LUXEMBOURG INSTITUTE OF SCIENCE AND TECHNOLOGY LIST

RSS-Hydro, S.à r.l.-S

Unlocking the full potential of complementary data streams during the Harvey flood disaster

Integration of EO, modeling and social media

Guy SCHUMANN, RSS-Hydro (L)

Patrick MATGEN, LIST (L)

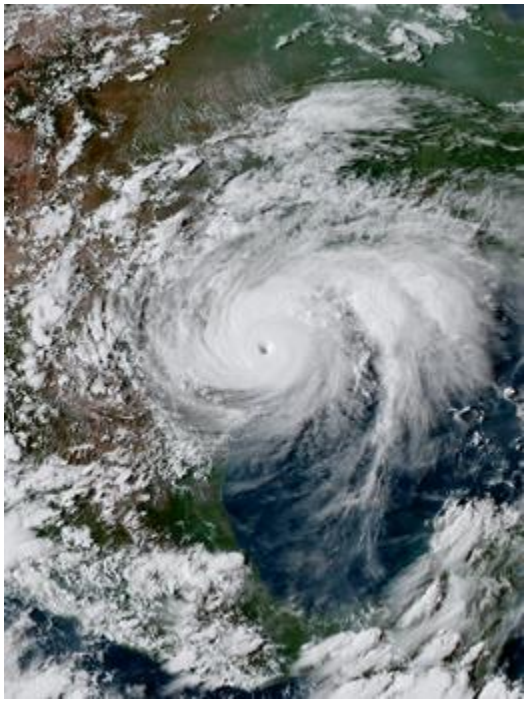
R. Pelich, E. Brangbour, P. Bruneau, M. Chini, R. Hostache, T. Tamisier

