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Key Points:

- Lack of reliable long-term records of small and regional floods across global tropics hinders understanding their dynamics and forecasting
- Inundation data derived from CYGNSS SmallSat constellation can detect onset and day-to-day evolution of even small scale floods
- Inundation anomalies over 0.1 observed within 15 km of a flood location constitute optimal conditions for objective flood identification

Supporting Information:

Supporting Information may be found in the online version of this article.

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Detecting Localized Floods in Tropical Regions With CYGNSS SmallSat Constellation: A Proof of Concept From the Maritime Continent

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Abstract Flooding events are a major contributor to natural disasters across the global tropics. However, reliable flood data are sparse, which limits our ability to understand flood dynamics across spatial and temporal scales. Here, data from the CYGNSS SmallSat constellation are utilized to identify small- to regional-scale flooding events in Sumatra. Three case studies show that CYGNSS-derived inundation data capture evolution of floods, with increased inundation detected near flood locations 1 day after the event. A comprehensive analysis of 555 floods records in Sumatra identifies key parameters for a flood detection: an inundation anomaly threshold (0.1) and maximum distance between observations and a flood location (15 km). This approach could enhance flood risk assessment and forecasting, benefiting tropical populations. Our methodology, reliant on low-cost small-satellites, shows promise for future scalability with a larger satellite constellation, enabling better flood detection and long-term, near-real-time monitoring of floods across the global tropics.

Plain Language Summary Floods pose a serious threat to people and economies, especially in the global tropics. While large-scale floods are often well-documented, smaller regional events frequently go undetected due to limited data. To address this gap, we used data from the CYGNSS small satellite constellation to track flooding in Sumatra, an island regularly affected by such disasters. Our analysis of three case studies shows that CYGNSS can detect daily changes in occurrence of surface water, even for small urban areas. By examining 555 flood events, we identified key parameters for detecting floods, including an inundation anomaly threshold of 0.1 and a maximum observation distance of 15 km. These findings provide a foundation for using CYGNSS to monitor floods consistently across different regions and scales. Our approach, based on low-cost satellites, offers a promising solution for improving flood detection and early warning systems. Expanding this method with a larger satellite network could enhance real-time monitoring and support better flood preparedness in tropical regions.

1. Introduction

Extreme rainfall and the resulting natural hazards pose significant threats to both human life and economic stability. According to the Emergency Events Database, floods were the most frequent type of natural disaster in 2023 worldwide (CRED, 2024), with quickly evolving events having the highest mortality rates per event (Jonkman et al., 2024). Due to naturally high precipitation rates, equatorial regions are particularly vulnerable to rainfall-related disasters. The densely populated Maritime Continent (MC) is particularly at risk of adverse effects of flooding, especially compared to more developed regions with stronger social safety nets.

Tropical weather systems on subseasonal-to-seasonal scale modulate rainfall variability across the global tropics and can lead to extreme events (Schreck, 2021). Over the MC regions, such systems have been recognized as leading contributors of both widespread as well as severe regional extreme precipitation events and floods (Baranowski et al., 2020; Latos et al., 2021, 2023; Lestari et al., 2019; Lubis et al., 2022; Muhammad et al., 2021; Ramadhan et al., 2024; Senior et al., 2023). However, most of this knowledge stems from individual case studies of particularly long (Tangang et al., 2008) or high-loss (Latos et al., 2021; Lubis et al., 2022) events. Hence resulting progress in understanding how tropical dynamics influences rainfall cannot be fully leveraged for improved flood hazards assessment, mainly due to the lack of reliable and long-term flood databases.

There is a broad spectrum of floods that occur frequently with adverse impacts on local to regional scales. According to the National Agency for Disaster Countermeasure in Indonesia (Badan Nasional Penanggulangan

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Bencana, BNPB), in 2023 there were in total 1,255 floods in Indonesia, which affected more than 3.87 million people (Pratiwi, 2024). Many of these were short-lived and small-scale events.

