Towards the combined use of SAR-satellite data and social sensing for flood mapping: A Case Study of Kerala Floods 2018

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ABSTRACT

Real-time flood information is critical for effective flood response. This study applied two methods for mapping flood extents using Sentinel-1 Synthetic Aperture Radar (SAR), simple comparison method and an Otsu thresholding method, for the 2018 floods in Kerala, India. Results were compared to social sensing impact mapping from four social platforms. It is demonstrated that even simple methods using SAR can be easily applied to generate reasonably accurate inundation maps rapidly for disaster response. Data fusion of social sensing and satellite imagery offers a promising emerging field to capitalise on the benefits of each data source and compensate for their inherent limitations creating a rich information source of spatial extent and impact for real-time flood response.

INTRODUCTION

Effective management of flooding and disaster response requires identification and monitoring of flood risk areas and impacts. In many countries particularly those vulnerable to extreme weather events, ground-based hydrometry sensors are limited due to the high costs of installing a telemetry infrastructure thereby lacking coverage to monitor real-time flood events. Hydraulic models have traditionally been used to model flood inundation but are limited in their implementation due to the development costs, the need for site specific inputs and calibration (Efstratiadis and Koutsoyiannis, 2010) and uncertainties in model outputs (Renard et al, 2010).

Alternative methods for flood monitoring have been developed using remote sensing due to their potential in providing real-time information at large spatial scales and low costs. Sentinel -2 optical imagery has been used extensively to calculate normalised difference water index for soil wetness and water boundaries for water management (e.g. Bhaga et al., 2020; Solovey, 2019). However, Sentinel-2 imagery is unable to penetrate clouds so is limited to clear-sky conditions and has long revisit times limiting its use in flood monitoring (Huang et al., 2018). Sentinel-1 Synthetic Aperture Radar (SAR) has the advantage of penetration through clouds and heavy rain, unaffected by light and has a high spatial resolution of 10m with short revisit times of 6 or 12 days depending on location (ESA, 2020), making it promising for monitoring and mapping flood areas.

An alternative perspective, where humans become the data source, is social sensing, a method of crowd-sourcing data from digital communications and social media. Arthur et al. (2018) demonstrated the potential of social sensing using Twitter as a source of real-time flood information to assist in flood response and track social impacts of events.

The aim of this study is to compare the potential of SAR and social sensing for mapping flooding. The focus is comparing the opportunities and limitations of both methods and the potential for development of fusion methods for improved flood detection. This paper will not describe the methods undertaken in social sensing of floods which are described elsewhere (Young et al, 2021, in draft).

Here the Kerala floods in 2018 will be used as a case study. During August 2018, Kerala was severely affected by flooding with 488 people killed, 1 million people displaced and an estimated economic loss of $5.8 billion USD (Times of India, 2018). Districts with reported heavy flooding included Thrissur, Kochi, Alappuzha and Pathanamthitta (Reuters, 2018).

METHOD

Satellite data from Sentinel-1 SAR was accessed via Google Earth Engine (GEE). Two methods were undertaken for the threshold calculation i.e. to classify pixels as flooded or non -flooded; firstly, a simple change comparison approach (UN, 2020) and secondly, a method applying histogram thresholding using an Otsu algorithm (Figure 1).

Sentinel-1 images are pre-processed before use in GEE which include orbital file correction, thermal noise correction, radiometric calibration and terrain correction to convert images into a map coordinate system. During this analysis, VH polarisation was used as it is considered more accurate for flood mapping purposes (UN, 2020).

