Earth Observation to Monitor and Redress Inequitable Post-Flood Recovery

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Key Points:

- Advances in Earth Observation to monitor flood recovery are needed to address growing flood risks and support equitable recovery.
- Earth Observation proxies of flood recovery should be locally defined and supplemented with non-Earth Observation data to assess recovery.
- A framework to guide Earth Observation-based flood recovery monitoring is presented, driven by gaps in current flood recovery monitoring.

Abstract

Floods impact communities worldwide, resulting in an estimated $651 billion (USD) in damages, countless fatalities, and threatened livelihoods over the last two decades alone. Climate change and urban development in flood-prone areas will continue to worsen flood-related losses increasing the urgency for effective tools to monitor recovery. Many Earth Observation (EO) applications exist for flood-hazard monitoring and provide insights on location, timing, and extent in near real-time and historically to estimate flood risk. Less attention has been paid to flood recovery, even though differing recovery rates and outcomes can have immediate and enduring effects within communities. Here, we define post-flood recovery as a change in land cover types, conditions, or land surface features in the days, weeks, months, or years following a flood event. EO data are uniquely positioned to monitor post-flood recovery and inform policy on hazard mitigation and adaptation but remain underutilized. We urge the EO and flood research community to renew focus on developing flood recovery applications to address growing flood risk. Both methodological innovations and translation of EO insights on flood recovery among flood-affected communities and decision-makers are necessary to address underlying vulnerabilities in social systems that exacerbate flooding. We identify an unequivocal need for EO to move beyond hazard mapping to post-flood recovery monitoring to inform recovery across geographic contexts. This commentary proposes a framework to use EO to advance flood recovery monitoring, characterize inequitable recovery, redistribute resources to mitigate inequities, and support risk reduction of future floods.

Plain Language Summary

Floods harm communities globally, with impacts expected to intensify due to increased development in flood-prone locations and climate change. Flooding impacts communities unevenly, and the recovery process itself can create additional disparities in flood risk and resilience. While Earth Observation (EO) data are commonly used to map flood events, they are underutilized to monitor recovery. This is a missed opportunity for documenting inequitable recovery outcomes, which can impact the preparation for, and mitigation of future floods. We argue for a renewed focus on EO to provide evidence-based information to remedy inequities in recovery planning and actions. We present a framework to operationalize and advocate for the integration of EO for flood recovery applications.

1 Introduction

More frequent and extreme flooding exacerbated by climate change stands to increase societal impacts that disproportionately affect marginalized populations (e.g., Douglas et al. 2008). Beyond climate change, flood risk is also driven by human behaviors, choices, institutions, and politics. Increased flood risk from rapid development and urbanization in flood-prone areas is enabled by outdated regulatory floodplain maps and deficient flood risk disclosures (Andreadis et al., 2022; Flores et al., 2022; Hino & Burke, 2021). Even where flood frequency or magnitude is unchanged, flood vulnerability is exacerbated where mitigation and recovery responses discriminate and reduce the adaptive capacity of marginalized groups (Elliott et al., 2020; Emrich et al., 2019, 2022). As a result of climate and social factors, flood mitigation and adaptation activities have often been insufficient in reducing the impact of flood events on affected communities (Kreibich et al., 2022). Inhibiting the planning and implementation of equitable adaptation measures are inadequate tools to monitor post-flood recovery over a broad range of contexts. We argue that Earth Observation (EO) data, now capturing imagery with unprecedented temporal and spatial frequency over Earth's surface, provides significant yet untapped potential to monitor flood recovery and glean important lessons on adaptation efforts.

To better manage flood risk, a suite of ever-expanding EO data has ushered in a marked increase in satellite-based emergency mapping (Voigt et al., 2016). Hazard monitoring systems routinely rely on EO to support early warning systems, impact-based triggers for forecast-based early action (Nauman et al., 2021), and enable more timely disaster response (Schumann et al., 2018). Specific to flood hazards and impacts, EO has made significant strides in flood detection in recent years, including providing unprecedented observations of flood extent and duration (Schumann, 2021). Critically, EO has added new perspectives on understanding changes in global flood risk where flood models remain coarse or lack consistency (McClain et al., 2022; Tellman & Sullivan et al., 2021).

Despite advances in EO to map floods, more attention is needed to understand how EO can be applied to detect and monitor post-flood recovery. Post-flood recovery is critical in mitigating the impacts of floods on communities. We define post-flood recovery as a change in land cover types, conditions, or land surface features in the days, weeks, months, or years following a flood event. For example, post-flood recovery could entail the identified removal of debris from roadways, the reconstruction of damaged buildings or infrastructure, or the restoration of agriculture or natural vegetation conditions. Identified changes may occur in flood-inundated areas or nearby non-flooded areas, which undergo changes in relation to recovery efforts, such as the construction of temporary housing.

Post-flood recovery can also go beyond post-event rebuilding, remediation, or return to a pre-flood state. Instead of returning to the pre-flood state, i.e., 'back to normal,' post-flood recovery can be a form of 'building back better' that addresses pre-flood inequalities and vulnerabilities (Forrest et al., 2019; De Ita et al., 2022). Another characterization of post-flood recovery could also entail no change to the flood-affected areas, such as flood-induced changes that remain stable post-flood. Given the continuous stream of diverse data resolutions and types, EO is uniquely poised to monitor different characterizations of recovery, a complex phenomenon that demands data of various resolutions and cadences. To encapsulate a wide-ranging array of context-specific recovery scenarios, the definition we propose of recovery is thus broad to best characterize place-specific recovery norms and trends (Rumbach et al., 2016). Data needs include local context, which is paramount to characterizing recovery and how recovery efforts differentially impact groups of people.