While widespread events are relatively easily recognizable, regional, and small scale floods remain often under-detected. Current methods for monitoring small floods usually rely on subjective data sources. Both government databases and social media tracking (Baranowski et al., 2020; de Bruijn et al., 2019; Guo et al., 2023) require two critical steps: the human observation of a phenomenon and its subsequent reporting. As a result, habits, culture, and education levels can influence reliability of flood detection. Hence, objective measurement-based methods offer clear advantages over human-reported systems. However, to date such methods face significant limitations. For instance, satellite-based optical sensors, such as Landsat, Sentinel-2, MODIS or VIIRS, struggle to provide usable data from areas with dense vegetation or dominated by cloudy conditions (Asner, 2001; Huang et al., 2018; S. Li et al., 2018; Tellman et al., 2021)—both common in the tropics and over the MC in particular. Active satellite radars, such as Sentinel-1 or PALSAR overcome some of these challenges (Arnesen et al., 2013; Muro et al., 2016) but often lack the temporal resolution needed to capture fast-evolving events. Flood products derived from microwave radiometers, like SWAMPSv3 (Jensen & McDonald, 2019) or GIEMS-2 (Prigent et al., 2020), offer an alternative to the above techniques, but their spatial resolution (>25 km) is too coarse to capture smaller-scale floods in a complex terrain.

A promising approach for flood monitoring across scales is to utilize data from the Cyclone Global Navigation Satellite System (CYGNSS) small-satellite constellation. The CYGNSS satellites are equipped with GNSS Reflectometry (GNSS-R) receivers, which opportunistically collect signals transmitted by GNSS satellites and reflected from the Earth's surface (Figure 1a). While smooth surfaces such as inland water bodies produce strong and coherent reflections, rough surfaces like sand or vegetation result in a diffuse signal. Hence, CYGNSS observations can be leveraged to study variations in inland water state (Chapman et al., 2022; Chew et al., 2018; W. Li et al., 2021; Morris et al., 2019; Zhang et al., 2021), including water features as small as 100–200 m wide (Chew & Small, 2018). Furthermore, CYGNSS uses L-band signals, which can penetrate dense vegetation more easily than C-band (e.g., Sentinel-1) sensors, making it particularly suitable for tropical regions. The constellation of currently seven small-satellites enables observations over a single location with higher frequency than traditional single satellite systems. Thus, CYGNSS has potential to provide inundation data with sufficient temporal and spatial resolution to monitor small-scale and regional flood events, making it an attractive alternative to existing methods of objective flood monitoring.

To date, CYGNSS data have been used to study widespread or long-lasting flooding events (Chew et al., 2018, 2023; Rajabi et al., 2020; Wei et al., 2023; Zhang et al., 2021) and seasonal variability in surface water extent (Al-Khaldi et al., 2021; Pu et al., 2024). These studies have demonstrated the ability of CYGNSS to track large-scale changes in inundation dynamics and show good performance against other available data sets. This study expands on the previous work and assesses whether CYGNSS data can be effectively utilized to fill in the gaps in detection and monitoring of small scale and regional floods. Our analysis focuses on the island of Sumatra, where floods have been studied through various data sources (Baranowski et al., 2020), providing a well-documented record of their spatio-temporal characteristics.

2. Data and Methods

In this study, we used the UCAR/CU CYGNSS product (CU-CYGNSS) (Chew & Small, 2022), which provides daily fractional inundation data with 3 km spatial resolution, based on 3-day aggregates of observations and their spatial interpolation (Figure 1b). However, we chose to only use grid cells with direct CYGNSS observations (Figure 1c) to derive both daily inundation (Figure 1d) and daily inundation anomalies with respect to long-term average (Figure 1e) in order to reduce any uncertainty caused by the spatial interpolation.

The daily CU-CYGNSS observations and inundation anomalies are analyzed in relation to flood occurrences using two data sources: governmental records from BNPB (“BNPB database”) and reports from local newspapers (“newspapers database”). The overlap between CYGNSS and both databases is between 20 March 2017 and 31 December 2018, which constitutes an analysis period for this study (Figure 2a). Variability in number of floods between BNPB and newspapers databases correlates well during this period, increasing confidence in utilized flood data. The number of CYGNSS observations increased after July 2019 due to a change in the onboard collection strategy such that observations were collected twice as frequently—from once every second to once every half second. It should be noted that there was a shift in CYGNSS data availability and characteristics in

