Earth Observation to Address Inequities in 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 loss of life, damaged infrastructure and natural assets, and threatened livelihoods. 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 distributional effects within communities. EO data are uniquely positioned to monitor post-flood recovery and inform policy on hazard mitigation and adaptation but remain underutilized. We encourage the EO and flood research community to refocus on developing flood recovery applications to address growing risk. Translation of EO insights on flood recovery among flood-affected communities and decision-makers is necessary to address underlying social vulnerabilities that exacerbate inequitable recovery outcomes and advocate for redressing injustices where disparate recovery is observed. We identify an unequivocal need for EO to move beyond mapping flood hazard and exposure towards post-flood recovery monitoring to inform recovery across geographic contexts. This commentary proposes a framework for remote sensing scientists to engage community-based partners to integrate EO with non-EO data 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 intensifying due to increased development in flood-prone locations and climate change. Flooding affects communities unevenly, and the recovery process 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 flood-affected communities' physical safety, homes, and livelihoods and prevent preparation for and mitigation of future floods. We present a framework for EO scientists and community partners to use EO for flood recovery monitoring. The goal of the framework is to outline steps to monitor local recovery progress so that inequities can be identified and addressed.

1 Introduction

More frequent and extreme flooding exacerbated by climate change increases societal impacts that disproportionately affect marginalized populations (e.g., Douglas et al. 2008). Institutions and policies also contribute to heightened flood risk as outdated flood maps and deficient flood risk disclosures drive development in flood-prone areas (Andreadis et al., 2022; Flores et al., 2022; Hino & Burke, 2021). In addition to poor urban flood governance, flood-adapted urbanization can intensify risk for communities that cannot access, benefit from, or are even harmed by such development (Ajibade, 2017). Flood vulnerability is also exacerbated where mitigation and recovery actions, including government assistance programs, reduce the adaptive capacity of marginalized groups (Domingue & Emrich, 2019; Elliott et al., 2020; Emrich et al., 2019, 2022), which are seldom prioritized in recovery (Muñoz & Tate, 2016), driving inequities in long-term household wealth (Howell & Elliott, 2019). Recovery post-flood shapes the ability of individuals, households, and communities to cope and prepare for future events (McSweeney & Coomes, 2011). Critically, inadequate post-flood recovery monitoring inhibits the planning and implementation of equitable adaptation.

Earth Observation (EO) data, available with unprecedented temporal and spatial scales, provides significant yet untapped potential to monitor flood recovery and evaluate adaptation efforts. In relation to EO, 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. Post-flood recovery detected with EO could entail the removal of debris from roadways, the reconstruction of damaged buildings or infrastructure, or restoration of agriculture or natural vegetation conditions. Identified changes may occur in flood-inundated areas or nearby non-flooded areas in tandem with recovery actions, such as the construction of temporary housing. EO can capture both change and lack thereof, enabling EO to capture a variety of recovery trends beyond just reconstruction to a pre-event baseline, such as changes to 'build back better' that address pre-flood inequalities and vulnerabilities (Forrest et al., 2019; De Ita et al., 2022).

Importantly, EO cannot monitor all aspects of recovery, with various spatial, temporal, and thematic limitations. Monitoring recovery at the household or neighborhood scale is particularly limited as recovery features may be too refined to be detected with high (< 5 meters) or very high (sub-meter) spatial resolution imagery. Similarly, recovery may occur at time scales unaligned with the temporal cadence that appropriate spatially scaled imagery is available. EO-monitored recovery indicators are constrained thematically to relative changes in land cover, conditions, or features that can be ascribed to recovery processes. Some outcomes commonly linked to disaster recovery, like financial shocks or public health impacts, are not directly observable with EO. That said, non-EO datasets can complement EO to aid in interpreting how such processes relate to observable change. For example, financial shocks may result in cropland abandonment observed with EO and market price data, and public health impacts may be triangulated by comparing co-located EO-flood extents and hospital records (e.g., Ramesh et al., 2021).