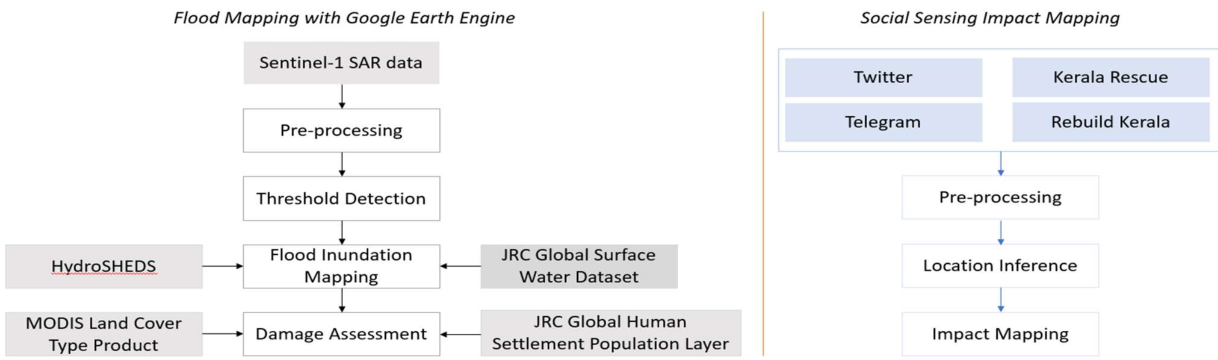

Figure 1: Research methodology (Social Sensing method was undertaken separately described fully in Young et al., 2021 – in draft)

Method 1: Simple method

This method uses a simple change comparison approach dividing the after-flood mosaic by the before-flood mosaic producing a raster layer where there is a degree of change per pixel. The higher value the greater the change. A user-defined threshold was applied with any pixels with a value greater than the threshold assigned to 1 indicating flooding or otherwise 0. Sensitivity testing was undertaken to determine the most realistic allocation of pixels avoiding false negative and false positive values with a value of 1.25 selected as the most representative.

Following classification of the flood pixels the extents were further refined by masking out areas of permanent water. The JRC Global Surface Water Dataset (updated version 2018, resolution 30m) was used to mask out all areas covered by water for more than 10 months of the year. Additionally, slopes greater than 5% from the digital elevation model (HydroSHEDS) were removed to avoid false positives. Speckling and noise were reduced by eliminating any flooded pixels that are connected to eight or fewer neighbours. Finally, the area of flood extent was calculated by summing all pixels and converting into hectares.

Method 2: Otsu method

Otsu's method is a technique in image analysis to automatically find an optimal threshold based on the distribution of pixel values (Otsu, 1979). It has widely been used in computer vision and image processing and has more recently been applied to satellite data for automatic image thresholding. This includes assessing change in surface water from Landsat images (Donchyts, 2016) and flood extents from Sentinel-1 SAR (Tiwari et al., 2020) with high accuracy reported.

The Otsu algorithm was used to classify pixels as flooded or non-flooded by partitioning the pixels at the point that maximises the between-class variance of the pixel brightness. The inter-class variance is defined as the Between-Sum-of-Squares (BSS) $/\rho$, where the Between-Sum-of-Squares (BSS) is:

$$BSS = \sum_{k=1}^{p} (\overline{DN}_k - \overline{DN})^2$$

ρ is the number of classes (in this case 2)
DN is the digital numbers in the band
$\overline{DN_k}$ is the mean digital number in class k
$\overline{DN}$ is the mean digital number of the dataset
Class k is every DN less than some threshold

This calculated the threshold that maximises the BSS and classified the pixels as foreground i.e. flooded or background i.e. non-flooded. Following the pixel classification, the flooded areas were further refined using the same steps as the simple method explained above by masking out permanent water (covered in water >10 months of the year), slopes greater than 5% and removing noise. As the Otsu method identified flooding from the 'darkness' of the pixels, topography affected the classification, for example, shady sides of mountains and valleys were identified as flooded. Masking slopes over 5% and increasing the noise filtering to 16 neighbours from 8 removed these false positives.

Damage Assessment

For both methods a damage assessment was also calculated by overlaying and calculating the intersection between the estimated flood extent layer with impact datasets. Exposed population was estimated using the JRC Global Human Settlement Population Layer (resolution 250m, updated 2015) which contains data on the number of people living in each cell. Similarly, affected cropland was estimated using the MODIS Land Cover Type Product (resolution 500m, updated annually). Two cropland classes from the Land Cover Type 1 band were used ('*class 12: at least 60% of area is cultivated*' and '*class 14: Cropland/Natural Vegetation Mosaics: small scale cultivation 40-60% with natural tree, shrub or herbaceous vegetation*'). Urban Areas were identified from the MODIS Land Cover Type using Urban Class 13.

Social Sensing Mapping

Social sensing data was collated from four platforms: i) unstructured social media platform Twitter, ii) social messaging platform Telegram, iii) Kerala Rescue, a platform created for emergency requests, and iv) Rebuild Kerala, a government initiative to gather requests on flood response and recovery. Posts from each platform were filtered for relevance, locations inferred and mapped. The data was normalised by population to reduce the distortion from highly populated areas. The full methodology is described elsewhere by Young et al. (2021 – in draft).