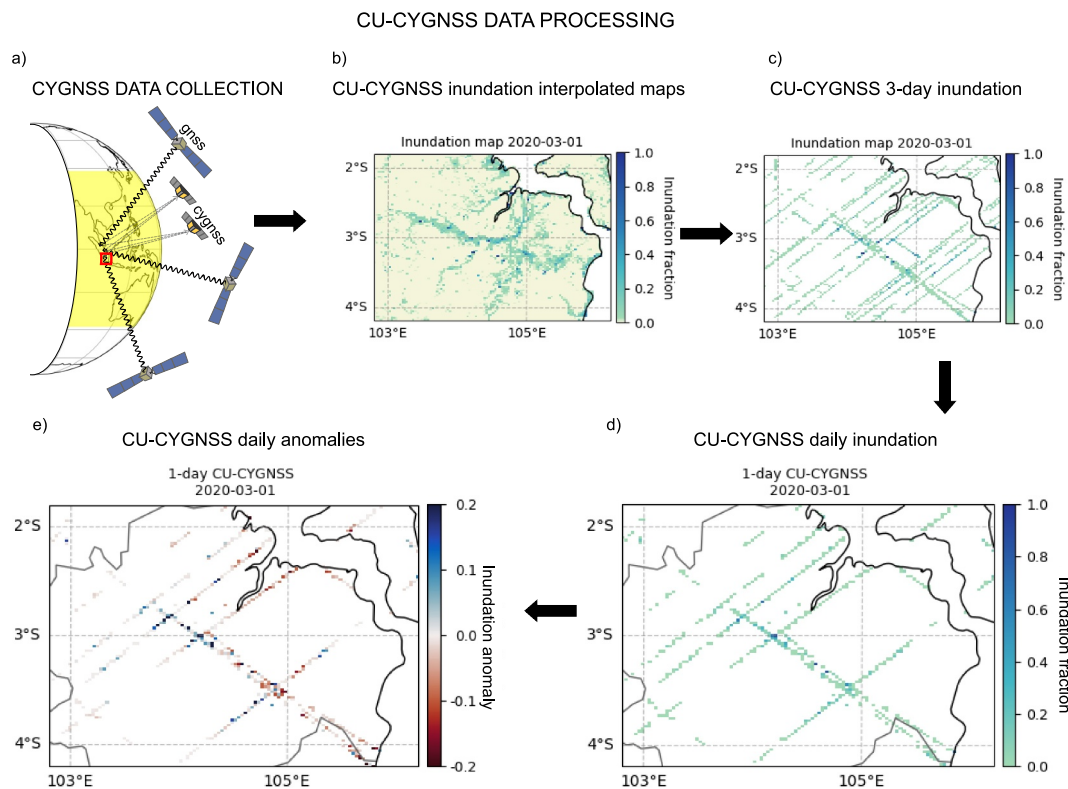


Figure 1. CU-CYGNSS Data Processing Scheme. (a) GNSS-R data collection schematic. (b) CU-CYGNSS interpolated inundation map. (c) Three-daily CU-CYGNSS inundation observations. (d) Daily CU-CYGNSS inundation observations. (e) Daily CU-CYGNSS inundation anomalies.

February 2020 due to change in GPS flex power mode (see Supporting Information S1 for additional details). However, the analysis presented here is based solely on data from before this event, when a number of available CYGNSS observations over Sumatra was relatively low, but constant (Figure 2a). The baseline climatology for CU-CYGNSS daily inundation anomaly calculations (Figure 1e) is based on an original, interpolated CU-CYGNSS data from before the shift (March 2017–February 2020). Inundation anomalies were calculated relative to this climatology. We focused on changes in daily anomalies from the day before (DOF – 1), the day of the flood (DOF), and 1 day after (DOF + 1). Our analyses consist of three case studies and statistics aggregated across all floods from the newspaper database. In the latter analysis, distributions representing known flood cases are also compared against a reference distribution of the same sample size but based on random observations. A detailed description of methodologies and data processing is provided in Supporting Information S1.

The number of available CYGNSS observations across global tropics is low in comparison with subtropical region (Figure 2b). This is a result of both the CYGNSS orbits—the CYGNSS satellites pass over the most northern/southern latitudes more frequently than the tropical ones—and the dense vegetation in the tropics that can result in noisy observations, which are removed during quality control in the inundation retrieval. CYGNSS data availability over Sumatra (Figure 2c) shows spatial distribution consistent with local orography. More observations are available in lowlands and valleys, characterized by dense population and more frequently affected by floods as well, then in mountainous regions.