Luxembourg Earth Observation and Integrated Applications Day

Space Applications in Environmental Management

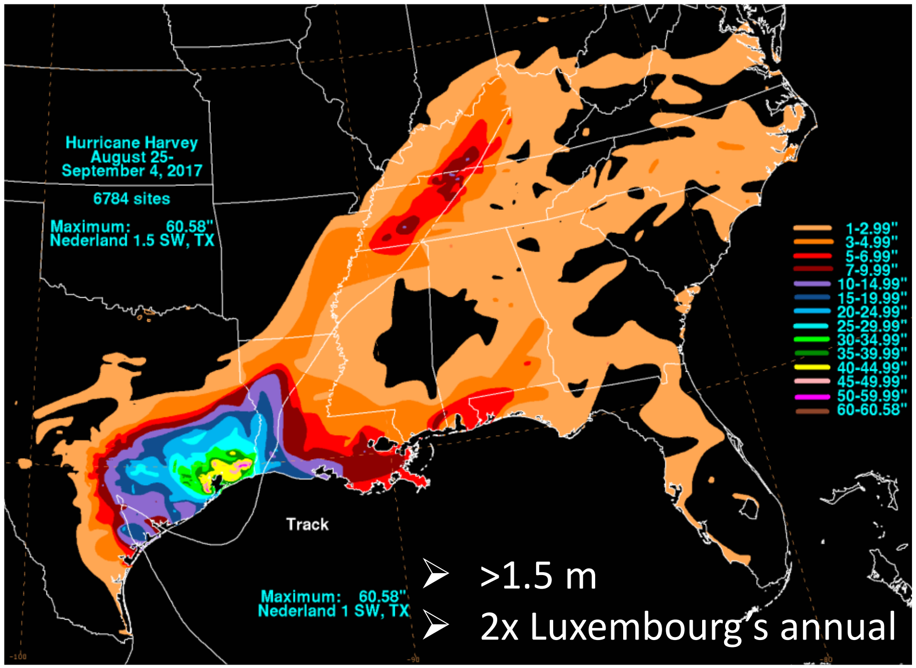
April 19 2018

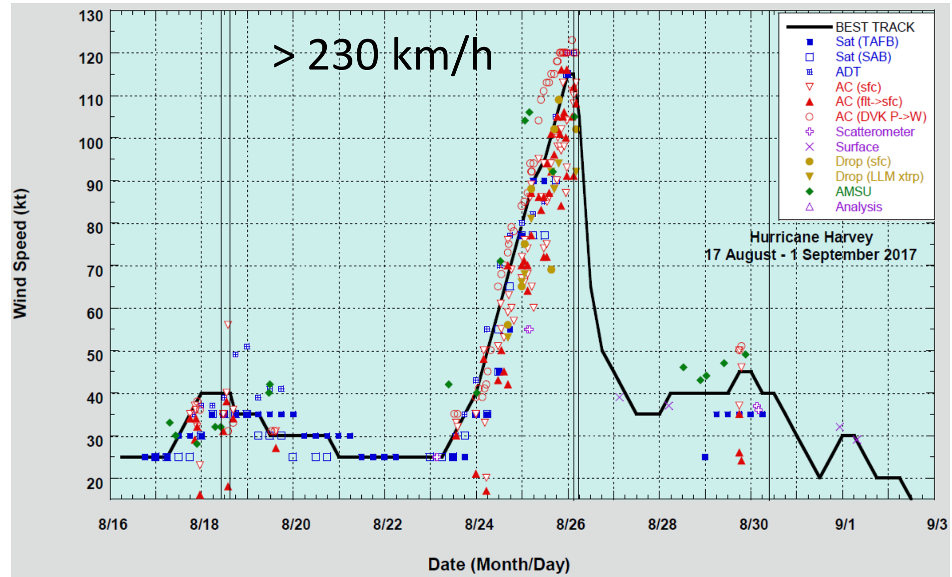
Motivation



- Floods are extremely disruptive & increasing in annual cost
- Resilience of many societies is still relatively low
- Response & recovery are still not supported by all available data; yet many data streams and products are available
- More research & innovation are needed to make products and services more interoperable & actionable
- Need to work with emergency management & response teams for effective valorization of EO products and services during disasters and elsewhere

Harvey: Putting America to the Test!





NATIONAL HURRICANE CENTER
TROPICAL CYCLONE REPORT

HURRICANE HARVEY
(AL092017)
17 August – 1 September 2017

Eric S. Blake and David A. Zelinsky
National Hurricane Center
23 January 2018

People take shelter at the George R. Brown Convention Center after flood waters from Hurricane Harvey inundated the city on August 29, 2017 in Houston, Texas. The evacuation center which is overcapacity has already received more than 9,000 evacuees with more arriving.

Photo by Joe Raedle/Getty Images.

County	Direct Deaths
Harris	36
Orange	9
Jefferson	5
Galveston	3
Montgomery	3
San Jacinto	3
Ft. Bend	3
Jasper	2
Newton	2
Hardin	1
Walker	1
Total	68