RESULTS

Flood extents from SAR

The Otsu method identified a greater extent of flooding (76,000 hectares) at the peak than the Simple Method (63,000 hectares) although there was consistency in distribution. These are visualised by taluk (lower administrative area) in Figure 2 i and ii. These flood extents identify significant flooding in the reportedly affected areas of Alappuzha and Thrissur, only limited flooding in Kochi and the surrounding area, but does not detect flooding in Pathanamthitta which was reportedly the worst affected district with thousands of people trapped in their homes (Reuters, 2018) (see Appendix – Figure A for detailed flood extents). Due to the satellite time intervals, the images available for these areas were 9th August 2018 and 21st August 2018 missing the flood peak of 16th August 2018 by 5 days. The population exposed to flooding (Figure 2iv) shows some spatial correlation to the flood extents whilst appearing to overestimate some locations and underestimate in others. Validation of the flood inundation maps was outside the scope of this study. A similar method undertaken by Tiwari et al (2020) validated their outputs by creating a confusion matrix and comparing to corresponding Sentinel-2 images, reporting an overall accuracy of 94%.

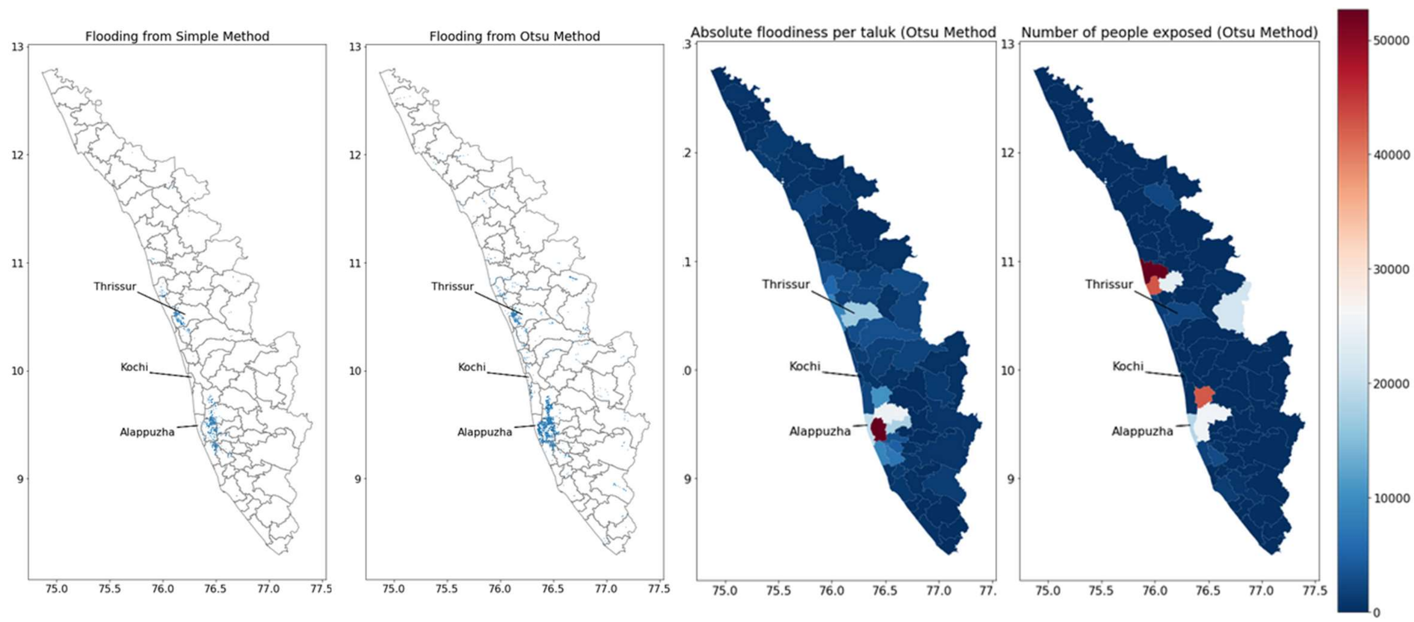

Figure 2: i) Flood extents from Simple Method ii) Flood extents from Otsu Method iii) Flooding level by taluk iv) number of people exposed by taluk

Temporal change in flood extents and damages

The temporal change in flood extent and associated damages was plotted using the flood extents generated from the Simple Method. The Otsu method was not robust enough to allow a comparison in change in over-time as the thresholding was applied to each image with differences in local pixel information. The Otsu method is based on the assumption that the images will produce a bimodal histogram distribution in pixels with a clear delineation between the two peaks (see Appendix – Figure B). This is effective when the image being assessed has a large area of foreground to background, as is the case during the monsoon season of July and August. However, if the foreground area is small compared with the background, then bimodality of the histogram is lost as the thresholding becomes less reliable.

