AI-POWERED FLOOD MAPATHON

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ABSTRACT

Floods represent a pervasive natural hazard with global ramifications, impacting a vast population and resulting in substantial property damage and severe mortality. Particularly worrisome is their disproportionate effect on the least developed countries, which exacerbates developmental imbalances, posing a significant obstacle to the attainment of the United Nations Sustainable Development Goals (UN SDGs). This paper introduces the AI-powered Flood Mapathon activity, co-organized by the Aerospace Information Research Institute under the Chinese Academy of Sciences, in partnership with GEOVIS Technology Co., Ltd., GEOVIS Earth Technology Co., Ltd., and IEEE GRSS IADF. The activity seeks to mobilize individuals worldwide to address the most prevalent natural hazard-floods by collaboratively mapping inundated regions through the analysis of satellite imagery. Gaining widespread attention, the activity has garnered 30,755 submissions from 310 participants across 34 countries. Through collective efforts, participants have curated a semantic segmentation dataset focusing on floods, incorporating annotations of pertinent features related to both floods and human activities. Additionally, the paper elucidates the custom crowdsourcing mapping system, which seamlessly integrates cutting-edge AI technologies to alleviate mapping complexities. The activity contributes to sustainability by drawing extensive public attention, creating a public flood dataset for academic research, and establishing an efficient and intelligent mapping system.

***Index Terms*—** Mapathon, flood, crowdsourcing, Artificial Intelligence, mapping

1. INTRODUCTION

Floods stand out as the most prevalent and severe natural hazards worldwide, affecting a larger population than any other environmental disaster [1]. The economic toll caused by inundation has soared to 651 billion US dollars, with the highest losses relative to Gross Domestic Product (GDP) observed in low-income countries [1]. Alarmingly, the population exposed to floods continues to rise, as indicated by satellite data [2]. Addressing the escalating risk of flood hazards is imperative to enhance resilience and promote sustainability [3].

(a) during flood period (b) non-flood period

Fig. 1: Satellite image pairs captured in Nigeria.

The utilization of artificial intelligence technology for detecting flood hazards from satellite images constitutes a fundamental approach in monitoring the Earth's surface. This method plays a pivotal role in implementing appropriate non-structural countermeasures, such as early warning systems and scheduling, to effectively address flood events. To facilitate the technologies, a set of datasets and benchmarks are proposed. Sen1Floods11 [4] involves the mapping of flooding and permanent water areas from 11 flood events based on Sentinel-1 data. FloodNet [5] provides high-resolution images captured by Unmanned Aerial Vehicle (UAV), demonstrating the post flooded damages at Ford Bend Country in Texas and other directed impacted areas after Hurricane Harvey. SpaceNet-8 [6] firstly combines building footprint detection, road network extraction and flood detection in a dataset, which comprises 32k buildings and 1,300 km roads of which 13% and 15% are flooded, respectively.

This Flood Mapathon aims to mobilize individuals globally to actively contribute towards the completion of a comprehensive map of flood zones, so as to raise public awareness regarding the most frequent natural hazards and to relieve the vulnerable people, especially in the least developed countries. It provides satellite images of inundation prone areas captured at two distinct timestamps: during flood and non-flood period, as illustrated in Fig. 1. The primary task involves mapping flood inundation areas and key ground features relevant

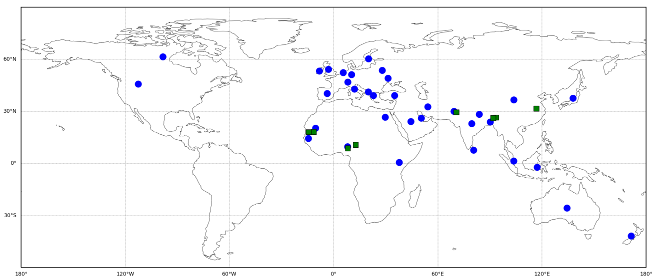

Fig. 2: The distribution of participants (circles) and inundation regions (rectangles)

to floods through a crowdsourcing approach, utilizing the provided satellite images. The contributions and key features of the Flood Mapathon are outlined as follows.

- It offers a sustainably evolving crowdsourced mapping system capable of generating an initial map derived through an AI program. The performance of the AI program is expected to improve with an increase in annotation quantity and quality.
- It integrates the latest segmentation tool to ease the trivial mapping work, which automatically segments ground features given prompts of points from the interactive web interface.
- A dataset pertaining to flood hazards is curated, comprising pairs of satellite images at two timestamps and the corresponding annotations. It serves academic studies and public management.
- The Flood Mapathon serves as a platform to draw public attention to the flood hazards, advocating for the establishment of resilient systems to combat and mitigate the effects of floods.

2. FLOOD MAPATHON EVENT

The Flood Mapathon event ran from October 16, 2023 to January 15, 2024 and received wide attention from all over the world. There are 30,755 submissions from 310 participants spanning 34 countries, involving China, Germany, Iran, Kenya, Nigeria, Nepal, etc, as exhibited in Fig. 2. To emphasize the collaborative nature of the event, the 200 top ranking participants received a prize ranging from pen containers to astronomical telescopes depending on their rank.