Recognition of the potential and limitations of EO-monitored recovery inspired a side meeting at the 2022 Global Flood Partnership Annual Meeting. A group of researchers and practitioners, including flood modelers, disaster management experts, social scientists, financial risk specialists, and public and private sector EO data providers, attended the workshop to share their perspectives. These experts concluded that EO's potential is underutilized to monitor flood recovery and thus inspired this Commentary to lead the field of EO flood monitoring in new directions toward flood recovery. We provide a brief overview of applications and operations of EO to monitor post-flood recovery and introduce a framework for applying EO to monitor post-flood recovery to redress inequities in recovery. EO evidence of unequal flood recovery could help build community-based flood resilience, autonomy, advocacy, and power in data-informed decision-making and support legal remediation to redress inequitable recovery. We invite the EO community of practice to collaborate with flood-affected partners to expand the application of EO to flood recovery to attain more equitable recovery outcomes.

2 Earth Observation Applications for Post-Flood Recovery

The diversity in EO data's spatial, temporal, and spectral resolution enables several applications for flood recovery. We identify four areas where EO can support flood recovery: mapping flood extent, monitoring impacts, flood risk reduction and financing, and flood-related adaptation program evaluation.

2.1 Mapping Flood Extent

A common application of EO for post-flood recovery is mapping flood extent change over time. EO-derived flood maps are often included in Post-Disaster Needs Assessments (PDNAs) produced for large-scale floods. For example, after the PDNA was released for the Pakistan floods in October 2022, the United Nations Satellite Applications Team (UNOSAT) monitored the flood extent over five months, finding that 1.8 million people remained exposed to stagnant flood water in February 2023. In this example, EO-delineated flood extent delineates ongoing post-flood recovery needs. An absence of ongoing, systematic analysis of the flood extent restricts longer-term response and recovery actions (Schumann et al., 2018). Flood extent maps can also be coupled with other socio-economic data to evaluate long-term impacts. For example, in Bangladesh, EO data was used to estimate an 8% increase in infant mortality over time from flood-affected areas (Rerolle et al., 2023).

2.2 Monitoring Impacts

EO can also identify flood-induced landscape changes to urban, agricultural, and natural resources like forests and coastal vegetation that offer natural flood protection (e.g., Marlier et al., 2022). EO provides critical insights into the obstruction of or damage to buildings, roadways, and other infrastructure (Butenuth et al., 2011; Ghaffarian & Kerle, 2019; Schnebele et al., 2014). Damage monitoring of infrastructure provides timely information on accessibility in the early recovery phases post-flood (Oddo & Bolten, 2019). The complexity of features and high spatial detail required to monitor urban damage has led to the expansion of datasets to train models to detect flood-related damage and recovery activities. For example, Hänsch et al. (2022) recently released the first training dataset of flooded and not-flooded building footprints and road networks.

The diversity in the spectral resolution of EO enables applications unrestricted by cloud cover that thwarts optical imagery. Interferometric synthetic aperture radar (InSAR) is used to detect anomalous changes in surface backscatter to map post-disaster damage (Plank, 2014; Stephenson et al., 2022). InSAR has been used in Damage Proxy Maps (e.g., Yun et al. 2015) to rapidly detect damage in urban contexts to support rapid response efforts by groups like NASA Advanced Rapid Imaging and Analysis (ARIA). Thermal nighttime lights imagery is used to measure the restoration of electricity post-flood (Gandhi et al., 2022; Levin et al., 2020; Qiang et al., 2020) and population movement within flood-affected areas (Mård et al., 2018). Román et al. (2019) used a time series of NASA Black Marble nighttime light imagery to assess the number of days without electricity for locations in Puerto Rico following Hurricane Maria (Figure 1). In this example, variation in the duration of electrical outages illustrates disparate recovery rates.