3. Results

First we assess whether CU-CYGNSS daily anomalies are capable of identifying individual flood events. To that end, we selected floods (based on the BNPB and newspaper data sets) in Sumatra that also had corresponding CU-CYGNSS observations in their vicinity. Overall, there were dozens of such cases and we closely analyzed three

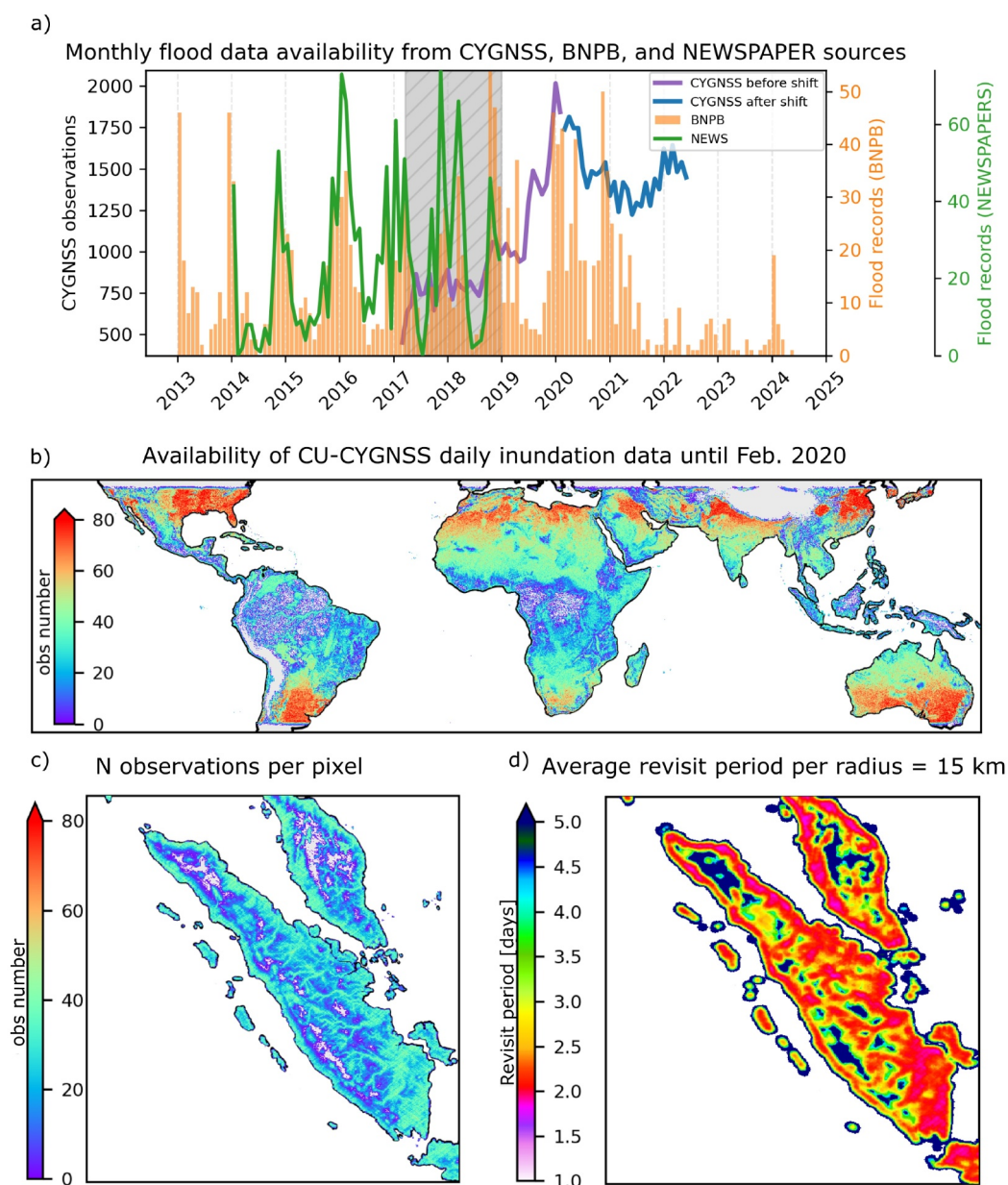


Figure 2. Flood data availability. (a) Time series of data availability from CU-CYGNSS, BNPB, and NEWSPAPER databases. (b) Number of CU-CYGNSS daily inundation data during 20 March 2017–31 December 2018 in each native CU-CYGNSS pixel. (c) Same as (b) but zoomed in on Sumatra, (d) the CU-CYGNSS average revisit time during 20 March 2017–31 December 2018 inside an area with a 15 km radius centered on each native CU-CYGNSS pixel.

unrelated ones (Figure 3a), exemplifying different scenarios for CU-CYGNSS data availability. We analyzed anomalies between 1 day before a flood and 1 day after a flood (Figure 3, rows b–d) to observe an evolution of an event.

