Integrating EO Data of Floods with a Hydrodynamic Event Model: Harvey 2017

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Floods can be devastating to society and the environment. Recent flood events around the globe, such as Harvey and Irma for instance, have been disastrous and broke records in damage and loss of life. Flood disasters often operate at spatial and temporal scales that far exceed local and regional, or even national, assessment and response capabilities. There is no doubt that remote sensing observations of floods, particularly from satellites, can be of great value. Earth observation (EO) data of floods can either be used directly through numerous services providing flood maps (Fig.1) and other datasets, or indirectly through integration with hydrodynamic models simulating events continuously in time and space. In this project, we demonstrate the value of satellite flood maps for Harvey 2017 and Twitter feeds during the event for integration with a forecast inundation model (LISFLOOD-FP). Initial results are illustrated and we discuss current challenges and next steps.





Fig.1. Mapping of Hurricane Harvey flooding as displayed using DFO's Web Map Service: Red is flooding mapped from NASA MODIS, ESA

Sentinel 1, ASI Cosmo SkyMed, and Radarsat-2 data.

http://floodobservatory.colorado.e du/WebMapServerDataLinks.html



Social media (citizen science & crowdsourcing), such as Twitter feeds, are quickly becoming a source of extremely valuable data to complement traditional fieldbased monitoring stations, existing EO satellite maps, and even forecast models. Preliminary investigation reveals the following capabilities:

- Social media streaming data clearly exhibit similar trend information as measurements of impactful physical processes (floods in this case);
- These streams of data have the potential to complement and augment existing flood maps as observed from satellites or/and as predicted by 2-D flood inundation models (Fig.2).

The challenge now lies in (i) how to derive useful information from social media feeds, such as tweets in the form of text and pictures (Fig.3), and in (ii) how to



Fig. 2. Many different data streams are now becoming readily available before, during and after a flood event.

During the Harvey event ESA S-1 satellite acquired several images of the floods. These were processed using a fully automated flood processor on ESA's G-POD system. This mapping facility is available for all users and free of charge. For registration, please email hasard@list.lu. HASARD

For forecasting flooded areas, we employed the 2-D LISFLOOD-FP model in sub-grid channel mode, using USGS NED-DEM and NHD+ river network. The diagnostic forecast was set up using NOAA RFC flow predictions; USGS measured Q and ECMWF forecast rain fields. Storm surge levels from NOAA at the coastal outlet were also included.

integrate these social media data with all the other existing sources of data.







- Fairly good agreement of optical EO, radar EO and model, but:
- SAR under-detects in densely vegetated areas and urban areas Model tends to overestimate extent of flooding when topography not
- well represented (cf. "tipping points")
- Twitter-derived flood information difficult to geo-localize as they refer to a city or a neighbourhood



- One of the best covered disasters in terms of open-access data;
- Globally and freely available datasets combined with modern IT enable simulating
- floods at large scale;
- Advanced image processing allows reducing classification uncertainties in risk-prone areas;
- Photos and texts social networks data complement EO and in-situ data and augment information content.

Challenges & next steps

- Fully exploit data sets to detect water bodies in built up environments;
- Need to better characterize classification uncertainties;
- Geo-localize social media data more precisely;
- Fully realize potential to jointly extract and assimilate into prediction model information from multiple sources.