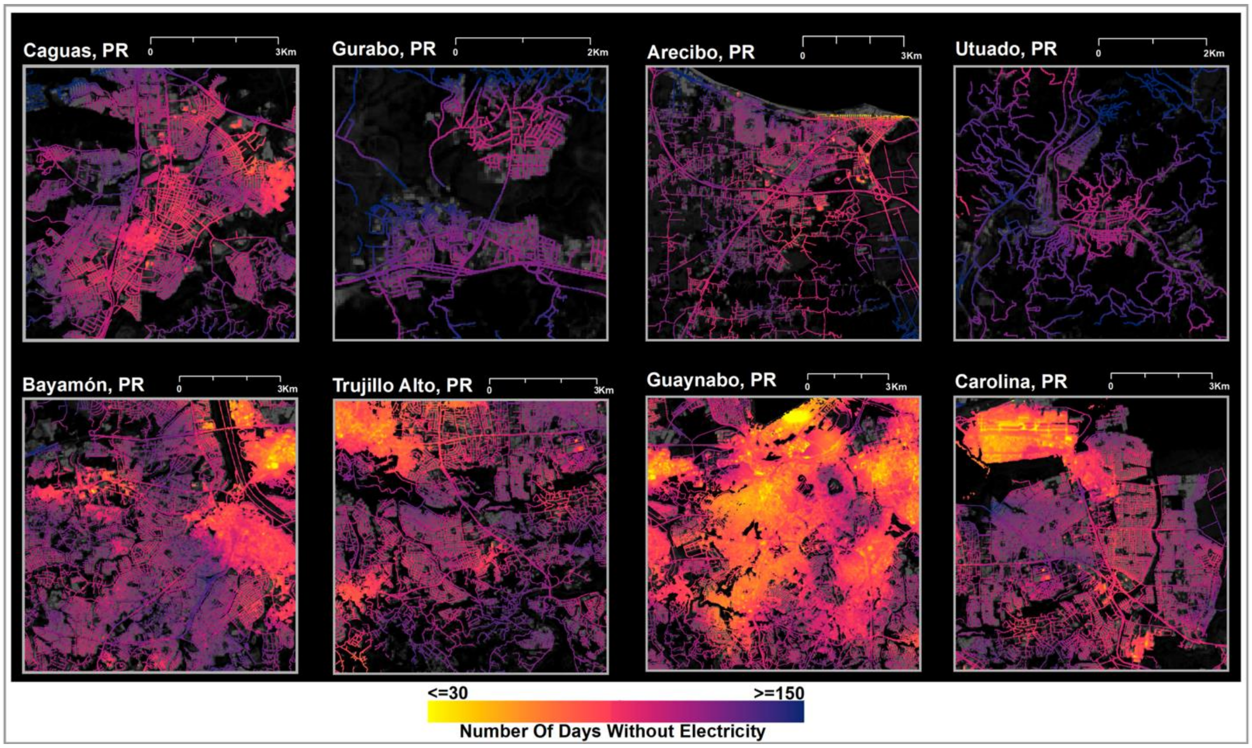

Figure 1. Variation in electricity outages for different locations in Puerto Rico following Hurricane Maria based on time series of NASA Black Marble nighttime light imagery. Image from Román et al. (2019).

2.3 Flood Risk Reduction and Financing

Humanitarian agencies use EO as inputs to anticipatory actions that reduce flood risk via early warning systems and forecast-based financing (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), EO data is employed to activate interventions when flood conditions breach pre-defined thresholds (e.g., Chen et al., 2019). An example of EO used to map agricultural impacts and support financing is from the Republic of Congo in December 2019, where Floodbase identified flood-damaged cropland so the World Food Program could target cash-based transfers for 145,000 households to improve food security (Figure 2). This exemplifies the value of EO to support end-to-end decision-making on flood response and long-term recovery. Similarly, EO is 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). Critically, EO recovery monitoring could help document the benefits of risk financing programs to support improved policy take-up where high exposure or significant gaps in risk coverage exist (Platt et al., 2016).