The first case was a flood in Padang on 31 May 2017, that was triggered by a strong Convectively Coupled Kelvin wave, and was well captured by both the BNPB and newspaper databases (Baranowski et al., 2020). In the newspaper database, five separate locations in the city were reported to be flooded. There were no CU-CYGNSS daily observations near reported flood locations on the day before, and few during the day flooding occurred. However, 1 day after the floods, more CU-CYGNSS daily anomalies were available in that area. While not every

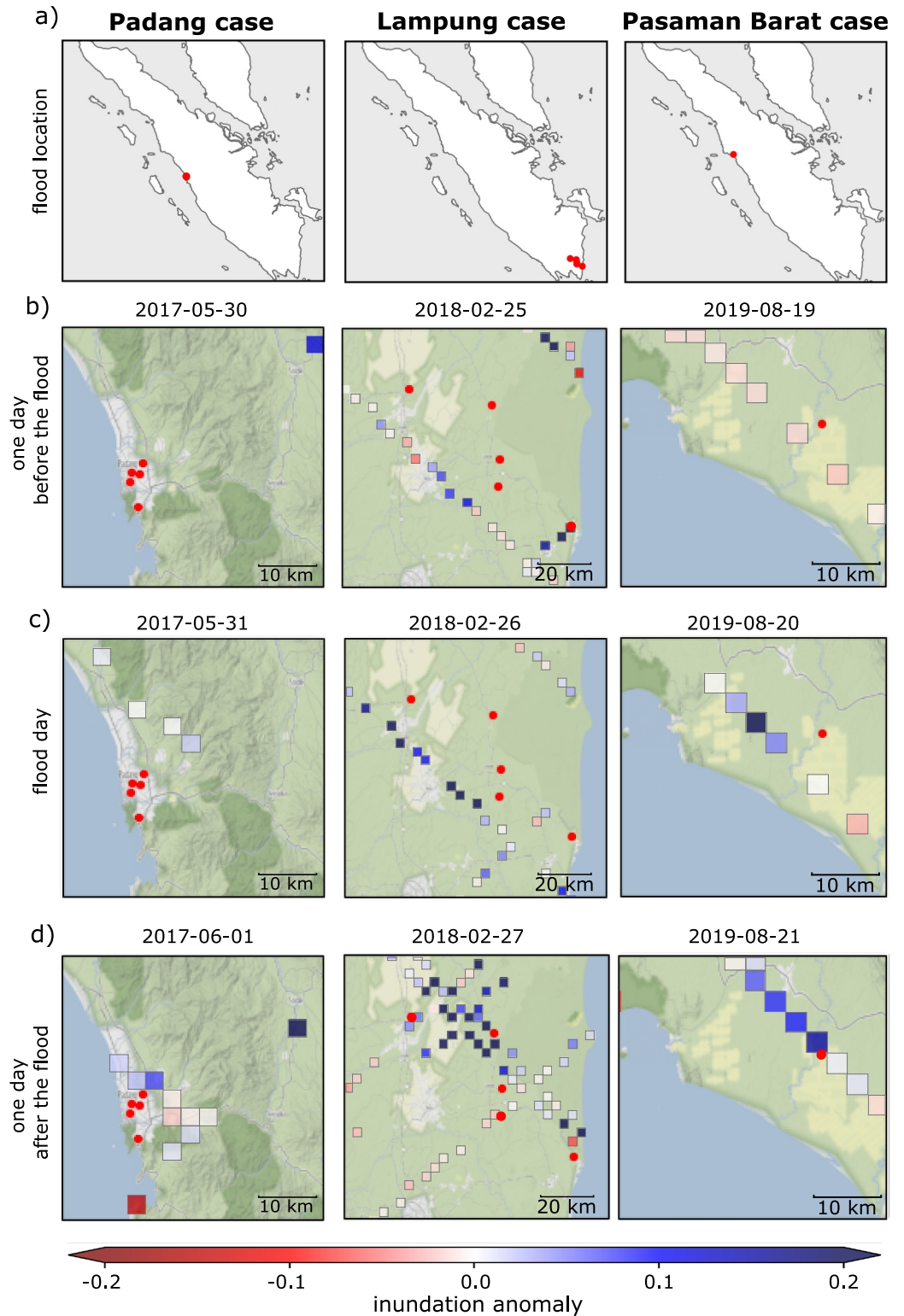


Figure 3. Three flood case studies: Padang (left), Lampung (middle), and Pasaman Barat (right). Row (a): Location of a flood. (b–d) CU-CYGNSS anomalies on 3 days relative to a flood. Shading indicates topography and surface type. Size of each CU-CYGNSS grid box is 3×3 km. Red dots: reported flood locations from newspapers and BNPB databases.

anomaly indicates positive values, the two largest of them were situated the nearest to the flooded areas. These points show increases in inundation up to 0.09 (9% more area submerged). This is a significant increase given a size of a single pixel (9 km²), especially in an urban environment. A strong positive anomaly in Solok area (north-east corner of the Padang case map) indicates possible flooding there as well, but this was not reported in human-dependent databases. A strong, negative anomaly south of Padang is likely not related to flooding and results from ocean contamination in the CYGNSS observations collected within grid cells significantly overlapping the coast.