As history illustrates, marginalized populations are seldom prioritized in recovery (e.g., Muñoz & Tate, 2016). EO evidence of unequal flood recovery could be particularly effective for building community-based flood resilience, autonomy, advocacy, and power in data-informed decision-making and supporting legal remediation to redress inequitable recovery. Recovery and adaptation actions taken post-flood have a significant bearing on the ability of individuals, households, communities, and countries to cope and prepare for future flood events (McSweeney & Coomes, 2011). Documentation of the spatial variability of post-flood recovery is essential to guide the equitable allocation of mitigation funding and prioritize resources for mitigation in locations still recovering from previous flood events. The stakes of failing to initiate adaptive recovery for future events are mounting and have already been witnessed in economic and non-economic loss and damage (Boyd et al., 2021).

Recognition of the potential of EO-monitored recovery inspired a side meeting at the Global Flood Partnership Annual Meeting in 2022 titled "Mapping Flood Recovery and Adaptation from Space." A diverse group of 18 researchers and practitioners, including flood modelers, disaster management and flood management experts, social scientists, financial risk specialists, and public and private sector EO data providers, attended the workshop to share their perspectives. The main conclusion from this meeting of experts was unequivocal that EO potential is underutilized to monitor flood recovery. This gap deserves increased attention from the EO community of practice, governments, emergency managers, planners, and community organizations involved in recovery planning and support.

Our Commentary Brief attempts to lead the field of EO flood monitoring in new directions beyond the study of flood events toward flood recovery. The following sections of the Commentary provide a brief overview of the institutions engaged in recovery monitoring and applications of EO to monitor post-flood recovery. The heart of the commentary lies in Section 4, where we introduce a framework for applying EO to monitor post-flood recovery in service of redressing inequities in post-flood recovery. Community participation and data translation among remote sensing scientists, recovery practitioners, and affected communities are vital to make the framework actionable. We conclude by inviting the remote sensing community to consider how to expand the application of EO to support recovery planning and evaluation to improve and achieve more equitable recovery outcomes.

2 The Institutional Landscape to Extend Post-Flood Recovery Monitoring

There is already wide recognition that EO is a key data element to support resilient disaster risk management, evidenced by existing institutional organizations and protocols in place to use EO for disaster response and recovery (Khan et al., 2020; Kruczkiewicz et al., 2022; Marlier et al., 2022; Percivall et al., 2013; Petiteville et al., 2015; Zuccaro et al., 2020). The Sendai Framework for Disaster Risk Reduction 2015-2030 promotes using satellite-based and in-situ information to support its first action, "Understanding disaster risk" (GP-STAR, 2017). The institutional landscape of international collaborations across space agencies is tasked to address this action item, including the International Charter Space and Major Disasters, Asia-Sentinel, National Aeronautics and Space Administration (NASA), National Oceanic and Atmospheric Administration (NOAA), the World Meteorological Organization (WMO), and Copernicus Emergency Management Services (CEMS).

Specific to mapping post-disaster recovery, the Committee on Earth Observations Satellites (CEOS) Recovery Observatory and CEMS Risk and Recovery Mapping service provide map services on recovery. However, these monitoring systems are ad hoc, with no systematic or long-term sustained monitoring. For example, the only instances of the Recovery Observatory being activated were in response to Hurricane Matthew in 2016 and Hurricanes Eta and Iota in 2020 (UNDRR, 2022). Established in 2012, the CEMS Risk and Recovery Mapping service has had a total of 135 activations, of which most of the flood-related activations have resulted in flood extent mapping with little to no representation of flood recovery monitoring (Copernicus, 2022). While these organizations have laid the foundation to mobilize EO data to aid in targeting resources in response to multiple types of disasters and providing information to decision-makers, more committed resources are needed to systematically monitor ongoing recovery from previous events (GFDRR, 2019).

While international and agency efforts have set a precedent for EO-based recovery monitoring, there are three important gaps in how existing initiatives monitor recovery. The first gap is an explicit measurement of how recovery trajectories differ across populations of varied demographics and local biophysical conditions in affected locations. Without analyzing disparate recovery impacts, insights are less conducive to prioritizing needs, assessing changing flood risks

(McClain et al., 2022), and informing future recovery efforts. The second gap is that long-term recovery monitoring often concludes months after the flood event, restricting the capacity of these protocols and programs to support monitoring of both short- and long-run recovery, which may last years after an event. Higher frequency and longer-term monitoring are required for the ever-evolving and, in many cases, long-term recovery processes that unfold post-flood. The third gap is that EO is used in very few events to monitor recovery, limiting our ability to understand recovery trends and build resilience for the next flood event.

3 Earth Observation Applications for Post-Flood Recovery

The diversity in EO data's spatial, temporal, and spectral resolution allows for its use in several flood recovery applications and scenarios. EO can be applied to various flood recovery activities related to the human-built and natural environment, agriculture, public health, climate finance, disaster risk reduction, and emergency response (Nauman et al., 2021). We distinguish four themes in which EO is applied to support flood recovery activities: mapping flood extent, monitoring impacts within flood-affected areas, flood risk reduction and financing, and flood-related adaptation program evaluation. The examples presented are not mutually exclusive to each theme; instead, the distinction differentiates unique thematic applications.