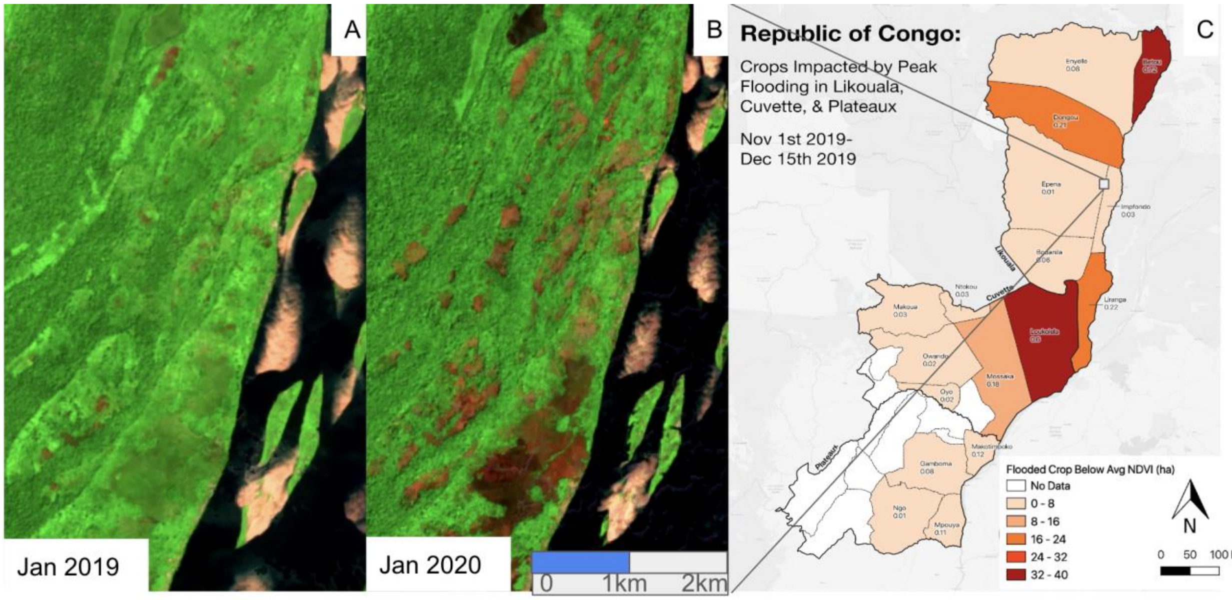

Figure 2. An example of EO to provide flood recovery decision support. Series of Sentinel-2 imagery in a flood-affected area before the December 2019 flood in January 2019 (2A) and after in January 2020 (2B) in the Republic of Congo. An inset from the Impfondo district shows estimated hectares of flood-affected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

2.4 Flood-related Adaptation Program Evaluation

Flood recovery and adaptation initiatives to reduce risk are inextricably linked. Program evaluations of flood-related adaptation interventions rely on household surveys and participatory workshops, which are costly and constrained to small geographies (Brown et al., 2010). EO can increase the spatial extent and temporal frequency of assessments, such as the effectiveness of rice variety adaptation after repeat flood disasters (e.g., Gumma et al., 2015). EO-based monitoring of post-flood agricultural changes, including erosion of topsoil (Trnka et al., 2016), can guide resilient food security strategies (Chen et al., 2019; Reed et al., 2022). In urban contexts, green infrastructure is a popular nature-based flood adaptation approach (Wingfield et al., 2019). By detecting changes in vegetation, EO can track patterns of green infrastructure development (Chrysoulakis et al., 2021).

3 Operational Entities Monitoring Post-Flood Recovery

EO can support resilient disaster risk management, as evidenced by institutional protocols that include 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; Voigt et al., 2016; Zuccaro et al., 2020). In particular, the Committee on Earth Observations Satellites (CEOS) Recovery Observatory and CEMS Risk and Recovery Mapping provide recovery mapping services. However, these monitoring systems are ad hoc, with limited resources to support systematic or sustained long-term monitoring (GFDRR, 2019).

There are three critical gaps in how existing initiatives monitor recovery. First, long-term recovery monitoring often concludes months after the flood event, restricting monitoring of long-run recovery years after an event. Second, there is no measurement of recovery 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. Third, 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. These three gaps are further entrenched by a common absence of flood-affected communities in characterizing relevant recovery indicators.

4 A Framework to Guide EO Monitoring of Flood Recovery and Redress Inequitable Recovery Outcomes

To address the three aforementioned gaps and include flood-affected communities and partners, we provide a framework (Figure 3) to expand applications of EO to monitor recovery and reduce disparities in recovery outcomes. Guided by community participatory processes, the framework is a blueprint for EO-based monitoring that accounts for local recovery governance and accountability approaches. The framework is flexible across scales and contexts, prompting multi-partner engagement with agreed-upon roles. Implementation ideally occurs pre-event, but post-event financial support increases the likelihood of adoption following a flood and may lead to broader partner participation. It is particularly advantageous to initiate the framework pre-flood to collect baseline data to improve estimation of deviations in recovery post-flood.