LUXEMBOURG INSTITUTE OF SCIENCE AND TECHNOLOGY LIST

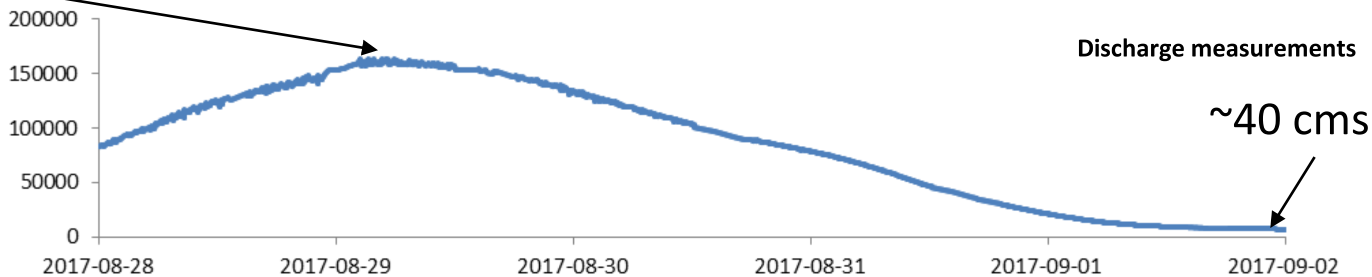
RSS-Hydro, S.à r.l.-S

Many Data Streams

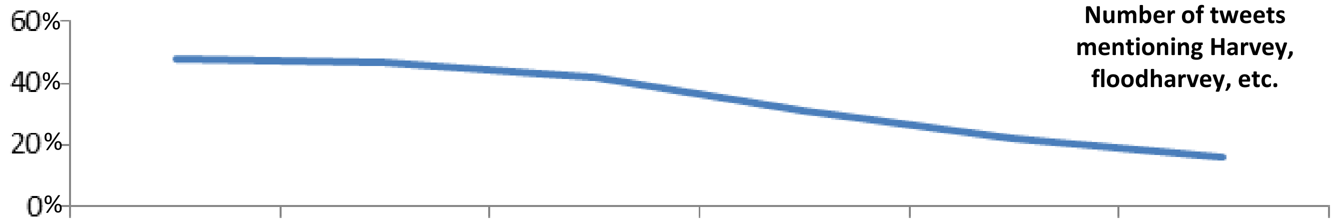
>4000 cms

Aug 28 | Aug 29 | Aug 30 | Aug 31 | Sep 1 | Sep 2 onward

In situ measurements

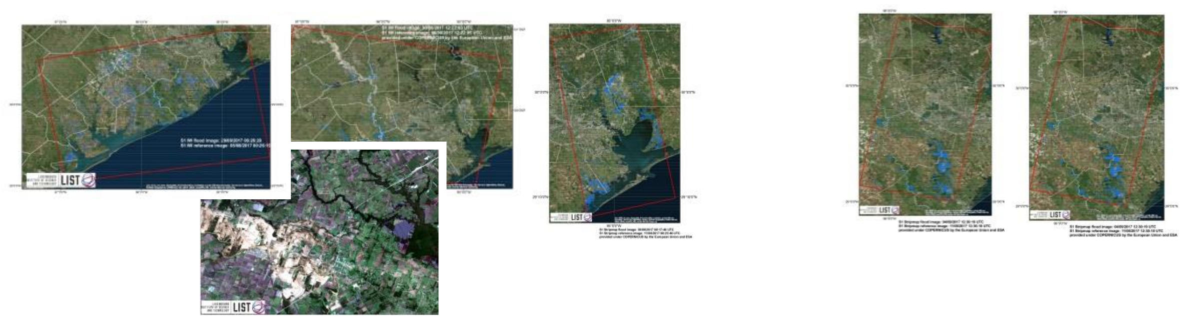


Tweets

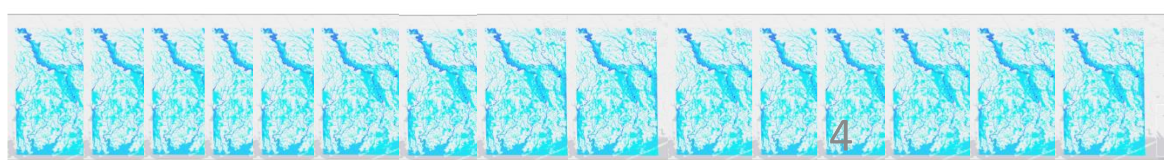


EO data (S1 & S2)