3.1 Mapping Flood Extent

A common application of EO for post-flood recovery is mapping the flood extent and monitoring flood water receding over time. EO-derived flood maps are often included in Post-Disaster Needs Assessments (PDNA) produced for large-scale flood events. PDNAs are produced by country-affected governments and international aid and development agencies directly following major events to estimate the costs of total damages, losses, and recovery needs. PDNA guidelines recommend that EO data be used, when available, to generate pre-disaster baseline information, rapidly assess the impact and extent of a hazard, and determine the scope of the recovery plan (GFDRR, 2013). A recent example of EO being used to monitor flood recovery is following the mid-June to October 2022 floods in Pakistan, in which EO data was relied on to produce flood maps for the PDNA (Government of Pakistan, 2022). After the PDNA release, longer-term EO monitoring of recovery progress conducted by UNOSAT (2023) reveals that 1.8 million people remained exposed to stagnant flood water as of late February 2023, and is an example of how EO can detect the limited to slow rate of ongoing post-flood recovery. The release of similar UNOSAT reports has been non-systematic, with daily to weekly releases in August and September 2022 shortly after the peak flood, but releases have become less frequent, slowing to monthly and later bi-monthly updates from October 2022 through June 2023. While these reports offer recovery insights at discrete snapshots, the lack of systematic data collection and analysis of additional recovery progress beyond the presence of floodwater presents a missed opportunity for more extensive post-flood damage and recovery monitoring.

3.2 Monitoring Impacts within Flood-Affected Areas

One way to go beyond the narrow focus of long-term standing water mapping is to monitor landscape changes within the flood-affected extent, such as urban, agricultural, and natural resources like forests and coastal vegetation that provide natural flood protection (e.g., Marlier et al., 2022). EO provides critical insights into the obstruction of or damage to buildings, roadways, bridges, and other public infrastructure (Butenuth et al., 2011; Ghaffarian & Kerle, 2019; Schnebele et al., 2014). Damage and recovery monitoring of infrastructure provides timely information on accessibility in the early recovery phase and reconstruction progress in the short and long-term post-flood (Oddo & Bolten, 2019).

An example of EO being applied to monitor infrastructure recovery comes from the CEMS (2018) Risk and Recovery final report for Hurricane Matthew, which struck Haiti in October 2016. In the CEMS report, multiple timestamps of imagery are used to estimate the evolution of the reconstruction status of damaged infrastructure affected by coastal and riverine flooding. In two examples from the report, pre-flood aerial imagery and post-flood EO imagery from two separate timestamps show initial post-Matthew damage to building and road infrastructure and subsequent reconstruction (Figure 1). While this example clearly shows recovery progress, the limited availability of two post-event images precludes more systematic monitoring of repairs. Additionally, the mix of true- and false-color imagery across the pre-Matthew image and two post-Matthew images may confuse viewers unfamiliar with recognizing stability and change in features in different spectral compositions across the imagery time series.

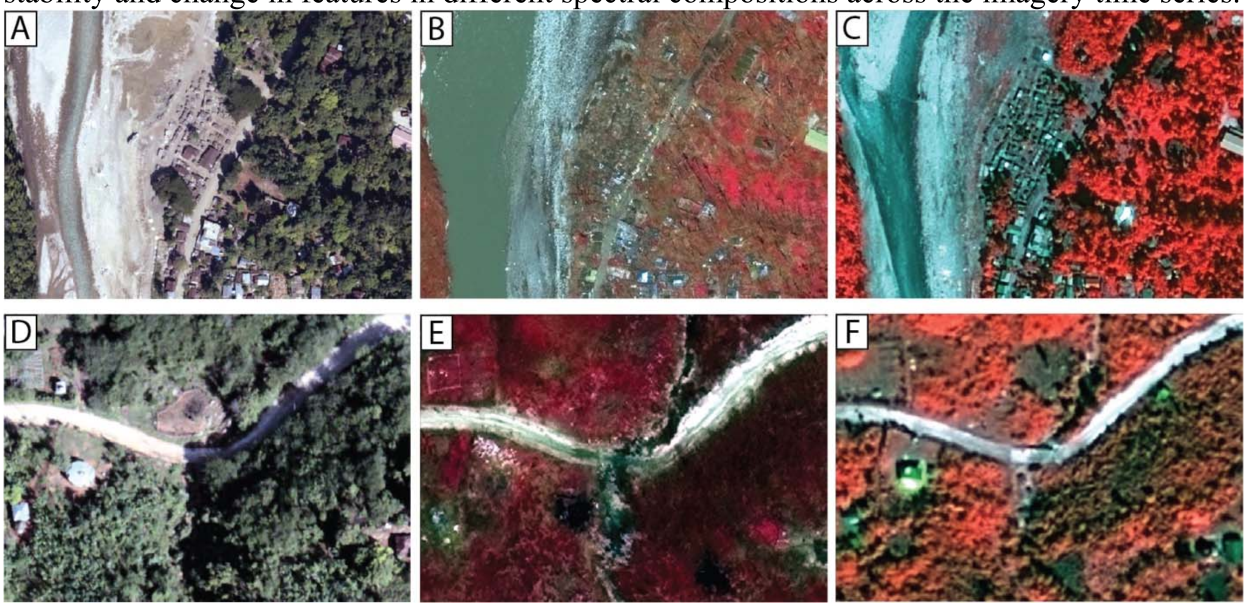

Figure 1. Imagery used in CEMS Risk and Recovery final report for Hurricane Matthew to show recovery and reconstruction for two sites (1A-C and 1D-F, respectively). The panel consists of aerial imagery acquired in 2014 before Hurricane Matthew (1A, 1D), false-color WorldView-3 imagery from 11 days after landfall of Matthew acquired on October 15, 2016 (1B, 1E), and false-color Pléiades imagery from 14 months after landfall acquired on December 15, 2017 (1C, 1F). 1A-C shows buildings in pre-damaged, damaged, and reconstructed conditions. 1D-F shows a bridge in pre-damaged, damaged, and reconstructed conditions. Image adapted from CEMS (2018) and provided by the European Union.

