rate is 1e-3 with periodic restarts at intervals of 100 steps, a multiplicative factor of 0.9 for learning rate decay, and an alpha value of 1e-7. This cosine decay schedule allows the learning rate to decrease progressively over the training period, improving model convergence and overall performance. The He uniform variance scaling initializer is applied for every Convolutional layer. A batch size of 64 is used, and the model is trained for a maximum of 1000 epochs. To mitigate overfitting, early stopping is applied when there is no improvement in validation loss for 10 consecutive epochs. Additionally, the model's weights are reverted to the minimum validation loss model during training. A ten-core PC with 40 Intel(R) Xeon(R) Silver 4210R CPU @ 2.40GHz CPU and two GTX 3090 GPUs is used for both training and testing.

Three widely used evaluation metrics are employed: Precision, Recall and F1-score(Sasaki, 2007 #21). Three metrics are computed based on the confusion matrix, which has True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Precision measures how many of the positive predictions made by the model are actually correct. High Precision means that when the model predicts a positive class, it’s often correct. Recall measure how many actual positive cases the model correctly identified. High recall means the model is good at identifying all the true positive cases, though it might contain more false positives. The F1-score is the harmonic mean of precision and recall.

Table 1 shows the performance comparison result between the original U-Net and the Multitask-learned U-Net. The F1-score of the original U-Net is 80.825% and the F1-score of the multitask-learned U-Net is 87.764%, which is 6.939% increased.

Table 1: Performance comparison of original U-Net and the proposed multitask learning U-Net.

Model	Precision	Recall	F1-score
Original U-Net	79.981%	82.62%	80.825%
Multitask learned U-Net	87.96%	88.308%	87.764%

To demonstrate the practicality of the automatic near real-time web-based flood monitoring system, the actual operation results of heavy rain season in Korea is shown. In August 9th 2020, Sentinel-1 captured the flood event that the levee of the Sangju Weir on the Nakdong River in South Korea suffered a collapse after heavy rainfall. The collapse of the embankment led to extensive erosion of the surrounding area including agricultural fields and infrastructure. Figure 5 displays the water detection result with the geospatial database of road and embankment. We could find the flooded area where the result of water detection protrudes from the river embankment.

Figure 5. The water detection result(blue) with the geospatial layers of the road(Policelli et al.), embankment(sky blue) and land use plan. The orange circle indicates the flood area by the collapse of embankment.

Additionally, SCV also displays the analysis result of high-resolution SAR images by Umbra. As these high-resolution SAR images are acquired through order system, we separately analyzed and delivered the results to SCV. We ordered five places(Paju, Osong, Pyeongtaek, Seosan, Dangin) where were expected to flood during heavy rain in July 15th to 20th, 2024. As the weather forecast changed, the detected water pixels were all in inside the embankment.

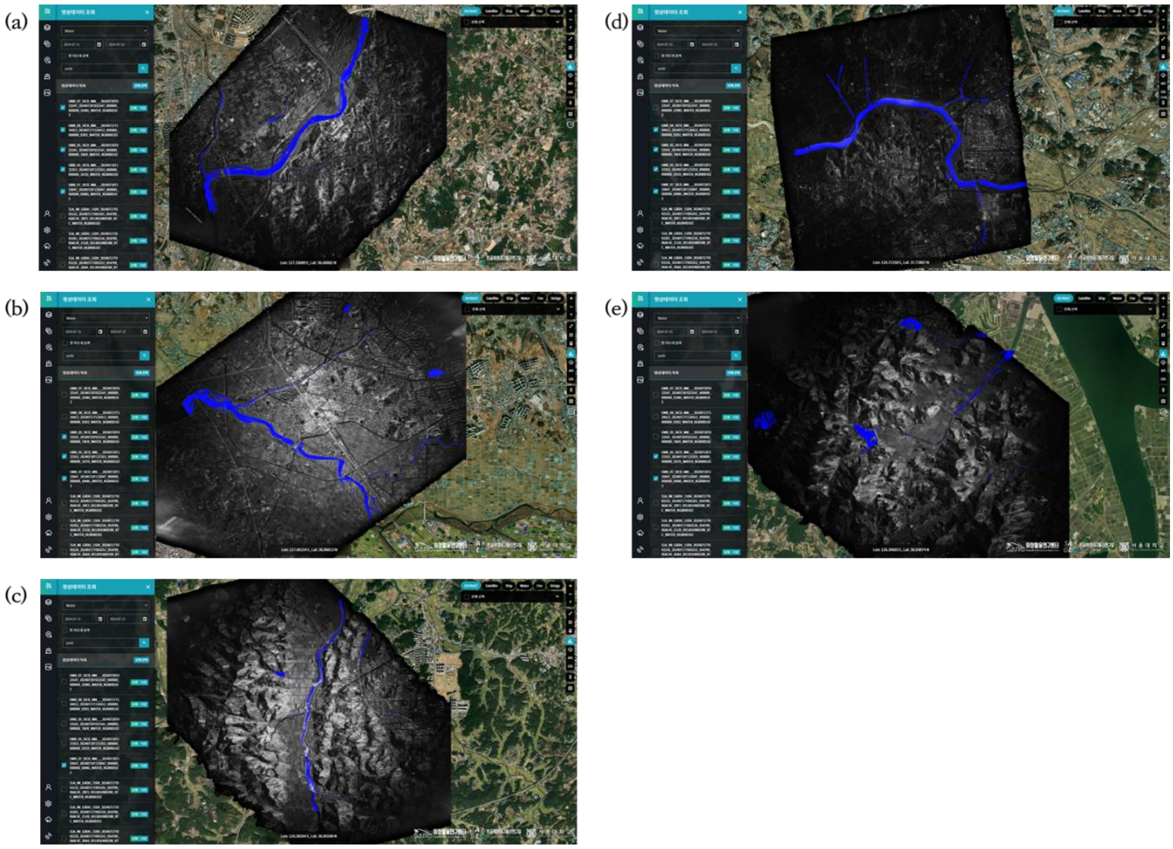

Figure 5. The water detection result of Umbra images: (a)Osong (b) Paju (c)Pyeongtaek (d) Seosan(e)Dangjin

Conclusion and Recommendation

In this study, we developed and successfully implemented an automated, near real-time flood monitoring system using multitask learning-based water detection on Sentinel-1 SAR images. By harnessing AWS's robust processing capabilities and advanced deep learning architectures, we effectively detected water bodies and river embankments, even in flood-prone areas characterized by smaller streams. The integration of both flood extent detection and embankment centerline extraction within a single multitask model proved advantageous, improving the detection accuracy of smaller rivers and streams.

The web-based visualization system (SCV) efficiently disseminates flood information, providing essential spatial data for disaster response and planning. The successful application of the system during actual flood events in South Korea, including the significant 2020 Nakdong River levee collapse and other cases in 2023, demonstrates its practical utility in real-world disaster management scenarios. Furthermore, the ability to process and visualize high-resolution SAR images from Umbra adds further precision in flood detection and analysis.

This system highlights the potential of combining cloud-based infrastructure with advanced AI techniques to support real-time disaster monitoring.

Beyond the flood monitoring functionality described in this paper, the Satellite Current View (SCV) system also automatically uploads a variety of additional analysis results utilizing SAR imagery. These include unidentified ship detection, bridge object detection, reservoir water level estimation, and ground displacement measurement. While monitoring primarily focuses on the Korean peninsula, the system's algorithms have demonstrated high accuracy when applied to international case studies. Future research will aim to further develop more generalizable algorithms, enabling the system to adapt seamlessly to regions beyond Korea, thereby reducing the damage from disasters.

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