The change in flood extents derived from the simple method (Figure 3) show that a level of 'flooding' is experienced most months of the year. It suggests this method is recording 'wetness' that may not be defined as flooding but could include paddy fields, wet ground due to the tropical conditions and other seasonal water features that weren't classified as permanent water (defined as wet for greater than 10 months of the year). The effect of the floods in August 2018 can be seen in the flood extents peak on 21st August with 63,000 hectares flooded and in particular in the number of people exposed which nearly doubles from July to August (230,000 people). The assessment did not record any urban areas as exposed at any point in the year and only minimal cropland (12,000 hectares). It is likely the affected cropland and urban areas are underestimated due to the low resolution of the MODIS dataset. The population exposed estimate also does not take into account people moving or evacuating in response to early warning systems or resilience of properties.

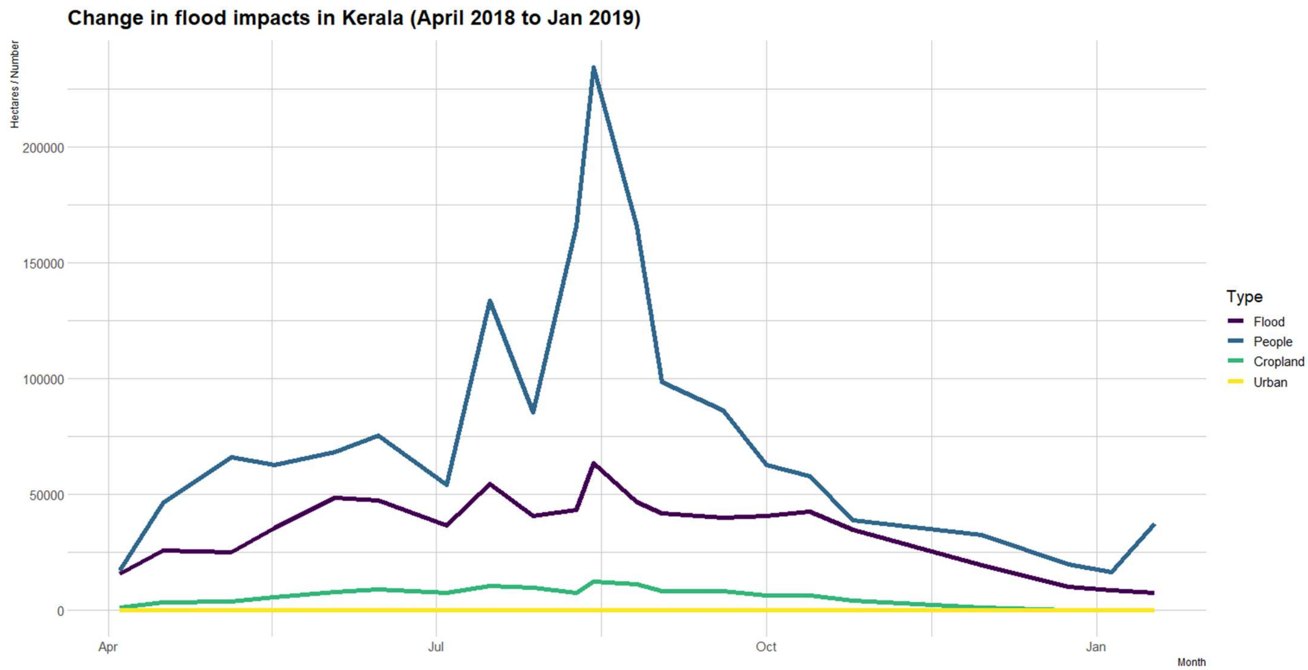

Figure 3: Change in flooding and damages over time from flood extents calculated using the simple method

Comparison with social sensing data

Flood extents are compared visually with normalised and smoothed social sensing data for each of the four social platforms at the taluk level (Figure 4) indicating spatial consistency. The flood area of Alapuzzah is well correlated however, the area to the north of Thrissur is not detected by social sensing data and the hotspot of social sensing data around the capital of Kochi is under-detected by the satellite data. Underestimation of urban areas and temporal constraints of the satellites likely contribute to these differences. Greater correlation can be seen between satellite data and social sensing data the more structured the platform (Figure 5).