The complexity of features and high spatial detail required to monitor urban infrastructure damage has led to expanded image sources and data to train models to detect flood-related damage and recovery activities. For example, drone imagery has also been used to map post-flood debris via semantic segmentation (Whitehurst et al., 2022), and recently the first training dataset of flooded and not-flooded building footprints and road networks was released (Hänsch et al., 2022). Beyond using optical or radar imagery to detect infrastructural impacts, other forms of remotely sensed data, like nighttime lights, could be used to measure the restoration of electricity post-flood (Gandhi et al., 2022; Levin et al., 2020; Qiang et al., 2020) and to understand adaptation responses like population resettlement away from flood risk areas (Mård et al., 2018). A clear example of nighttime lights data being used to measure electrical outages following a disaster is by Román et al. (2019), who use time series of NASA Black Marble high-definition nighttime light data to show differences in the number of days without electricity for different locations following Hurricane Maria (Figure 2). In this example, variation in the duration of an electrical outage can be used to help support claims of inequitable recovery.

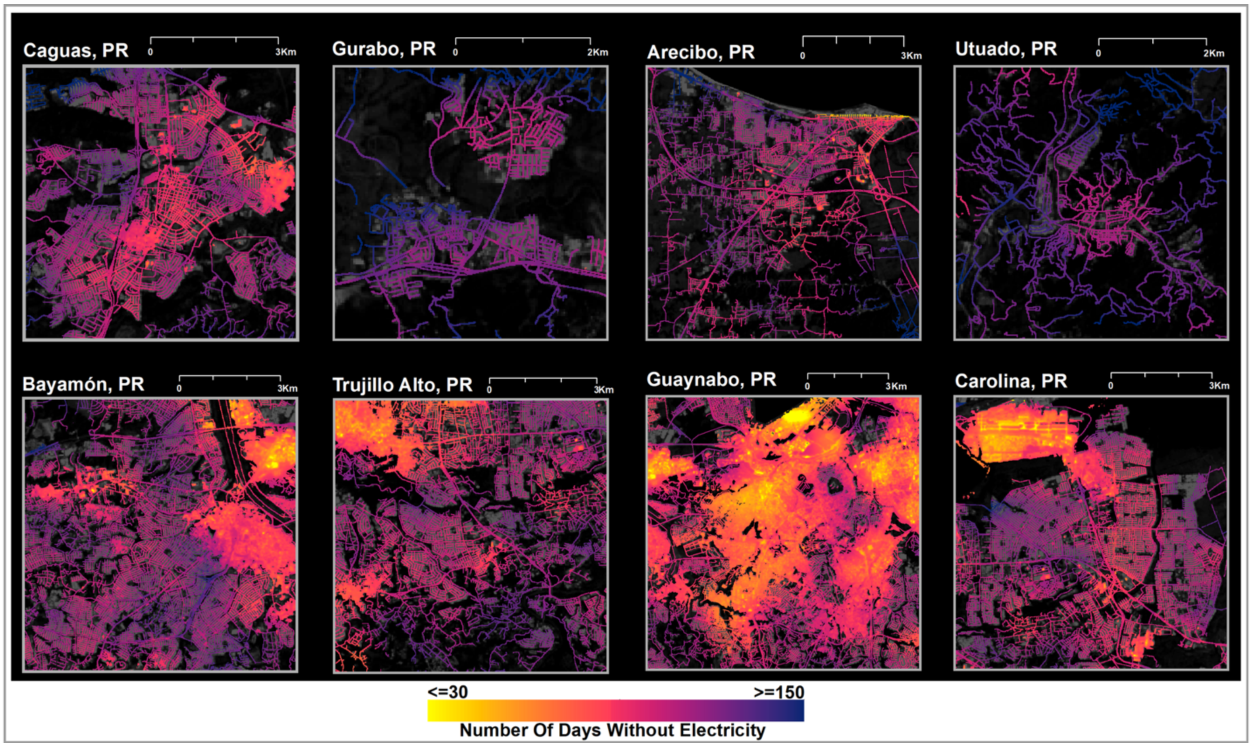

Figure 2. An example of remotely sensed NASA Black Marble high-definition nighttime light data to track the duration of electricity outages at different rural and urban centers in Puerto Rico following Hurricane Maria. Image from Román et al. (2019).

3.3 Flood Risk Reduction and Financing

The measurement of post-flood recovery also has direct relevance for flood risk financing both before and after the flood event. In the last two decades, humanitarian agencies have put extensive efforts into establishing early warning systems, anticipatory action, and forecast-based financing using real-time or predictive models to estimate the potential number of people impacted and potential impacts on crop productivity as a proxy for food security impacts (Kruczkiewicz et al., 2021a; Nauman et al., 2021). While anticipatory action programs for floods typically use forecast models rather than EO (Coughlan de Perez et al., 2016), remote sensing data is commonly employed to activate interventions when inferred crop conditions breach pre-defined activation thresholds (e.g., Chen et al., 2019).

An example of EO used to map agricultural impacts and support flood risk reduction is from the Republic of Congo in December 2019, when the World Food Program identified flood-damaged cropland to target cash-based transfers to improve food security (Figure 3). The inundated area was observed using the Sentinel-2, Sentinel-1, Landsat 8, and PlanetScope sensors via the Floodbase monitoring system for the World Food Program and the Republic of Congo government (Ho et al., 2021). A custom crop map was produced within the inundated area because the globally available cropland map (GFSAD Global Cropland Extent Product, Thenkabail et al., 2021) was of poor quality for the region. Crop pixels where the Normalized Difference Vegetation Index (NDVI) was lower than the pre-flood baseline (3A) were marked as flood-damaged (e.g., appearing as brown in 3B). Damaged cropland areas data identified by Floodbase allowed the World Food Programme to target 145,000 households with cash-based transfers in the most insecure food regions where crops were affected most by inundation (3C). Importantly, this exemplifies an end-to-end approach for decision support and demonstrates the value of using EO to support decision-making around flood response and long-term recovery.