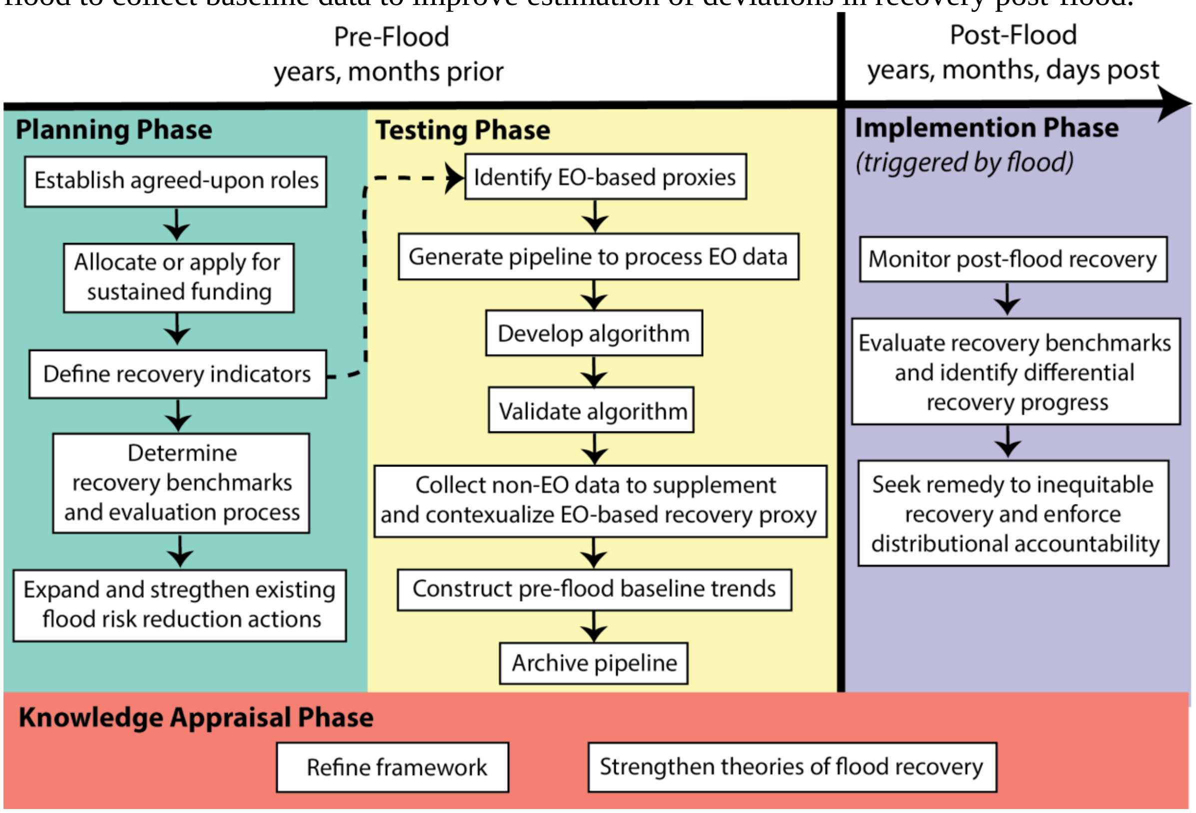

Figure 3. Framework to guide EO monitoring flood recovery and redress inequitable post-flood recovery outcomes. The framework spans both pre- and post-flood stages, with a planning and

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.

4.1 Planning Phase

The planning phase lays the foundation to enhance multi-partner engagement to identify locally relevant recovery indicators and evaluation processes to track recovery and reduce flood risk. Components of the planning phase incorporate lessons from the literature on knowledge co-production (e.g., Davis & Ramírez-Andreotta, 2021; Meadow et al., 2015).

The first component is to *establish agreed-upon roles* to acknowledge capacities and agree upon responsibilities, communication, and systems of accountability (De Ita et al., 2022). Based on skills or knowledge, some roles and responsibilities are more apparent. For example, remote sensing specialists are most apt to lead the EO-based recovery monitoring. Meanwhile, partners, including community members, organizations, and government officials, are best suited to identify and guide recovery priorities. Lessons from environmental justice research suggest community members hold meaningful funded positions, so community partners should hold leadership roles in implementing the framework (Davis & Ramírez-Andreotta, 2021). Emergency management professionals, social workers, and planners can support the interpretation of disparate flood recovery outcomes. Data "translators" are familiar with the technical limitations and insights that EO can lend and can identify gaps in data-sharing and decision-making among partners (Kruczkiewicz et al., 2021b). Ultimately, assigning roles and responsibilities will depend on individuals' capacities and the context in which the framework is implemented.