Task. The Flood Mapathon is dedicated to mapping water and flood inundation areas in pairs of high-resolution RGB satellite images captured during flood and non-flood periods, which are pivotal for evaluating the impact of flood events. Additionally, key features closely related to floods, such as buildings, forests, agriculture, roads and barren lands, are involved for the assessment of damage, formulation of humanitarian assistance plans, and the estimation of flood trends.

Pipeline. To accommodate the diverse preferences of participants, three mapping options are made available. The first option involves manual mapping from the ground up. The second option enables participants to employ our AI program to generate an initial map. The third option involves leveraging an automatic segmentation tool [7], which can generate segmentation polygons based on the point prompts provided by the participants through the interactive web interface.

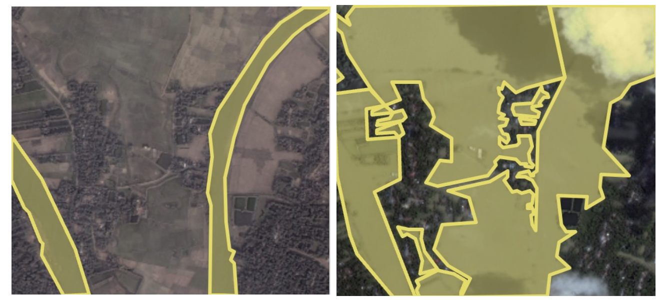

Fig. 3: Two image tiles labeled by the participants (only water and inundation areas are displayed). As can be seen from image pairs, the flood inundated the agriculture lands.

A relay-style pipeline is designed to effectively map flood vulnerable areas in a collaborative way. Specifically, it contains the following steps:

- **Step 1**: Each satellite image is partitioned into tiles of about 1000×1000 meters.
- **Step 2**: The participant who applies to label an unmapped tile acquires the first relay baton for that tile. Then, that tile is locked, and others cannot label the tile until the baton is released. The participant who owns the first baton can choose to label from scratch, from the default AI results, or from annotations derived via their own algorithms.
- **Step 3**: The participant releases the relay baton after the annotation is completed so as to label other tiles, which allows other participants to acquire the relay baton for this tile to continue labeling.
- **Step 4** : Participants who receive a non-first relay baton can only continue labeling based on the previous result.

3. DATASET

For the Flood Mapathon activity, we utilize satellite images captured by Gaofen-2 and Gaofen-7. The Gaofen-2 satellite is able to collect imagery of 0.8 m panchromatic and 3.2 m multispectral bands on a swath of 45 km. Gaofen-7 is the first civil-use optical transmission 3D surveying and mapping satellite, equipped with two cameras. The data of one camera is leveraged, with a GSD of 0.8 m panchromatic and 2.6 m multispectral bands on a swath of 20 km. Pansharpening is conducted to all the images before presented to participants, resulting in a GSD of 0.8 m.

Specifically, we collect eight pairs of satellite images capturing expansive scenes at two distinct timestamps, which

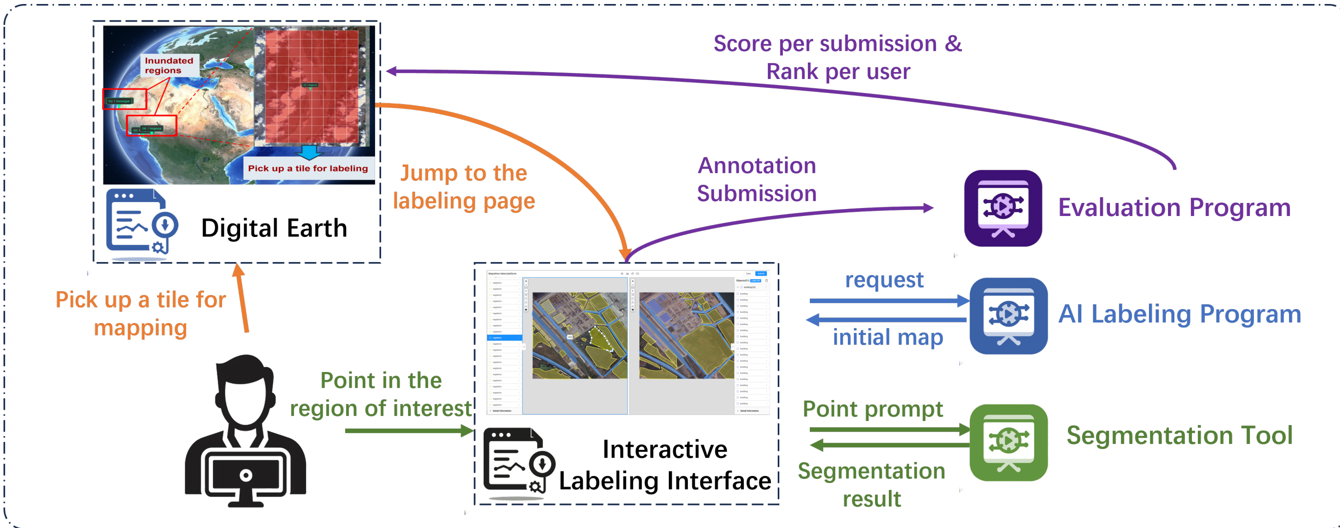

Fig. 4: The crowdsourcing mapping system with different data/control flows represented by distinct colors.