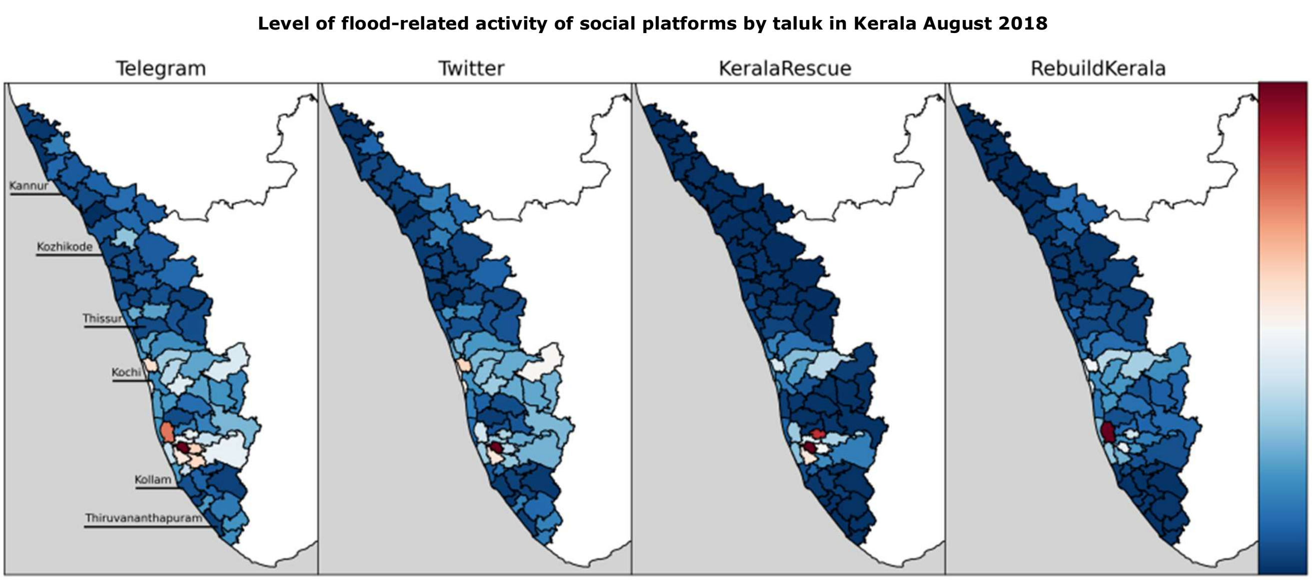

Figure 4: Number of posts per taluk smoothed and normalised by population for Telegram, Twitter, Kerala Rescue and Rebuild Kerala social platforms (blue indicates few posts - red indicates most posts)

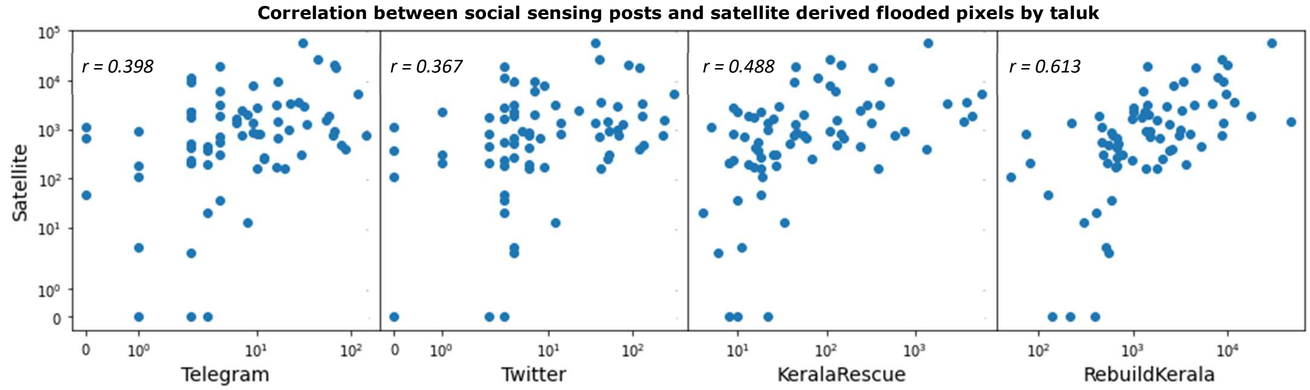

Figure 5: Correlation between extent of flooding from satellite data (number of pixels) and social platforms (number of posts) by taluk