Two other cases show a similar progression: an increasing data pool as the flood develops, with the maximum amount of available data 1 day after the event. As a result, CU-CYGNSS daily data are more common during “wet” periods as increased water presence enhances and makes reflected GNSS signals more coherent. Consequently, the CU-CYGNSS daily observations statistics can be skewed towards larger inundations and result in exaggerated mean values (Figure S2 in Supporting Information S1). Hence, even small positive anomalies can indicate significant flooding.

The Lampung flood case (Figure 3, middle column) occurred on 26 February 2018, when 5 flood locations across a 50 × 40 km area in the southeastern part of Lampung province (southeast Sumatra) were reported in the newspaper database. Here, flood markers are scattered across a larger and less urbanized area compared to Padang case study. This region is also predominantly flat, which may have influenced the extent and distribution of flooding. CU-CYGNSS daily anomalies 1 day before the event already show some positive values across the region (Figure 3, row b). This may result from the fact that while the major flood event was reported on 26 February, high precipitation already started on 25 February and could have led to increased surface water area (Figure S3 in Supporting Information S1). On the DOF, there was another flyover of the CYGNSS satellite, very close to the track from the previous day (swaths south of flood markers) showing positive anomalies with a larger amplitude (Figure 3, row c). On 27 February, a significant increase in the number of available data points, as well as the number of large anomalies (exceeding 0.1), is observed.

The last case is a flood that occurred in Pasaman Barat on 20 August 2019, as indicated by the BNPB database (Figure 3, right column). One can observe a clear change in the character of the CU-CYGNSS daily anomalies. On 19 August CU-CYGNSS daily anomalies near the flood location show conditions that were marginally drier than usual. On 20 August, available data points are located very close to those from the previous day, but show positive anomalies west and northwest of the flood location. On 21 August, the available observations are still close to those from previous days, but show higher than usual inundation over a larger area. The evolution of CU-CYGNSS anomalies indicates that flooding started northwest of the marked flood location on a DOF and increased in flooded area towards southeast on the next day. This is consistent with the evolution of precipitation patterns on those days (Figure S3 in Supporting Information S1).

These case studies indicate that CU-CYGNSS is sensitive to surface water variability, including even small-scale and short-lived floods. Other satellite platforms commonly used for flood detection didn't have capacity to track those events (lack of data or obstructed view; see Figure S1 in Supporting Information S1). A few important features of the CU-CYGNSS data arise from the analyzed cases: the largest data pool appears to be available 1 day after a flood, even relatively small inundation anomalies can be important for flood detection and the largest anomalies are observed near flood locations. Furthermore, anomalously wet observations from several different satellite passes provide an opportunity for cross-referencing data from independent CYGNSS platforms. This serves as a proof-of-concept for CYGNSS-based, objective flood identification. However, two crucial parameters still need to be defined: the maximum distance between CYGNSS observations and a flood location, and the threshold for inundation anomaly amplitude.

In order to quantify these parameters, we analyzed the characteristics of CU-CYGNSS inundation anomalies around each of the 555 records in the newspaper database. We have identified all flood events that had any CU-CYGNSS daily anomalies in their vicinity 1 day before a flood (DOF − 1), on a day of a flood (DOF) or 1 day after a flood (DOF + 1). A number of flood records with matching CU-CYGNSS observations depends on a maximum radius from which those observations are considered. To better understand this impact, we analyzed all data within different radii, ranging from 3 to 45 km, independently.