Participatory efforts are time-consuming, expensive, and preferably led by a third-party organization independent of EO scientists and community partners. In addition, marginalized groups are often less able to engage in traditional participatory efforts due to time and resource constraints (Gerlak and Zuniga-Teran, 2020). As such, the next component is to *allocate or apply for sustained funding* for, ideally, multiple years, with the potential for renewals and longer-term support. This step is necessary to compensate for the time spent engaging partners, building capacity, and repairing broken trust among disenfranchised communities with local governing entities and technical partners. Within the US, new funding opportunities could be leveraged, such as the EPA-funded Environmental Justice Collaborative Problem-Solving Cooperative Agreement, NASA Environmental Justice Program, or NSF-funded Civic Innovation Challenge. Sustained funding is also critical to scale monitoring systems that include more robust recovery indicators and support longer-term monitoring.

Next, the group *defines a recovery indicator(s)*. Community partner involvement in identifying recovery indicators ensures indicators are locally relevant based on their experience (Hino & Nance, 2021). Next, partners can *determine recovery benchmarks and evaluation processes*. Benchmarks are defined levels of recovery progress, while evaluation processes are the criteria by which to assess whether the benchmarks have been achieved. Recovery benchmarks could entail stages of recovery (e.g., electricity restored for all low-income neighborhoods). Benchmark evaluation processes could include community-first reporting practices (Emmett et al., 2009) and actions to be taken if benchmarks are yet to be met at specific points of time post-flood.

Lastly, aligning EO-based recovery monitoring with community priorities is vital to *expand and strengthen existing flood risk reduction actions*. This component determines how EO can bolster existing flood risk management and addresses the third noted gap, highlighting how ad hoc recovery monitoring inhibits actions to build flood resilience and reduce risk. Funding to expand and strengthen flood risk reduction should prioritize nurturing relationships and building local capacity for the long term so partners' involvement continues if/when funding concludes.

4.2 Testing Phase

In the testing phase, EO and non-EO data are collected and analyzed to assess recovery benchmarks and enable evaluation processes decided upon in the planning phase. Undertaking this task post-flood can be inefficient, where personnel, capacity, and resources are strained. Ideally, the testing phase occurs in anticipation of future floods to have EO proxies, non-EO data, processing pipelines, and baseline data defined pre-flood. Given their technical expertise, EO experts should lead activities directly engaging EO, while partners can identify recovery proxies and non-EO data sources and provide feedback on the construction of baseline trends.

After defining the recovery indicator(s) in the planning phase, EO experts can work with partners to *identify EO-based proxies* representative of the indicators (dashed line in Figure 3). EO-based proxies entail land cover types, conditions, or 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.

After proxies are identified, EO experts *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 refine existing models with additional training data or generate a new model to detect a novel recovery-specific feature. To determine an appropriate model design, EO experts should *validate the algorithm* to assess if a pre-existing algorithm or new model needs to be developed to monitor the defined recovery proxy.

In tandem with establishing the EO data pipeline, the next step is to *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, and policies governing recovery mechanisms to critically assess inequities (e.g., Cian et al., 2021; Schwarz et al., 2018). Data translators play a vital role in this task to enable EO scientists and partners to co-identify relevant non-EO datasets to elucidate recovery trends. 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, Rerolle et al., 2023), policy variables and responses, and information on the economic impacts of floods (Wen et al., 2022). To understand local social processes that contextualize recovery progress, non-EO data could also be collected through semi-structured interviews, surveys, participatory mapping approaches, and serious games (e.g., Forrest et al., 2022).

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 (Jain, 2020; Marlier et al., 2022). This requires a dense archive of pre-flood imagery to model pre-flood trends. If this action is taken pre-flood, less time is needed to construct baseline trends immediately following an event, and efforts can be placed instead on monitoring flood recovery.

To ensure replicability and iteration, steps are taken to *archive the pipeline*, conforming to FAIR (Findability, Accessibility, Interoperability, and Reuse) data practices (Wilkinson et al., 2016). This step enables the pipeline to be utilized in other and future flood recovery contexts, addressing the third noted gap among existing recovery monitoring operations, which is constrained to standalone events, limiting opportunities to reduce risk.