DISCUSSION

Remote sensing strengths and limitations

The potential of Sentinel-1 SAR for flood mapping is from the high spatial resolution and all-weather, publicly available data. Applied to flood inundation mapping, SAR can easily be automated to identify flood extents over large areas, be applied to different areas with little processing time thereby giving near real-time monitoring anywhere in the world. As demonstrated by this study, even simple computation methods can easily be applied to generate reasonably accurate inundation maps.

However, the temporal resolution of 6 or 12 days is a significant limitation which in the case of the 2018 Kerala floods meant the satellite pass missed the peak flood by 5 days. The temporal constraints are particularly a problem in flashier catchments where the time intervals could mean the flood is not even detected by satellite. As a result, drones have been used to achieve higher temporal resolution for floods (Komarkova et al, 2019, Imam et al, 2020) however, these are not suitable for large areas and require deployment with the associated resource and costs.

Compounding this issue, flood extents in urban areas as well as highly vegetated areas, are likely to be underestimated due to a 'double bounce effect' whereby the SAR electromagnetic beams bounce twice, once off the water surface and then again off vegetation or buildings resulting in high values detected (Anh Tuan et al, 2020).

Whilst satellite data can easily map spatial extents, it does not include impact information which is crucial evidence for disaster planning and response. Severity of flooding is a combination of velocity and depth of water. Remote sensing data only provides flood extents and therefore the severity of flooding is not differentiated.

Table 1: A summary of strengths and weaknesses of each method (informed by Huang, 2019, Arthur et al., 2018)

Remote Sensing Data: Sentinel-1 SAR	Social Sensing Data: Social Media Platforms
Strengths	
Rapid and detailed mapping available across large areas with cloud penetration so available during all weathers and 30m resolution	Can identify impacts in real-time
Near real-time available data	Real-time information and high volume of observations
Reliable and accurate information source	A variety of platforms providing different information sources
Enables rapid assessment with reasonable accuracy for real-time flood response	Captures the human impact and also emotional impact – not just economic or physical impact
Limitations	
Inundation mapping only - identifies extents and does not provide any information on severity of flood or impacts	Limited by access to technology – biased to large populations and more affluent areas with higher smartphone use
Damage assessment methods to understand impacts are limited due to spatial resolution of impact datasets.	Low level of location-information associated with content
Constrained by temporal resolution	Inconsistent, unverified and subjective reporting
Difficulties in detecting flooding in urban and vegetated areas	Distortion of activity to high population areas

To provide higher accuracy information multiple sources of satellite data can be fused together such as optical and microwave data to overcome the temporal limitations (Khan et al., 2014, Anh Tuan et al, 2020) and combining SAR with Landsat and a DEM (Townsend and Walsh, 1998). Other techniques to improve mapping include using deep learning models with SAR reportedly outperforming threshold-based algorithms (Bonafilia et al., 2020), computer vision methods to improve models (Bonafilia et al, 2020), supervised classifers to automatically map flood extents (Benoudjit & Guida, 2019), Convolutional Neural Networks reducing computation time by 80% (Nemni et al., 2020).

Social Sensing strengths and limitations

The results of this study suggest there is consistency between social sensing data and large-flooded areas particularly in the significantly affected rural area of Alappuzah. Whilst the reliability and confidence level of social media data has been criticised due to a lack of verification (Huang et al, 2019, Schnebele et al., 2014), other studies have reported value in social sensing in flood response (Arthur et al, 2018). Graham, Poorthuis and Zook (2012) found a visual comparison of Twitter data reflected the location of UK floods in November 2012 and Schnebele et al. (2014) found overall tweet volume corresponded well to the progression of the flood event.