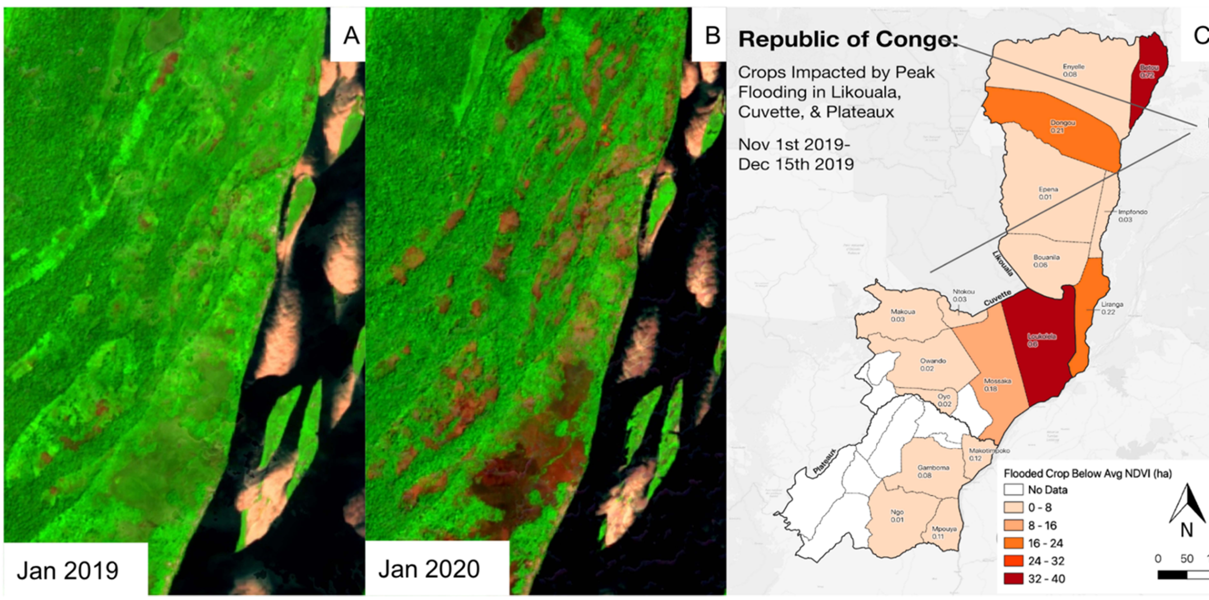

Figure 3. An example of EO to map crop recovery and provide decision support. Series of Sentinel-2 imagery in a flood-affected area before the December 2019 flood in January 2019 (3A) and after in January 2020 (3B) in the Republic of Congo. An inset from the Impfondo district shows estimated hectares of flood-affected crop area for flooded pixels from December 2019, where NDVI values were -0.1 or less than the value in January 2019 (3C). Images provided by Floodbase.

EO can also be used to identify the need for aid, insurance, and other disaster risk finance initiatives in flood recovery, which has heretofore been challenging due to a need for historical, fine-grained, and longitudinal data (Kousky, 2019). EO is being used to trigger insurance payouts to Bangladeshi farmers (Tellman et al., 2022; Thomas et al., 2023), forgive loans for Colombian farmers (World Bank, 2023), support insurance payouts in Southeast Asian countries (World Bank, 2023), and provide grants to New York City neighborhoods (Evans, 2023). EO recovery monitoring could be particularly relevant to provide evidence of insurance benefits for programs attempting to increase policy take-up rates, such as in government-sponsored insurance pools (Platt et al., 2016). The systematic documentation of post-flood recovery at the building or household level, which high spatial resolution EO data products could provide insight on, may aid in filling data gaps on the efficacy of indemnity- and index-based insurance and inform future improvements in flood risk finance initiatives.

3.4 Flood-related Adaptation Program Evaluation

The assessment of flood recovery and adaptation initiatives to reduce flood risk are inextricably linked. Traditional assessments of flood-related adaptation interventions rely on monitoring and evaluation programs to conduct household surveys and participatory workshops (Brown et al., 2010), which can be costly and demanding to implement across large spatial scales. EO can be used to scale up adaptation assessment over large areas, as has been done to measure yield variation due to the inability to plant in waterlogged soils (Lawal et al., 2021). An adaptation measure that has emerged in rice farming communities in response to disastrous flooding is the adoption of flood-resistant rice varieties. For example, 30% of India's cultivated rice area is prone to damage due to prolonged flooding, but submergence-tolerant rice has been estimated to increase yield by 45% compared to non-flood-tolerant rice varieties when submerged for ten days (Dar et al., 2013). EO can help to map the spatial distribution of rice areas (e.g., Gumma et al., 2015; Xiao et al., 2005; Zhan et al., 2021), offering a cost-effective way to monitor changes in rice cultivation over large areas and multi-year periods. Thus, EO has the potential to provide information helpful in evaluating the effectiveness of rice variety adaptation, often adopted after significant or repeated flood disasters. Additional potential for EO lies in monitoring post-flood landscape changes in agricultural regions, including erosion of arable land's topsoil (Morton & Olson, 2014; Schad et al., 2011; Trnka et al., 2016). Such evaluations can subsequently inform other locations' agriculture and food security strategies (Chen et al., 2019; Reed et al., 2022).

Reducing flood risk and increasing flood resilience in urban spaces using nature-based solutions such as green infrastructure practices to mitigate flood losses has become popular as a flood adaptation strategy that could be initiated during recovery (Wingfield et al., 2019). EO-monitoring can contribute a unique role in tracking the spatial and temporal patterns of development of flood mitigation and adaptation activities that include increased installation of green infrastructure practices (e.g., Chrysoulakis et al., 2021).