4.3 Implementation Phase

Triggered by a flood event, the goals of the implementation phase are to track variability in recovery and identify inequities in recovery progress. The first component is to *monitor post-flood recovery*, which employs EO proxies, monitoring algorithms, and non-EO data determined in the testing phase. Post-flood recovery trends are manifold and could denote ongoing inundation, persistent damage, or a return or improvement to pre-flood type and condition based on partner-defined indicators. Deviations from baseline trends can aid in characterizing post-flood recovery trends. Post-flood recovery monitoring temporally extends to when all benchmarks are met and addresses the first noted gap of existing operations characterized by short-term, infrequent recovery monitoring. Safeguards should be put in place to ensure partners are properly supported to monitor recovery if a flood occurs outside the funding timeline. For example, EO specialists could commit technical support or training to designated partners who can lead the recovery monitoring. Successful demonstrations with these considerations in place may increase funders' responsiveness to the utility and value of sustained funding.

Concurrent with ongoing monitoring, EO scientists and partners *evaluate recovery benchmarks and identify differential recovery progress* using benchmarks and evaluation criteria defined in the planning phase. This is a crucial element of the framework and fills the second noted gap in existing recovery operations, which often fail to measure recovery inequities, such as comparing rebuilding rates in a flood-affected area by neighborhood characteristics. If available, data on EO-based flood extent, depth, or duration could be used to control for variable flood exposure. By comparing recovery rates, such as how quickly flood waters recede or debris is removed from streets, disparities could be identified and contextualized with non-EO data.

If differential recovery is detected, these are grounds to *seek a remedy to reduce the recovery gap and enforce distributional accountability*. EO-based recovery measures documenting disparate recovery trends can prioritize equitable recovery efforts. Moreover, there are multiple examples of how communities have addressed flood injustice by suing the federal government for discriminatory flood relief (Rivera et al., 2019), galvanizing new investments for storm drainage (Rivera, 2023), and advocating for accessible flood risk data and grants to support flood mitigation (McLean, 2023). EO-monitoring of disparate recovery can aid community-led efforts like these to buttress legal processes to remedy unjust flood recovery. EO detection of unequal recovery can assist in identifying community groups that can be involved as partners working to redress recovery inequities (Zuniga-Teran et al., 2021).

4.4 Knowledge Appraisal Phase

The framework is designed to be reflexive and iterative, and thus, the knowledge appraisal phase spans the entire framework. First, it is important to *refine the framework* to account for shifting community needs or capacities following adaptive management principles (Varady et al., 2016). As the framework is tested in practice, contemporaneous refinement of recovery indicators, EO-based recovery proxies and algorithms, and development of novel combinations of EO and non-EO data sources may be necessary. Through iteration, there is the potential to *strengthen theories of flood recovery*. While various theories have been posited for flood damages (Bakkensen & Blair, 2020), disaster recovery 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 or tested. EO-based documentation of recovery patterns could test working theories of flood recovery and elucidate insights on how inequity is exacerbated or potentially mitigated through recovery actions. This phase further addresses the third noted gap by encouraging systematic monitoring beyond singular flood events through refinement of the framework and theory testing.

5 Prospects in EO to Reduce the Flood Recovery Gap

We write this commentary at a time when decisions on how we adapt to current and future flood risks are past due. Expanding EO monitoring systems to support systematic documentation of divergent recovery is urgent to address the outsized impacts of recovery inequities on future flood event outcomes. To spur collaboration among EO experts and partners towards innovation, we offer a framework to expand EO to monitor flood recovery using locally defined recovery processes to understand variation in recovery outcomes and redress inequities. The framework is a roadmap to fill the three prevailing operational gaps, including long-term recovery monitoring, omission of disparate trend detection, and monitoring across numerous events by outlining how EO scientists and partners can collaborate to use EO to monitor relevant recovery indicators and identify disparities in trends. These insights can guide more equitable distribution of resources, enable adaptive recovery, and mitigate future flood events.

The proposed framework requires significant finance and time to build relationships and properly compensate participants, especially flood-affected community members. We recognize that funding constraints within existing programs may explain why current recovery monitoring is limited in scope. To this end, we urge the EO community of practice to pursue funding sources that enable partnerships with communities to leverage EO to monitor flood recovery and for funders to direct resources toward sustaining engagement and operationalizing recovery monitoring. We argue scientific and policy agendas should include EO-based approaches that include flood recovery monitoring to justify action to redress inequities, improve adaptive recovery strategies, and strengthen flood risk reduction strategies.

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Open Research

No datasets were generated or analyzed during this study.

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