However, there are notable differences identified between satellite recorded flooding and flood locations derived from social sensing. One limitation of social sensing data is the distortion of activity in high population areas that does not necessarily reflect a high flood occurrence. However, whilst the lower correlations between the satellite data and social sensing data in the state capital of Kochi could be attributed to this distortion, it could equally be attributed to the time interval of the satellite pass. The networked aspect of social media data may contribute to this distortion through the spreading of more extreme or unusual events as individual posts are not independent data points (Arthur et al., 2018). Yet, value can be derived from the activity of re-sharing posts on platforms such as Twitter, as it acts as a form of informal recommendation with retweets able to reveal an overview of the situation unfolding during a flood emergency (Palen et al, 2010).

Social sensing data has inherent biases towards more affluent, urban and younger populations - in 2020, 35% of the population of India owned a smart phone with the majority of users between 18 and 35 years (Statista, 2020). However, smart phone use is increasing 10-30% year on year (Statista, 2020) and there is expected to be 99% 4G coverage of India by 2021 (ETTelecom, 2020) providing promise for future application of social sensing methods. Despite these limitations, social sensing has been demonstrated to offer significant value particularly in identifying the human and social impacts of disasters in real-time that satellite data cannot detect such as sentiment mapping to detect the emotional impacts (Young et al., 2021, unpublished) and 'live' flood tracking (Arthur et al., 2018).

Data Fusion

Satellite imagery and social media can be viewed as complimentary sources with potential to compensate for the others inherent limitations thereby improving accuracy and richness of information available to flood responders. The range of opportunities from fusing data includes improving the temporal resolution, spatial resolution, accuracy and richness of information available (Huang, 2019). Initial attempts made to fuse social media data with remote sensing are crude. Schnebele et al. (2014) incorporated traffic cameras, power outage data and volunteer generated photos and tweets with satellite data by weighting sources by confidence. Fohringer et al. (2015) integrated water level information derived from social media and stream gauges to interpolate satellite imagery and create flood inundation maps improving the temporal limitations of satellite data alone. However, this method was limited by the varying availability of social media data and "ignorance of hydraulic flow" (Fohringer et al., 2015). More sophisticated fusion methods are sparse but include Li et al. (2017) using Twitter data to create a kernel-based flood mapping model based on the water height points derived from tweets and stream gauges with spatiotemporal twitter activity patterns. Whilst these attempts show promise they utilise very different methods, requiring comparison and benchmarking (Huang et al, 2019) to identify future directions and effectively tackle the challenges of fusing data from multiple modalities (Wang et al. 2018).

CONCLUSION

It can be concluded from this study that SAR data has good potential for flood mapping due to the availability of data in all weather conditions and high spatial resolution. It is demonstrated that even simple methods using SAR can be easily applied to generate reasonably accurate inundation maps rapidly for disaster response. The Otsu thresholding method has potential for automatically detecting flooded areas but requires further refinement to take into account changes in pixel-level local information. Data fusion offers a promising emerging field to capitalise on the benefits of social sensing and satellite data, compensate for their inherent limitations and create a rich information source. This is an emerging field with potential to apply sophisticated algorithms to fuse complementary data sources and maximise the availability of real-time flood information for improved decision-making. With the wide range of techniques being explored to improve the accuracy and automation of flood mapping there is a need to compare and benchmark their performance to inform the direction of future research.

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I'd like to thank James Young for sharing his research outputs on social sensing of Kerala Floods which enabled the comparison in this paper - I hope I did his great work justice! Thanks to Hywel Williams for your supervision, support and discussions to shape this study. To Rudy Arthur for your comments and critiques and Josh Buxton to help solve the endless Google Earth Engine errors! A great team to work with – thanks! 😊

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APPENDIX – SUPPORTING FIGURES