GFP activation



Flood inundation model

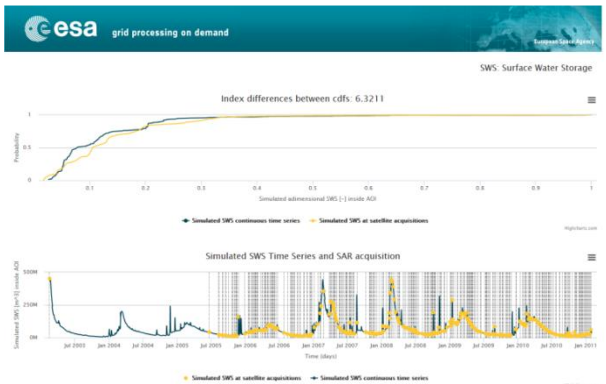


S-1 Flood Mapping

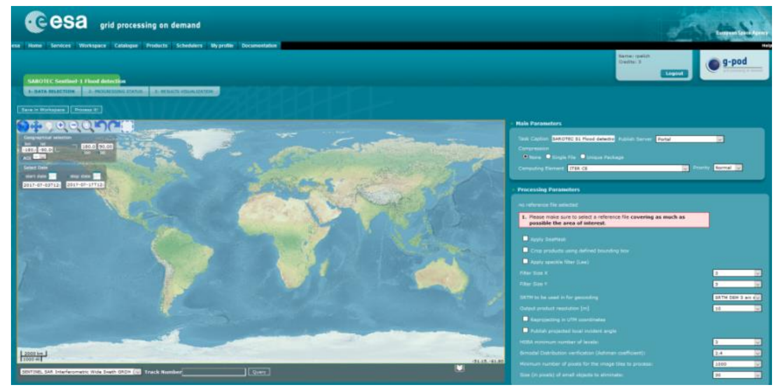
RSS-Hydro, S.à r.l.-S

- Consultation of data collection w.r.t. to ECMWF-based simulations of flood inundation

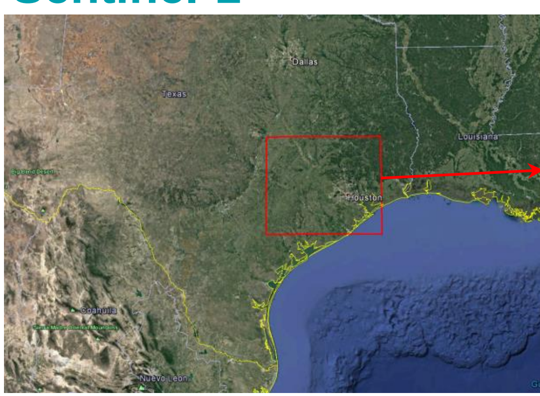
https://gpod.eo.esa.int/

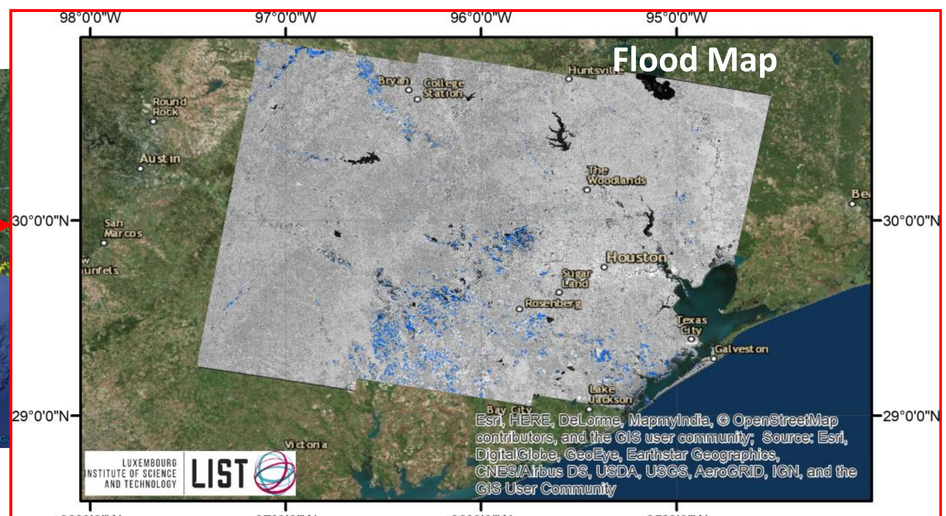


- Manual selection of “flood images” from ESA data collection
- “on demand” flood mapping
- Download of results