4 A Framework to Guide EO Applications to Monitor Flood Recovery

To address gaps in existing institutional approaches and extend current uses, we provide a framework (Figure 4) to expand applications of EO to monitor recovery and reduce disparities in flood recovery outcomes. The framework offers a generalized approach flexible to different geographic scales and flood risk contexts. The framework attempts to marry the practice of planning for flood recovery with EO-based monitoring of recovery alongside community participatory processes, recovery governance, and systems of accountability. The framework is split between pre-flood and post-flood stages, with a planning and testing phase within the pre-flood stage, an implementation phase within the post-flood stage, and a knowledge appraisal phase spanning both stages. The pre-flood stage could entail years or months leading up to the flood event, with the post-flood stage consisting of years, months, or days following a flood event.

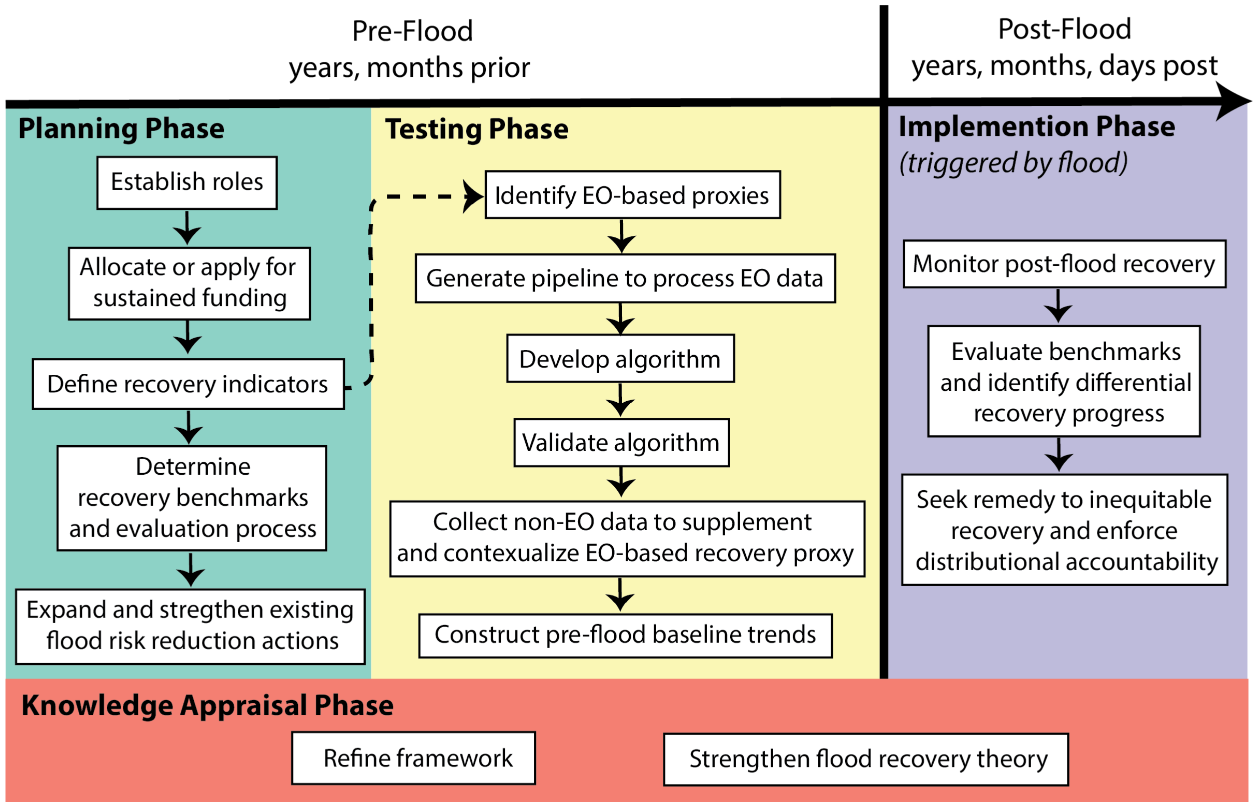

Figure 4. Framework to guide EO to monitor and redress inequitable post-flood recovery.

4.1 Planning Phase

The planning phase lays the foundation to achieve equitable participation, identify locally relevant recovery indicators, evaluate processes to track recovery and explore ways such information could reduce flood risk. Components of the planning phase draw on lessons from the literature on co-production (e.g., Davis & Ramírez-Andreotta, 2021; Meadow et al., 2015) and authors' experiences engaging alongside communities in their research.

The first component is to *establish roles* within a flood recovery governance system to determine expectations and accountability, acknowledge capacities, and agree upon responsibilities, communication, and coordination (De Ita et al., 2022). Stakeholders include local community members with experience in previous recovery efforts, organizations and government officials involved with flood recovery and risk reduction, emergency and disaster management professionals, social workers, urban and transportation planners, social and physical scientists, and remote sensing scientists to perform EO-based recovery monitoring. Data "translators" familiar with the technical limitations and insights that EO can lend are important to include to identify data sharing issues and strategic gaps in recovery planning (Kruczkiewicz et al., 2021b). Local residents representing a diverse set of community interests should be involved in planning and in assigning roles. Lessons from successful participatory environmental justice research suggest community leaders hold a meaningful position in research projects, project design includes decision-makers and specific policy goals, and long-term partnership is sustained through several funding sources (Davis & Ramírez-Andreotta, 2021). Outlining and agreeing upon roles is a primary step to achieving these outcomes.