cover 1,609.18 km^2 in total, across eight distinct areas spanning six countries (i.e., Mauritania, Senegal, Bangladesh, Nigeria, Pakistan, and China) as exhibited in Fig. 2. Each pair consists of one image captured during a flood period in 2022 and another during a non-flood period. For the crowdsourcing activity, all the images are split into tiles of about 1000×1000 meters, resulting in a total of 1,068 titles.

After comprehensive crowdsourced annotations from participants worldwide, the images and annotations are exported to form a standardized dataset pertaining to floods. Illustrative examples of the annotations are depicted in Fig. 3, showcasing exclusively water and inundated areas. The mapping considers water and flood inundation areas, as well as features highly relevant to floods in terms of impact evaluation, trend estimation and damage assessment. Specifically, the features of interest include *building*, *road*, *water*, *barren land*, *forest*, *agriculture*, and *others*.

4. CROWDSOURCING MAPPING SYSTEM

The crowdsourcing mapping system consists of five independent programs, which are connected via remote HTTP communications, as illustrated in Fig. 4.

Digital Earth. The digital earth program offers an interactive interface for the participants to explore inundation regions. Each tile is also color-masked to represent its status, comprising occupied, unlabeled, partially labeled, finished and disabled. Participants can select any unoccupied tile by clicking on it, at which point the interface will automatically transition to the interactive labeling page.

Interactive Labeling Interface. The interactive labeling interface provides a user-friendly platform for participants to map the interested ground features. It loads two image tiles corresponding to the same geographical region at two distinct timestamps, representing during flood or non-flood periods. The interface provides a toolkit to facilitate mapping, including an AI program capable of generating an initial map, a segmentation tool for segmenting ground features based on a point prompt, and a lasso function to simplify the labeling of nearby features.

AI Labeling Program. The AI labeling program generates an initial map for an unmapped tile by running a semantic segmentation network [8] trained on publicly available land-use and land-cover datasets [9, 5]. Due to differences in sensor characteristics and scenes between the datasets used for training and the data employed in the Mapathon event, the default AI labeling program can only provide reasonably fair results. We equip the program with evolution capacity via training the network on the labeled data periodically. With improvements in both the quality and quantity of annotations, the performance of the AI labeling program is expected to improve.

Furthermore, the masks derived from the segmentation networks contain abundant points representing the contours of specific objects. Given the impracticality for participants to manually adjust such a multitude of vertices, a pivotal procedure involves reducing the vertex count through the application of the Douglas-Peucker algorithm [10].

Segmentation Tool. The segmentation function provides an easy-to-use tool for the participants, which is able to automatically segment objects given a point prompt within the object area via the interactive labeling interface. The segmentation function offers participants a user-friendly tool capable of automatically segmenting objects based on a point prompt within the object area through the interactive labeling interface. For this event, we employ RingMo-SAM [7], inspired by the Segment Anything Model (SAM) [11], specifically designed for remote sensing scenes.

Evaluation Program. The evaluation program assesses each submission and computes a score for each one. To gauge the labeling quality, we employ the widely used mIoU metric, commonly utilized in semantic segmentation evaluations.

Evaluating the submissions poses a significant challenge due to the absence of ground-truth data. We formulate the evaluation rules under the assumption that labeling quality will progressively enhance and eventually stabilize, exhibiting only slight fluctuations among consecutive submissions. Consequently, the final results are treated as pseudo-references. Since the last participant will always have the highest metric in this relay-style pattern and collaboration is highly encouraged in this activity, the contributions of the participants are computed according to the improvements instead of the submitted status for each submission. The final score is accumulated across all submissions.

5. CONCLUSION

In this paper, we present the AI-powered Flood Mapathon, covering the activity, the derived dataset, and the crowdsourcing mapping system. The event called for individuals from all over the world to pay attention to flood hazards via collaboratively completing the mapping of inundation regions from high resolution satellite images. Over 300 participants from 34 countries actively participated in the event, culminating in a collaborative effort to create a semantic segmentation dataset focused on floods. This dataset includes features such as buildings, roads, water bodies, barren land, forests, agriculture, and others, which hold significant relevance for damage assessment, impact evaluation, and trend estimation in flood scenarios. In addition, we introduce a tailored crowdsourcing mapping system, which integrates multiple AI tools to alleviate mapping challenges and enhance efficiency. The event not only successfully raised public awareness about flood disasters but also released of a publicly available dataset via crowdsourcing for academic research purposes. Furthermore, the development of an effective crowdsourcing mapping system stands out as a notable outcome of the event.

6. ACKNOWLEDGEMENT

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