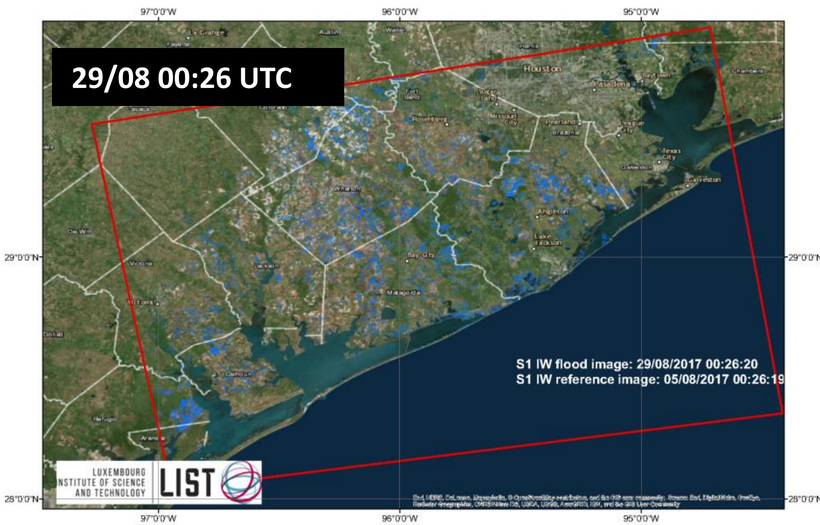
Sentinel-1

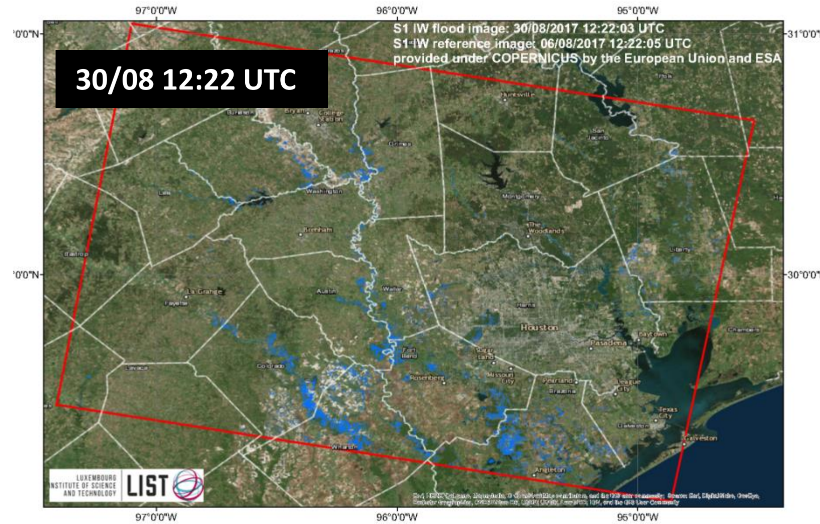


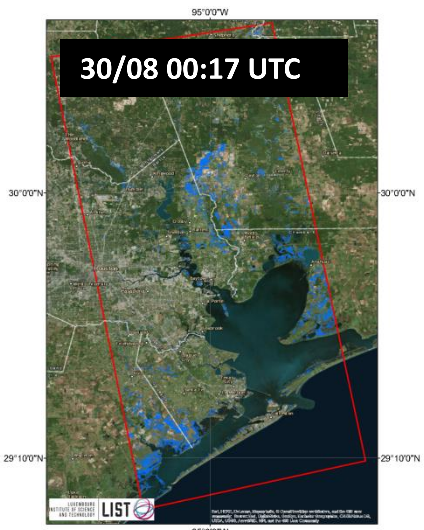


HASARD

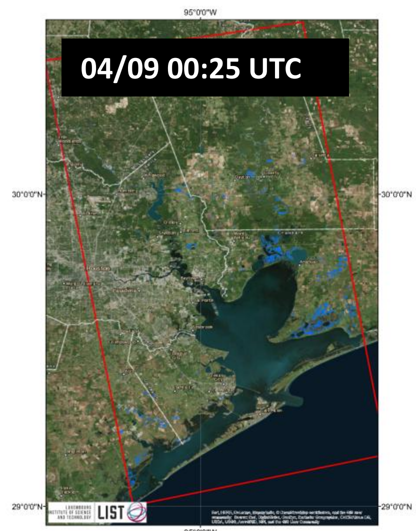
hasard@list.lu



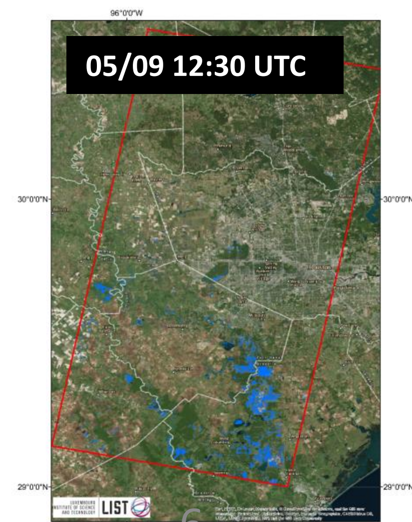




S1 Stripmap flood image: 30/08/2017 00:17:40 UTC
S1 Stripmap reference image: 11/08/2017 00:25:48 UTC
provided under COPERNICUS by the European Union and ESA



S1 Stripmap flood image: 04/09/2017 00:25:49 UTC
S1 Stripmap reference image: 11/08/2017 00:25:48 UTC
provided under COPERNICUS by the European Union and ESA

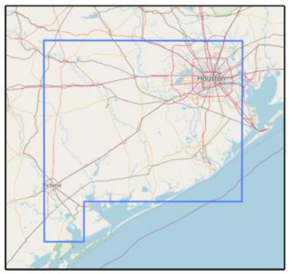


S1 Stripmap flood image: 04/09/2017 12:30:19 UTC
S1 Stripmap reference image: 11/08/2017 12:30:18 UTC
provided under COPERNICUS by the European Union and ESA

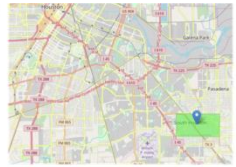