The number of floods with corresponding CYGNSS observations increases as the maximum radius grows. This increase is the fastest for small radii. Only 72 flood events (13%) have matching observations within 3 km radius, while almost 164 events (30%) have available data within 9 km distance. For larger radii this increase becomes

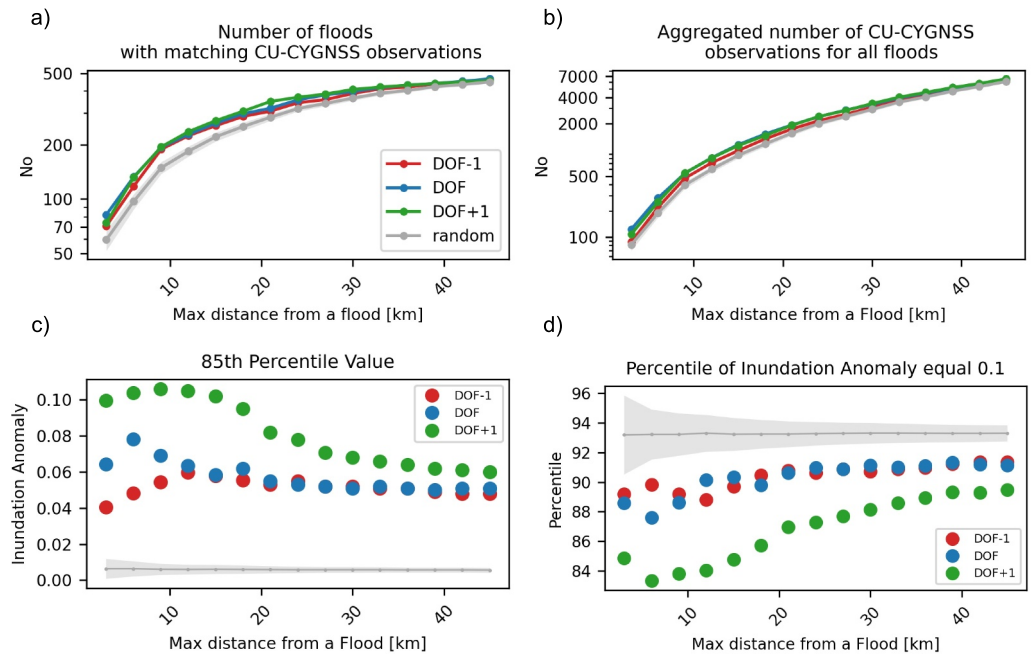


Figure 4. CU-CYGNSS daily anomaly statistics relative to day of flood (DOF, colors) and distance from a flood (x-axis). (a) Number of floods with matching CU-CYGNSS daily data. (b) Number of available CU-CYGNSS observations around a flood. (c) The 85th percentile of the cumulative density function of CU-CYGNSS anomalies for a given day and maximum radius. (d) A percentile value for anomalies equal to 0.1 for a given day and radius. In each panel red indicates distribution for DOF − 1, green for DOF and blue for DOF + 1. Gray shows a CU-CYGNSS distribution from 555 randomly selected times and locations in Sumatra, bootstrapped 100 times (line: mean and shading: standard deviation).

slower (e.g., for 15 km radius it is 40%). The aggregated number of observations also increases with the growing radius (Figure 4b), but the rate of this growth is much faster (more observations of the same event are possible, resulting in a larger data pool). As an example, for 15 km radius, 858 aggregated observations corresponding to 221 flood events were found. The available data pool is larger on DOF and DOF + 1 than DOF − 1, consistent with case studies. Furthermore the number of CYGNSS observations near flood locations exceeds the average derived from randomly selected locations in Sumatra. Hence, the available data pool related to a flood is larger than on a random day. We took advantage of this fact and constructed cumulative density functions based on all available data (Figure 4b) for each radius. Differences in those distributions during flood evolution are the largest for 85th percentile (see Supporting Information S1) so we choose this level for further analysis.

The 85th percentile of the inundation anomaly distribution is the largest on DOF + 1 (Figure 4c), with the biggest day-to-day changes when the maximum radii is smaller than 20 km. Specifically, for DOF − 1 and DOF the 85th percentile value is always less than 0.1, while for DOF + 1 it is nearly constant and exceeds 0.1 for all maximum radii up to 15 km. Thus, at this spatial scale, there is a distinct separation between distributions derived for consecutive days, along with a clear difference from a random sample. To further understand if inundation anomaly value of 0.1 can constitute a threshold for flood detection, we calculate which percentile of all distributions it accounts for. For maximum radii up to 15 km, the inundation anomaly value of 0.1 accounts for 85th percentile for DOF + 1, 89–90th percentile for DOF − 1 and DOF, and 93rd percentile for a random sample (Figure 4d).

Thus, the above analysis of 555 known flood cases allows to quantify the two thresholds crucial for objective flood identification: the minimum inundation anomaly and the maximum radial distance between flood location and CYGNSS observation. For the island of Sumatra, these thresholds are 0.1 and 15 km, respectively. Therefore, inundation anomalies exceeding 0.1 indicate a potential flood within an area with 15 km radius around them. The threshold inundation anomaly value can be recalculated for other regions as it corresponds to the 93rd percentile of a local inundation anomaly distribution. The threshold for maximum radius is a compromise between sample size (Data Availability) and separation between consecutive days around a flood as well as random sample.

