Toward minute-level flood stereoscopic intelligence: Real-time multimodal remote sensing under an on-orbit AI paradigm

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Global climate change has intensified the hydrological cycle, substantially increasing the frequency and intensity of extreme precipitation and flood hazards, particularly in highly urbanized basins. Floods remain among the most frequent global disasters, causing severe human and economic losses (2000–2019).[1] However, many recent floods exhibit fast onset and strong spatial heterogeneity, exposing critical limitations in conventional ground-based monitoring and satellite workflows with hour- to day-level latency. Although optical imaging, Synthetic Aperture Radar (SAR) and radar altimetry have advanced post-event inundation mapping and three-dimensional water level retrieval, delayed data downlink and ground processing still hinder timely response.[2]

To address this gap, an emerging Real-time Remote Sensing paradigm under integrated Communication–Navigation–Remote Sensing constellation enables rapid revisit, multimodal sensing and on-orbit artificial intelligence (AI) processing (Figure 1). Building on this progress, this Comment formalizes the concept of minute-level flood intelligence, aiming to close the loop from flood detection to actionable decision-making within minutes,[3] as shown in Figure 1A.

REAL-TIME SATELLITE REMOTE SENSING FOR FLOOD RISK MANAGEMENT

Extreme rainfall events are increasingly short-lived, localized and intense, transforming many floods into fast-onset emergencies in which hydrological conditions can change within minutes. In this context, Real-time satellite remote sensing refers to an integrated observation-processing-transmission mode that delivers actionable information within minutes rather than hours or days.[3] A defining shift of this paradigm is that satellites evolve from passive image providers to active on-orbit processors. Instead of downlinking raw data, satellites perform on-orbit geolocation, basic corrections, water-body extraction, change detection and strong compression, so that the ground segment distilled flood situation.

This approach contrasts with conventional satellite-based flood monitoring, which relies on sparse revisit cycles, bulk data downlink and offline processing. Such latency is often incompatible with emergency decision timelines for flash floods, urban pluvial flooding, and water intrusion into underground infrastructure.[2] Here, information timeliness, rather than detection accuracy alone, becomes the dominant constraint for effective disaster risk reduction.

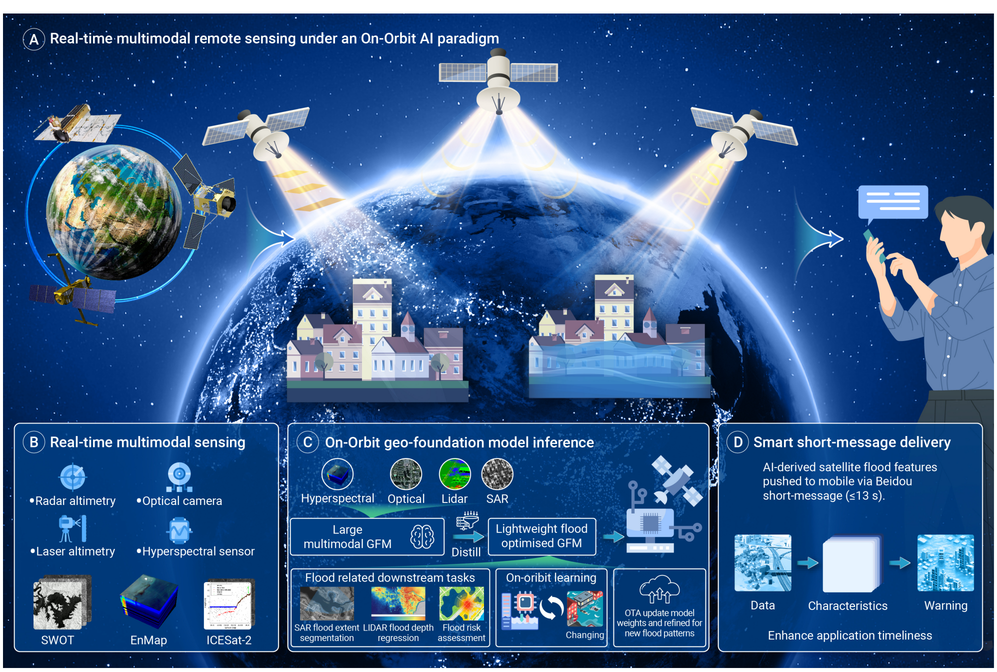

Figure 1. A new paradigm of flood Stereoscopic intelligence via next-generation multimodal satellite remote sensing with on-orbit AI (A) Real-time Multimodal Remote Sensing under an On-Orbit AI Paradigm, where next-generation flood intelligence imposes new requirements and challenges on sensors, models, and data transmission. (B) Real-time multimodal sensing, enabling synchronous monitoring of flood extent, water surface height, and inundation depth through multi-sensor collaboration. (C) On-orbit geo-foundation model inference, achieving in-orbit information interpretation using a lightweight, multimodal, and multi-task deep learning framework. (D) Smart short-message delivery, transmitting critical flood information to mobile terminals via BeiDou short-message technology with bandwidth-optimized routing.