Interested in using this ESA G-POD service? Just email hasard@list.lu

A Social Media Probability Flood Map

Tweet collection over an area of interest



Spatial cues



place: tweet field that specifies a bounding box associated to a named place, e.g. 'full_name': 'South Houston, TX'

Coordinates: field with point GPS coordinates. Might be inaccurate (see Wharton example)

Named Entities in text
e.g. 'Exit blocked due to flooding in #SouthSide on S Sam Houston Tollway WB at '

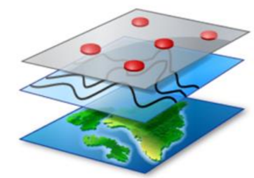
ground-to-aerial localization from pictures

Semantic cues (i.e. related to a flood?)

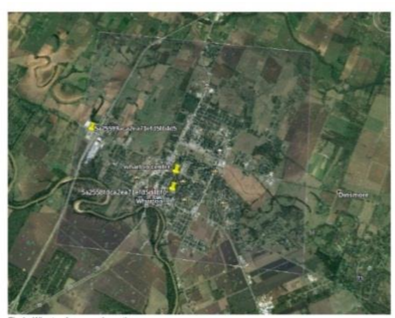
Tweet text classification
Positive class = «is the tweet related to the flood?»

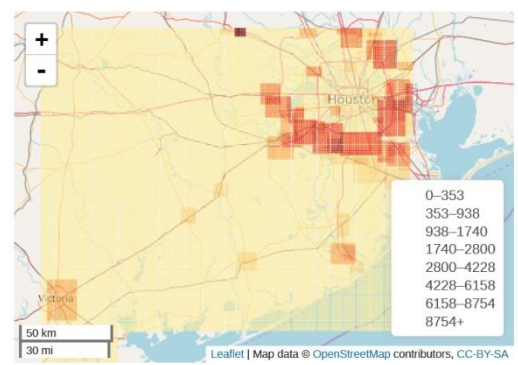
Image classification : «does the image show a flooded scene?»

