Flood Inundation Mapping with Data Assimilation

December 2018

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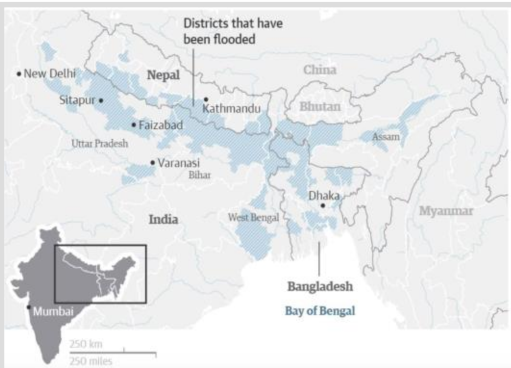

Figure 1: Districts flooded in India and Bangladesh, August 2017
Source: ReliefWeb (2017)

Climate change means that flooding is predicted to increase in frequency and intensity across the globe. Real-time and forecast flood models are becoming ever more crucial to support decision-makers before and during floods. In the latest models, this includes spatial maps of flooding. In this project we investigate if observations of floods from satellite images can help us improve the accuracy of forecast flood maps.

Our methods are tested using JBA Consulting's Flood Foresight system, which can generate near real-time flood maps anywhere in the world as deterministic outputs, or as ensembles to produce probabilistic estimates of flooding.

Project aims

Investigate if a probabilistic ensemble weighting method can improve Flood Foresight ensemble flood map forecasts using satellite observations during a flood event that occurred in August 2017 in the Brahmaputra river basin, India. Additionally, investigate if binary skill scores can inform us about the ensemble performance.

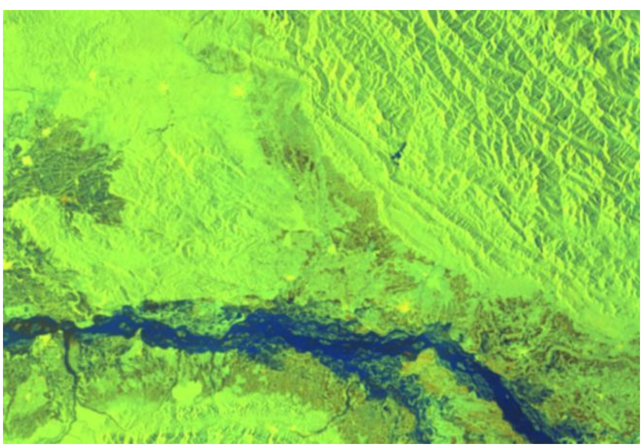

Figure 2: Raw Sentinel-1 satellite data on 12th of August 2017 over part of Brahmaputra river.

What we did

Compare model and observation data then produce a contingency table.

Implement, test and apply a simple importance sampling method to the produced contingency maps.

Implement and apply binary skill scores to the same contingency maps.

Methodology

We compared the Flood Foresight model output with the observational information from the satellite. Flood Foresight provided 51 ensemble members of flood extent over the entire Brahmaputra river basin in India for nine forecast days initialised on 11th August 2017. The observational data was a binary flood extent map derived from the Sentinel-1 Synthetic Aperture Radar satellite image on 12th August 2017 over a smaller section of the Brahmaputra region. We compared the ensemble and observation data using a pixel-by-pixel approach, producing a contingency table for each ensemble member (see Figure 3).

Next, we implemented and tested the importance sampling (IS) method applied to the contingency table. The IS method allows us to compute the importance of each ensemble member relative to observations, where ensemble members closest to the observations will have the largest importance (or weights). However, this method suffers from a degeneracy issue in large dimensions, with the result that one ensemble member becomes dominant very quickly, making rest of the ensemble redundant (see Figure 4). With this in mind, we restricted the area of the investigation to a small subdomain of about 1.5 km by 1 km in size. Finally, we calculated a number of skill scores from the contingency table values.

The research described here is based on a study completed by Zhiqi Hu for her MSc in Atmospheric Ocean & Climate at the University of Reading. Zhiqi's work was supported by Prof. Sarah Dance, Dr. Sanita Vetra-Carvalho (Reading) and Dr. John Bevington and Dr. Beatriz Revilla-Romero (JBA Consulting.)

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The importance sampling method is a simple and natural way of combining model predictions with observations. However, restricting the investigation domain to 1.5 km by 1 km due to the degeneracy problems of IS reduced the ensemble size from 51 to 3 members. This is because the Flood Foresight ensemble does not have enough small scale variability at short lead times (+ 1 day) due to the spatial resolutions of various model components and driving data. Hence, the results from the IS method are inconclusive here.