It is critical to acknowledge that participatory efforts are time-consuming, expensive and should ideally be led by a third-party organization. As such, the next component is to *allocate or apply for sustained funding* for ideally multiple years. This step is necessary to build capacity in the established flood recovery governance system, repair broken trust with disenfranchised communities and support participatory collaborations with EO scientists and decision-makers. Within the US, efforts to address environmental and climate injustice are reflected in new funding opportunities that could be leveraged to co-produce recovery metrics, such as the EPA-funded Environmental Justice Collaborative Problem-Solving Cooperative Agreement, NASA Environmental Justice Program, or NSF-funded Civic Innovation Challenge. Internationally, Climate Change AI funds co-produced data applications for adaptation. Sustained funding will also be critical to scale monitoring systems that include more robust recovery indicators and longer-term monitoring in a later phase of the framework.

Once roles have been established within a flood governance system and funding identified, the group *defines a recovery indicator(s)*. Involving residents in identifying relevant recovery indicators pre-flood (or between flood events) is necessary to ensure participation and ensure indicators capture what the community knows to be relevant to tracking inequitable recovery based on experience (Hino & Nance, 2021). Next, all stakeholders should be involved to *determine recovery benchmarks and evaluation processes*. Recovery benchmarks could entail stages of recovery (e.g., electricity restored for all low-income neighborhoods). Evaluating the benchmarks could include community-first reporting practices (Emmett et al., 2009) and actions to be taken if benchmarks are not being met at certain points of time post-flood.

Aligning EO-based recovery monitoring with community priorities within the planning phase is vital to *expand and strengthen existing flood risk reduction actions*. This component is geared at using the outcomes of the framework to assess and redress inequity of flood recovery to bolster existing risk reduction activities. Building off prior components of the planning phase, the relationships required to elevate the use and impact of EO for flood risk management and decision-making span jurisdictional boundaries, government agencies, non-profit and community-based organizations, academia, and industry. Funding to expand and strengthen flood risk reduction should prioritize how to effectively nurture relationships and build local capacity long-term so residents' resident involvement continues if/when funding ends and partnerships move on.

4.2 Testing Phase

In the testing phase, EO and non-EO data collection and analysis are undertaken to develop a methodology aligned with the recovery monitoring processes agreed upon in the planning phase. Undertaking this task after a flood where personnel, capacity, and resources are strained can be inefficient and result in inadequate non-EO data being used to inform the EO-based data. As such, the testing phase should occur in anticipation of a future flood to have EO proxies, non-EO data, processing pipelines, and baseline data well-defined before a flood occurs. While all stakeholders can contribute, EO scientists should lead the activities outlined within the testing phase, given their technical expertise and familiarity with operationalizing EO data.

After defining the recovery indicator(s) in the planning phase, EO scientists can work with stakeholders to *identify EO-based proxies* representative of locally defined indicators (dashed line connecting the two components in Figure 4). EO-based proxies entail land cover types, conditions, or EO-derived land surface features that best capture and characterize the defined recovery indicator. For example, a recovery indicator could be flood water receding from agricultural fields, and an EO-based proxy could be Sentinel-1 imagery to detect and monitor surface water post-flood.

Once an EO proxy has been identified, EO scientists and stakeholders should *generate a pipeline to collect and process EO data* and *develop an algorithm* to monitor pre-flood trends and post-flood recovery. Algorithm development may entail refining an existing model with additional training data or creating a new model to detect a novel recovery-specific feature. To determine an appropriate model design, EO scientists should *validate the algorithm* to assess if a pre-existing algorithm can be used or if a new one needs to be developed to monitor the defined recovery proxy. This includes establishing data processing protocols during the subsequent implementation phase.

In tandem with establishing the EO data pipeline and analysis approach, the larger group should take stock of and *collect non-EO data to supplement and contextualize the EO-based recovery proxy*. Measuring flood recovery requires coupling EO with non-EO-based data to contextualize baseline flood risk, socioeconomic vulnerabilities, recovery resources, and policies governing recovery mechanisms and critically assess inequities (e.g., Cian et al., 2021; Schwarz et al., 2018). Non-EO data could be collected through semi-structured interviews, surveys, participatory mapping approaches, and serious games to understand local social processes (e.g., Forrest et al., 2022) and complement EO-based data on post-flood recovery. Non-EO data could include, for example, data from in-drain sensors (Gold et al., 2023), high water marks, photos from social media (Hultquist & Cervone, 2020), residents' experience or memory of inundated events (Tellman et al., 2015), census-based population and demographic data, health records data to track hazard-related mortalities (Parks et al., 2021), and information on the economic impacts of floods (Wen et al., 2022).

As part of this process, learning exchanges between all actors with roles identified in the framework could demonstrate how resident-defined recovery indicators can be monitored with EO and what non-EO-based data is needed to fill gaps in recovery monitoring that EO cannot adequately capture. To achieve this, the identified data translators should facilitate discussion among stakeholders identified in the planning phase regarding how EO and non-EO data can be operationalized to monitor flood recovery. By facilitating stakeholder engagement, knowledge may be co-produced to agree upon relevant and necessary non-EO datasets that need to be collected and generated to elucidate recovery trends.

To characterize what recovery means for a particular geography or flood event, *constructing pre-flood baseline trends* is critical to assess post-flood changes and compare recovery trajectories against them (Jain, 2020; Marlier et al., 2022). Constructing baseline trends is also helpful for refining expected changes associated with recovery activities. This may require a temporally dense archive of pre-flood imagery to model pre-flood trends. If this action is taken pre-flood, though, less time and resources are required to construct baseline trends immediately following an event, and efforts can be placed instead on monitoring flood recovery. Establishing pre-event trends is also an opportunity to test and develop detection and monitoring algorithms that perform well for the specific location and available EO data.