probabilistic «social» map of the flood event



-> assimilation workflow





Just posted a video @ Wharton, Texas https://t.co/fdlN3WXznF (https://t.co/fdlN3WXznF)

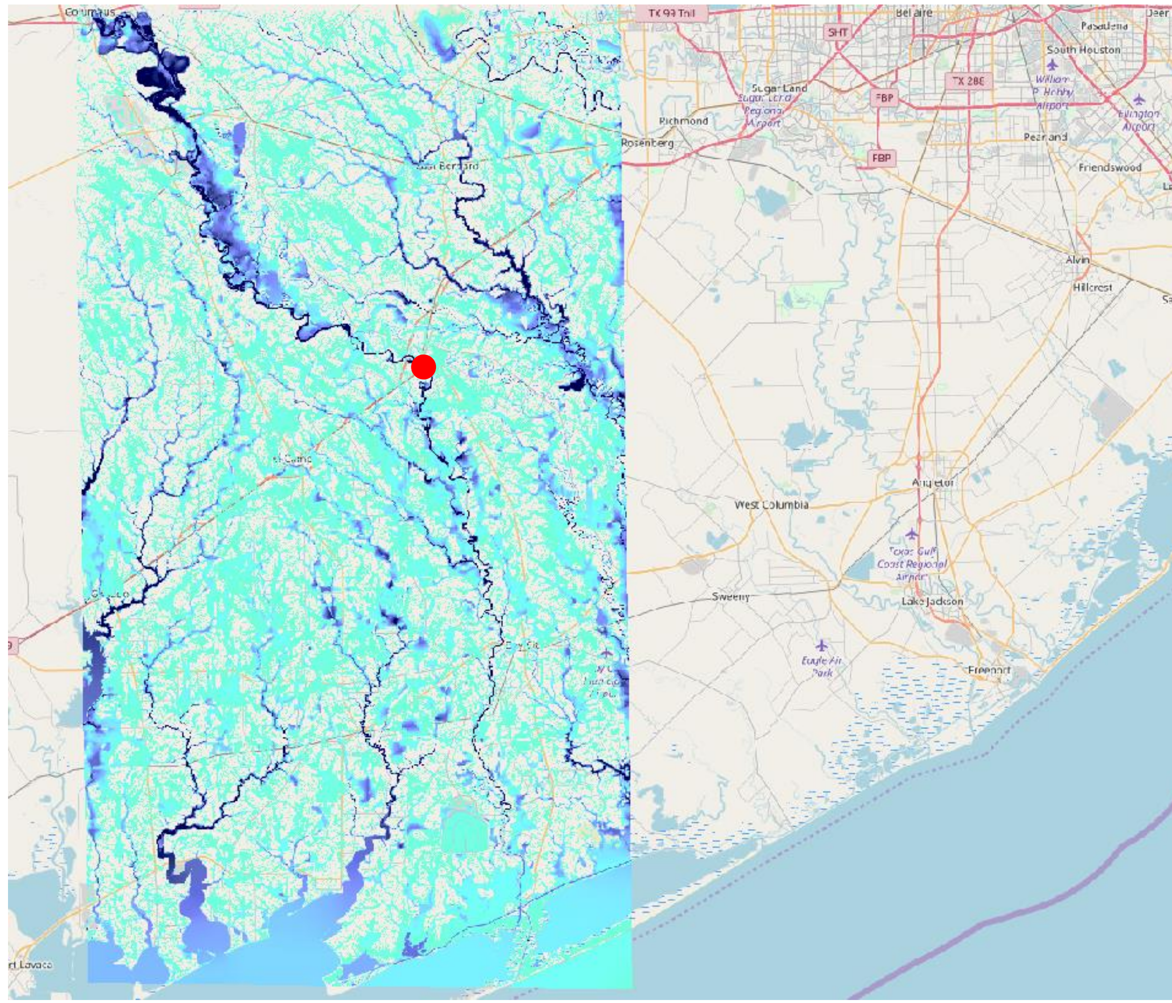
Wed Aug 30 16:29:14 +0000 2017

Generating a probabilitic flood map

Flood Inundation Prediction

- Simulation of 2-D LISFLOOD-FP model using sub-grid channel mode, using USGS NED-DEM and NHD+ river network aggregated to 100 m cells.
- Diagnostic forecast setup: NOAA River Forecast Center flow predictions; USGS measured Q & ECMWF forecast rain fields.
- Storm surge levels from NOAA at downstream coastal outlet of Colorado River included but effect is negligible