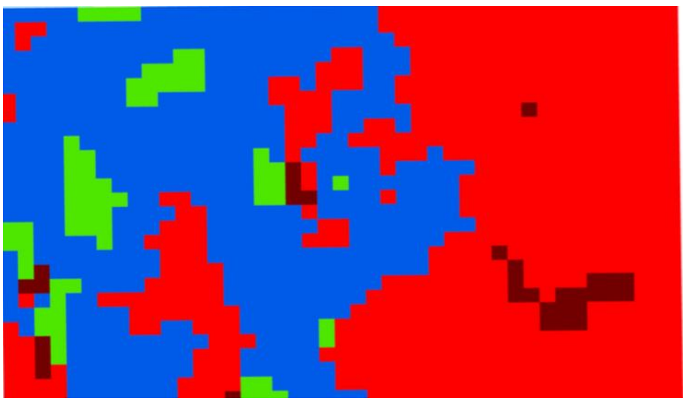

Figure 3: Example of a map plotting contingency table values for each pixel comparing an ensemble member against observations. The green means both ensemble member and observation are wet, both brown means dry, red means pixel is wet in observations but not in the model and brown means pixel is dry in observations but not in the model.

We also implemented various binary ensemble skill scores to investigate how well such scores could inform us about the Flood Foresight system ensemble performance.

Table 1 shows the various skill scores calculated for the effective three ensemble members in the same restricted domain as for the particle importance sampling method. This initial investigation indicates that for this ensemble the Flood Foresight system driven by the flood forecasting data over-predicts the flood compared to the observations (the bias score) while group 2 members have more agreement with observations over dry areas than flooded (better proportion correct or PC score but lower hit rate score). Also, group 2 has a much lower false alarm rate than other two groups.

The binary skill scores can be applied to any number of observations and thus in future it would be useful to calculate them for larger areas.

Table 1: Binary skill scores for each ensemble group when using real observations on restricted spatial area.

Group	Bias	PC	Hit Rate	False Alarm Rate	$F^{<1>}$	$F^{<2>}$	$F^{<3>}$
Group 1	1.69	0.45	0.72	0.74	0.36	-0.12	0.22
Group 2	1.99	0.47	0.88	0.85	0.42	-0.11	0.36
Group 3	1.24	0.53	0.58	0.50	0.35	-0.05	0.09

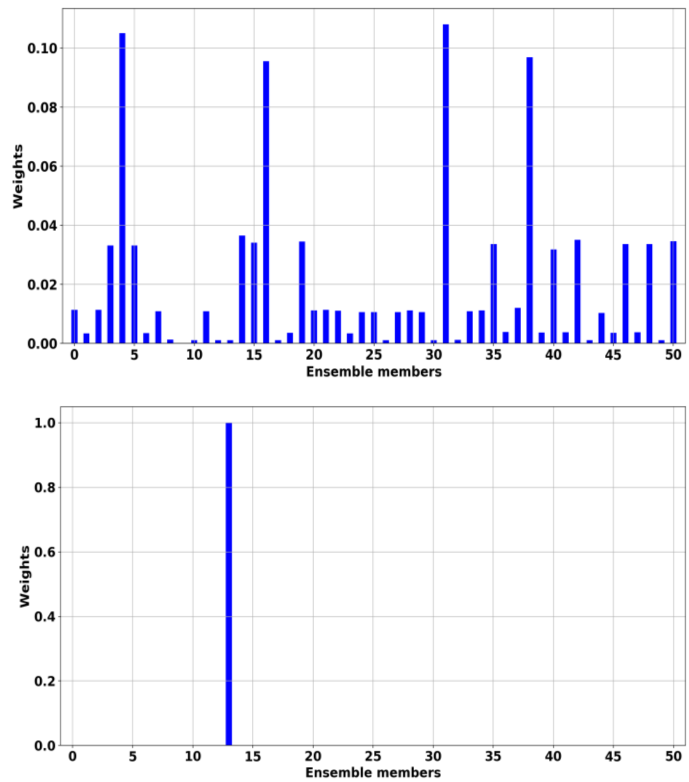

Figure 4: Particle importance weights after assimilating observation information for 10 and 1000 observations.

Conclusions and future work

The particle importance sampling method can be applied to small areas with limited number of observations.

However, more work needs to be done to assess the potential benefit of the IS method, e.g. using weight tempering method.

The binary skill scores have been informative about the effective ensemble members but this should be investigated further with larger ensemble sizes and on larger areas.

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