Technically, Real-time remote sensing is enabled by constellations integrating Earth observation sensors, high-throughput communication links and on-board AI accelerators (Figure 1). A representative example is the LuoJia3–01 internet intelligent remote sensing satellite, which supports on-orbit DL inference and minute-level delivery of processed products to end users. Such capabilities establish a new temporal backbone for reservoir operation, urban drainage management and .rapid emergency response.

MULTIMODAL SATELLITE COLLABORATION FOR FLOOD FEATURE ACQUISITION

Real-time flood monitoring relies on multimodal satellite constellations that integrate complementary sensor to synchronously capture flood extent, water level, and inundation depth (Figure 1A). Radar altimeters and interferometric height imagers measure water surface elevation and slope along rivers and across reservoirs, enabling a shift from two-dimensional inundation mapping three-dimensional flood characterization. Laser altimeters further refine key cross sections and small water bodies, while optical and multispectral imagers provide high-resolution delineation of open water and surrounding land cover. SAR ensures all-weather and day–night flood detection under cloud-covered conditions.

A representative multimodal configuration combines existing missions: Surface Water and Ocean Topography (SWOT) constrains water levels and slopes, ICESat-2 refines channel geometry, and Sentinel-2 captures detailed inundation patterns. Together, these systems support dynamic estimates of flood extent, elevation and volume estimates from local reservoirs to large basins.

Recent chinese developments push this paradigm toward minute-level services. The LuoJia3-01 internet intelligent remote sensing satellite demonstrates on-orbit processing and real-time delivery of interpreted flood products.[4] Building on this concept, next-generation multimodal constellations aim to provide consistent flood feature acquisition across surface and urban environments, forming the observational basis for Minute-Level Flood Intelligence.[5]

ON-ORBIT INTELLIGENT FLOOD ANALYTICS WITH DEEP LEARNING AND GEO-FOUNDATION MODELS

Flood information extraction and semantic compression increasingly rely on DL. Convolutional neural networks, encoder-decoder architectures and spatiotemporal models are widely applied to floodwater segmentation, change detection and hazard assessment, achieving near real-time performance.[2] Recent advances move toward Geo-foundation models (GFM), which learn generalizable spatio-spectral-temporal representations from large Earth observation archives, enabling flood-related tasks through adaptation of a shared backbone. For on-orbit deployment, models must be lightweight, energy efficient and robust. As shown in Figure 1C, key strategies include channels and layer pruning, weight quantizing and knowledge distillation from a large teacher models into compact task-oriented student networks. These optimizations enable on-board inference for inundation mapping, depth classification, and breach detection under satellite hardware constraints.

Recent demonstrations, such as the LuoJia3-01 internet intelligent remote sensing satellite, show that dedicated onboard processors can support DL inference, task-driven compression and minute-level delivery of flood products.[4] By transmitting semantic products instead of raw imagery, on-orbit analytics form the algorithmic core of Minute-Level Flood Intelligence, enabling interpreted results to reach mobile terminals within a practical minute-scale window (Figure 1D).

CHALLENGES AND FUTURE DIRECTIONS

While individual components of the proposed framework, such as on-orbit deep learning inference and real-time product delivery, have been demonstrated by experimental satellites (e.g., LuoJia3-01), achieving a fully integrated minute-level flood intelligence system still faces several technical challenges.

Flood-oriented multimodal sensor design: Most existing satellite payloads were not specifically designed for flood intelligence. Future constellations should integrate wide-swath water level measurements, all-weather SAR and high-resolution optical imaging, with orbital configurations optimized for river networks and urban low-lying areas, under realistic constraints of payload capacity and revisit frequency .

Lightweight on-orbit intelligent analytics: Although on-orbit deep learning inference has been demonstrated by experimental missions, routine deployment remains challenging. A key forward-looking research direction is how to design compact, energy-efficient, robust deep learning, and geo-foundation models that can operate reliably under strict on-board power, memory, and thermal constraints, using pruning, quantization, and task-oriented inference.

Bandwidth-aware products and short-message services: Achieving minute-level flood intelligence requires prioritizing semantic compression over raw data transmission. How to balance information completeness with extreme bandwidth limitations, and to deliver concise yet actionable flood indicators via BeiDou short-messages services, remains flood risk management.

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AUTHOR CONTRIBUTIONS

Conceptualization: J.Y., N.X.. Methodology and framework design: J.Y., M.W., N.X.. Investigation and case analysis: J.Y., C.M., Y.Y., Z.L., X.Z., X.L.. Data curation and technical support: F.L., B.B., J.W., G.W.. Writing – original draft: J.Y., M.W.. Writing – review & editing: N.X., C.M., Y.Y., Z.L.. Funding acquisition and supervision: N.X., J.Y. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.