Selected ROI: Colorado River, TX



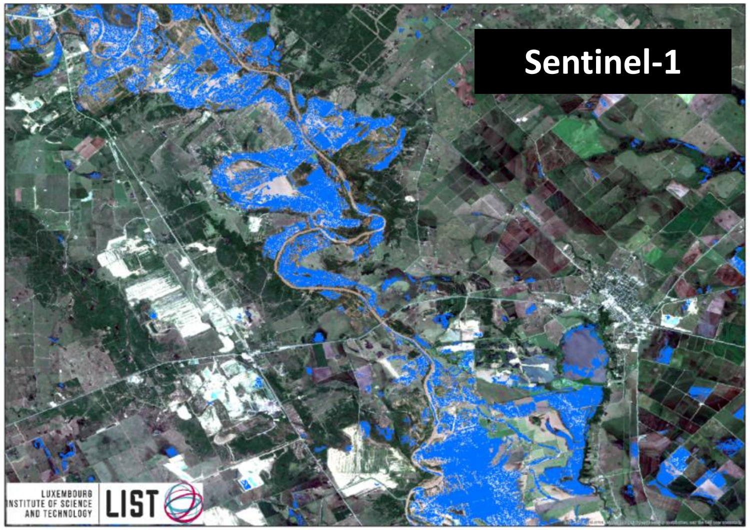
At the Wharton flood level gauge, the “best” model simulates channel levels to within 30 cm on peak on 31 Aug

LUXEMBOURG INSTITUTE OF SCIENCE AND TECHNOLOGY | LIST

RSS-Hydro, S.à r.l.-S

Data Stream Inter-Comparison

Colorado River, La Grange



Photos posted on Twitter

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

Bringing it all together!

Conditional probability : binomial pdf

$$p(k,n\backslash\Theta)=\binom{n}{k}\Theta^{k}(1-\Theta)^{n-k}$$

k = # successes
n = # trials (n=1)

Attributing weights to ensemble members based on their similarity to observation data

$\text{MODEL}_{t,i}$

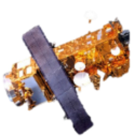
1	0	1
0	1	1
1	0	0

$$w^{t,i}_{1,1}=\Theta_{1,1}$$

Simulated Water pixel (k=1)

$$w^{t,i}_{3,3}=1-\Theta_{3,3}$$

Simulated Dry pixel (k=0)



Observation

$\Theta_{1,1}$	$\Theta_{1,2}$	$\Theta_{1,3}$
$\Theta_{2,1}$	$\Theta_{2,2}$	$\Theta_{2,3}$
$\Theta_{3,1}$	$\Theta_{3,2}$	$\Theta_{3,3}$

$w^{t,i}_{1,1}$	$w^{t,i}_{1,2}$	$w^{t,1}_{1,3}$
$w^{t,i}_{2,1}$	$w^{t,i}_{2,2}$	$w^{t,i}_{2,3}$
$w^{t,i}_{3,1}$	$w^{t,i}_{3,2}$	$w^{t,i}_{3,3}$

Spatial Weights aggregations

$$W^{t,i}=\frac{\prod_{j,k}\left(w^{t,i}_{j,k}\right)^{\alpha/NrOfPixels}}{\sum_{i}\left(\prod_{j,k}\left(w^{t,i}_{j,k}\right)^{\alpha/NrOfPixels}\right)}$$

Concluding Notes

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

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.

Thanks!

Supported by

Luxembourg National Research Fund

rss research & service support

GFP global flood partnership https://gfp.jrc.ec.europa.eu

Copernicus Relays

NASA