4.3 Implementation Phase

A flood event triggers the implementation phase, in which the goals are to track and determine variability in recovery progress and redress identified inequities in recovery progress. The broad scope of the implementation phase and potential action needed during this phase should therefore involve all stakeholders identified in the planning phase. The first component of this phase is to *monitor post-flood recovery*, which relies on EO proxies, monitoring algorithms, and non-EO data determined in the testing phase. Post-flood recovery trends could show ongoing inundation, persistent damage or impacts, a return to a pre-flood type and condition, or some improvement via changes associated with recovery based on the locally defined indicators in the planning phase.

While recovery monitoring is ongoing, the concurrent task is to *evaluate benchmarks and identify differential recovery progress*. One example of disparities in recovery progress could be comparing rebuilding rates in a flood-affected area by neighborhood characteristics. If available, data on EO-based flood extent, depth, or inundation duration could be used to control for variable flood exposure. By comparing recovery rates, such as how quickly flood waters recede, and debris is removed from streets or yards, disparities could be identified and contextualized with non-EO data. Without burdening affected communities, including residents' interpretation of benchmarks is crucial to assessing post-flood recovery trends.

If differential recovery is measured, this is absolute grounds to *seek a remedy to reduce the recovery gap and enforce distributional accountability*. EO-based recovery measures can provide documentation of unequal recovery rates across affected populations to allow government and non-government actors to prioritize recovery efforts. It can also be used to buttress legal processes to remedy unjust flood recovery by addressing unequal flood recovery processes. Examples of flood-impacted communities addressing flood injustices abound. There are multiple examples of how flood-affected residents and organized social movements have successfully sued the federal government for discriminatory flood relief (Rivera et al., 2019) or galvanized new investments for needed drainage (Rivera, 2023). Horry County Rising, a community organization based in South Carolina established after catastrophic flooding from Hurricane Florence in 2018, successfully advocated for accessible flood risk data and grants to support flood mitigation (McLean, 2023). EO monitoring of disparate recovery impacts can aid community-led efforts like these to remedy flood injustices. Distributional injustice can lead to the identification of marginalized community members that can be part of the recovery monitoring team and address potential procedural injustices (Zuniga-Teran et al., 2021).

4.4 Knowledge Appraisal Phase

The knowledge appraisal phase is active in both the pre-flood and post-flood stages, with the sub-components occurring throughout the entire process of the framework. The proposed framework is intended to be reflexive and iterative. Thus, an important step to evaluate the framework in the knowledge appraisal phase is to *refine the framework* and adapt it to portray shifting community needs, gaps, or capacities following adaptive management principles (Varady et al., 2016). As applications to monitor recovery are tested, this could lead to refined monitoring methods, identification of new recovery indicators, an improvement upon EO-based recovery proxies and algorithms, and the development of novel combinations of EO sensors and non-EO data sources. As such, refinement of the framework may occur contemporaneously while addressing additional components in other phases. If the framework is applied to existing monitoring platforms, such as the CEMS Rapid Response and Recovery Platform and WG Recovery Observatory, this appraisal could complement a formal review of program goals, operations, and internal evaluation processes to elevate EO insights to prioritize equitable recovery efforts.

Lastly, the knowledge appraisal phase provides opportunities to *strengthen the theory of flood recovery*, a poorly understood process that deserves concerted attention to guide how recovery monitoring could reduce flood risk and vulnerability inequities. The challenge in leveraging EO to characterize recovery is reflected in a shortage of examples beyond ad hoc damage assessments (Lallemant et al., 2017). While various theories of flood damages (Bakkensen & Blair, 2020) and disaster recovery have been proposed concerning ecosystems (Berke & Glavovic, 2012), sustainable urban systems (Smith & Birkland, 2012), and economics (Chang & Miles, 2004), to our knowledge, little to no theorization of post-flood recovery informed by EO has been developed. EO-based documentation of recovery patterns could be used to test underlying assumptions in theories of flood recovery and elucidate new insights on how inequity is exacerbated or potentially mitigated thru recovery actions.

5 Opportunities for EO Monitoring to Reduce the Flood Recovery Gap

We write this commentary at a time when decisions are past due on how we adapt to current and future flood risks. Promoting resilient and adaptive flood recovery is necessary to close the adaptation gap (UNEP, 2022) and prevent further unnecessary harm concerning the loss of life and economic, environmental, social, and community damage and disruption. Expanding EO monitoring systems to support systematic calculation or documentation of divergent recovery and the outsized impacts recovery inequities have on future flood event outcomes is urgent. This commentary brief calls for a more comprehensive approach to post-flood recovery monitoring, which measures locally defined recovery processes to understand variation in recovery outcomes. We recommend that EO close a recovery gap by adopting a proactive approach and pinpointing areas of greatest need long after the initial response. EO-derived insights on recovery progress can guide the redistribution of resources more equitably to enable adaptive recovery and lessen the impact of future flood events.

Importantly, EO is an incomplete tool to monitor all aspects of recovery. This commentary calls to ensure that scientific and policy agendas to document and respond to floods include flood recovery. This will require collaboration across remote sensing scientists, earth and environmental scientists, flood practitioners, and flood-affected community members and advocates. We offer a framework to expand EO to monitor flood recovery in a participatory way and document and redress post-flood recovery inequities. Improved accounting of flood recovery efforts and progress has the potential to further develop and refine adaptive recovery strategies, advocate for more equitable outcomes, and strengthen flood risk reduction strategies. To actualize novel actions of EO for flood adaptive recovery, we aim to inspire broad participation across disciplines to tackle this challenge that impacts communities globally.

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Open Research

No datasets were generated or analyzed during this study.

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