Hence, methodology presented here is transferable and can be used to leverage CYGNSS data for flood identification in other regions as well by taking into account their local variations in a base line and Data Availability. Furthermore, day-to-day changes in available data pool and distribution of inundation anomalies can help increase confidence in potential flood identification, as more data and larger anomalies are expected on DOF + 1 than on previous days.

4. Discussion and Conclusions

Recent advances in understanding the link between precipitation variability and subseasonal variations in large-scale atmospheric circulations have enabled longer and more accurate predictions of hazardous weather in the tropics (Latos et al., 2021, 2023; Lubis et al., 2022; Schreck, 2021). Although similar advances should be achievable in understanding and predicting flood dynamics, progress is hindered by the lack of consistent, long-term flood records across all spatial and temporal scales. This study demonstrates that daily inundation estimates derived from CYGNSS, a constellation of small-satellites, can help close that gap.

The analysis presented in this paper focuses on the island of Sumatra, which is frequently affected by small-scale and regional floods (Baranowski et al., 2020; Senior et al., 2023). We used gridded CU-CYGNSS daily inundation data (individual swaths) alongside two independent and reliable flood databases. While CYGNSS was originally designed to study wind speeds over the ocean (Ruf et al., 2016), it has already demonstrated the ability to monitor long-term variations in surface water over land, including widespread, seasonal flooding (Chew, 2023; Chew & Small, 2018; Chew et al., 2018, 2023; Pu et al., 2024; Rajabi et al., 2020; Zhang et al., 2021). However, using CYGNSS to detect small-scale and short-lived floods is a novel application. Here, based on case studies and the analysis of a 21-month period we demonstrate that CYGNSS-based inundation estimates can follow such events.

The three case studies (Figure 3) demonstrate that CYGNSS measurements offer the unprecedented ability to monitor day-to-day changes in surface water extent from space, even at the spatial scale of small urban floods. Since CYGNSS-based estimates appear to be skewed toward wet values (Figure S3 in Supporting Information S1), even small positive inundation anomalies may indicate flooding conditions. As a result, more observations can be expected once flooding has already started. In fact, all case studies reveal the largest data pool occurring 1 day after event onset.

The CYGNSS data sensitivity to flooding conditions was further tested by analyzing 555 floods in Sumatra. This was achieved by analyzing cumulative distributions derived from CYGNSS data as functions of time and distance. This analysis confirmed that characteristics of CYGNSS observations change during a flooding conditions and allowed to constrain two parameters crucial for CYGNSS-based flood detection. The first is a threshold for inundation anomaly, which value was determined to be 0.1. While it may appear small, it means that 10% or more of a total pixel area is inundated, corresponding to 90 ha of anomalously submerged surface. This threshold can be recalculated from any local distribution of CYGNSS observation, ensuring that it accounts for local conditions. The second parameter is maximum distance between observations and flood locations, which secures sufficient data-pool for robust separation between flooding and non-flooding conditions. We determined that 15 km is a good compromise and can be applied in other regions with similar characteristics (e.g., across tropics). Although it may result in missing very local events, the growing number of GNSS-R satellites (Ruf & Gleason, 2025) lead to an increase in the available data pool and therefore allow for the decrease of the maximum radial distance parameter. Additionally, this parameter can be directly translated into a radius of influence of a single CYGNSS observation, thus significantly increasing a number of data that characterize any given location (Figure 2d).

This proof-of-concept clearly demonstrates that CYGNSS data can be leveraged for detection of a small-scale and short-lived floods. While this methodology relies on a relatively low-cost small-satellites, observed miniaturization of satellite platforms (Stephens et al., 2020), as well as interest from private sector (Al-Khaldi et al., 2024; Masters et al., 2024; Setti & Tabibi, 2023), will expand an available data pool in the future and shall lead to a better flood detection. This would fulfill a crucial requirement to improve understanding of flood dynamics across all scales, and allow identification of their drivers. As a result, a reliable flood risk assessment and better floods forecasts would benefit population of the global tropics.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

CU-CYGNSS data (Chew & Small, 2022) are available at <https://data.cosmic.ucar.edu/gnss-r/inundation/cygnss/>. The BNPB database can be derived from <https://dibi.bnppb.go.id/>.

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