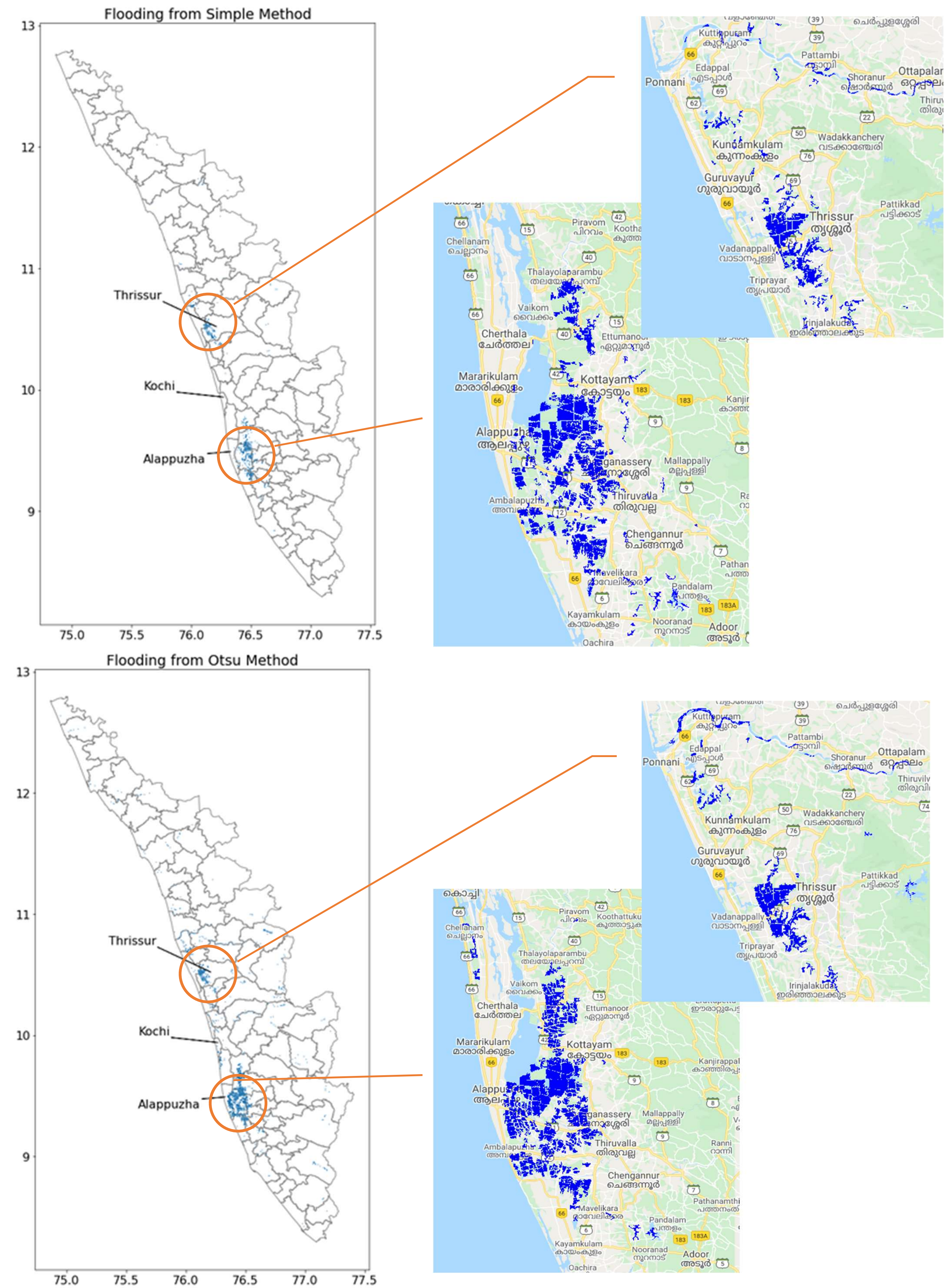

Figure A: Detailed flood extents from i. Simple Method and ii. Otsu Method

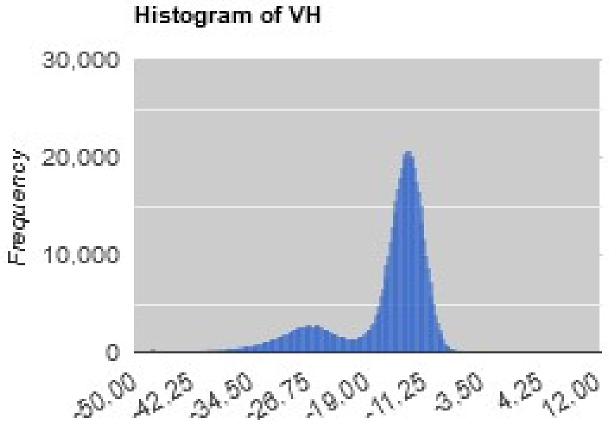

Figure B: Bi-modal histogram generated from Otsu Method distribution of pixels