IAHR/IWA Joint Committee on Hydroinformatics

UFMRM WG webinar series

# DARE to use CCTV images to improve urban flood forecasts!


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@UFMRM

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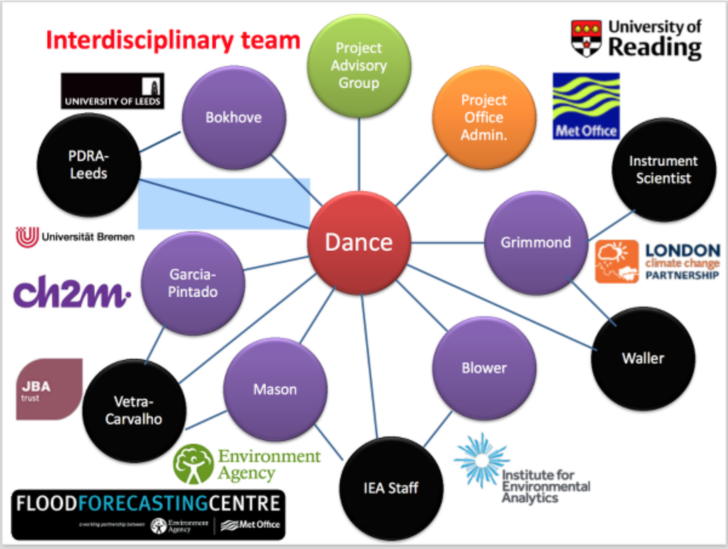
**1600 - 1630 BST**

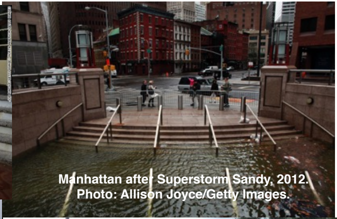
https://goo.gl/im1kKg

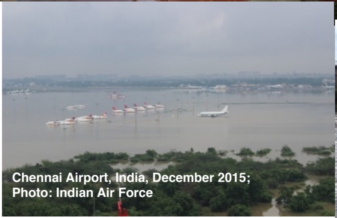
# DARE team and partners



# Complex and vulnerable city


Miami Beach, Florida, September 2015


Manhattan after Superstorm Sandy, 2012.
Photo: Allison Joyce/Getty Images.


Chennai Airport, India, December 2015;
Photo: Indian Air Force


Latvia, July 2017

**Population Growth + Climate Change + Urbanisation**

# What can we do - the DARE project

**The aims of the DARE project are:**

- to improve urban flood prediction through data assimilation using novel and standard observations of urban floods;
- to produce algorithm and working code for SAR delineation in urban areas;
- to understand error structures of urban weather observations;
- to network and achieve goals through collaboration.

*DARE is funded by EPSRC Senior Fellowship in Digital Technology for Living with Environmental Change (EPSRC EP/P002331/1).*

EPSRC Pioneering research and skills

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# What is data assimilation?


**All models have errors** and inundation models have a number of error sources e.g. inflow errors, bathymetry parameters, model errors, etc.

# How DA works?

On one hand we have a discrete **MODEL**:

$$\mathbf{x}^{n+1} = \mathcal{M}\left(\mathbf{x}^{n}\right) + \mathbf{e}_m^{n+1}$$

where

- $\mathbf{x} \in \mathcal{R}^{N_x}$ is a state vector;
- $\mathbf{e}_m \in \mathcal{R}^{N_x}$ is the model error distributed according to the covariance matrix $\mathbf{Q}$.

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On the other hand we have discrete **OBSERVATIONS** of the system: $\mathbf{y} \in \mathcal{R}^{N_y}$ which also have an associated observation error distributed according to the covariance matrix $\mathbf{R}$.

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On one hand we have a discrete **MODEL**:

$$\mathbf{x}^{n+1} = \mathcal{M}\left(\mathbf{x}^{n}\right) + \mathbf{e}_{m}^{n+1}$$

where

- $\mathbf{x} \in \mathcal{R}^{N_x}$ is a state vector with associated error covariance matrix $\mathbf{P}$;
- $\mathbf{e}_m \in \mathcal{R}^{N_x}$ is the model error distributed according to the covariance matrix $\mathbf{Q}$.

On the other hand we have discrete **OBSERVATIONS** of the system: $\mathbf{y} \in \mathcal{R}^{N_y}$ which also have an associated observation error distributed according to the covariance matrix $\mathbf{R}$.

We map between model and observation spaces using **observation operator**:

$$\mathbf{y}_m = \mathcal{H}\left(\mathbf{x}\right). \tag{3}$$

# How DA works?

We combine MODEL and OBSERVATIONS as follows:

$$\mathbf{x}^a = \mathbf{x}^f + \mathbf{K}\left(\mathbf{y} - \mathcal{H}(\mathbf{x}^f)\right) \quad (4)$$

$$\mathbf{P}^a = \left(\mathbf{I} - \mathbf{K}\mathbf{H}^T\right)\mathbf{P}^f \quad (5)$$

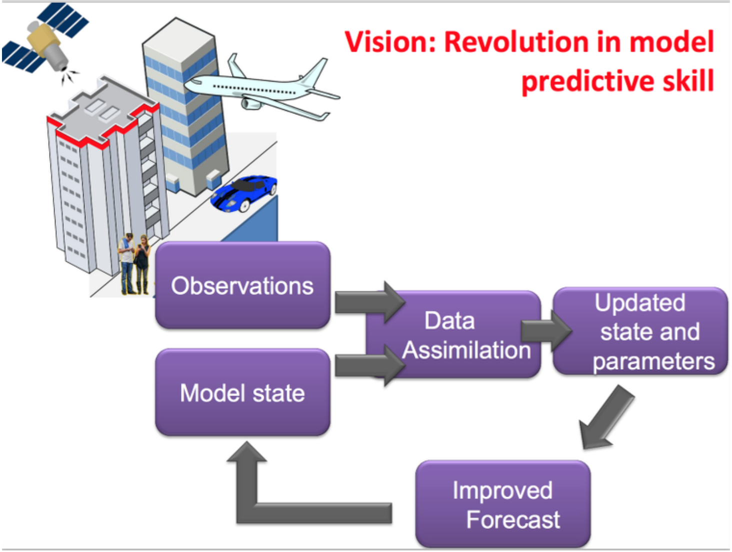
where Kalman gain matrix

$$\mathbf{K} = \mathbf{P}^f\mathbf{H}\left(\mathbf{H}\mathbf{P}^f\mathbf{H}^T + \mathbf{R}\right)^{-1}$$

weighs forecast/state errors against observation errors.

Above are known as Kalman Filter equations and all ensemble data assimilation methods are based on these equations approximating eq. (5). Other popular data assimilation methods include variational methods (e.g. 3DVar or 4DVar), particle filters, and a growing list of hybrid forms between the mentioned methods.

# How DA works?


Vision: Revolution in model predictive skill
Observations
Model state
Data Assimilation
Updated state and parameters
Improved Forecast

# Why use data assimilation in urban flooding?

**Using available observations along with the uncertain model forecast allows us to:**

- produce more accurate flood forecasts analysis;
- produce more accurate flood forecasts uncertainties;
- improve model;
- assess observation network;
- estimate uncertain model parameters/inputs.

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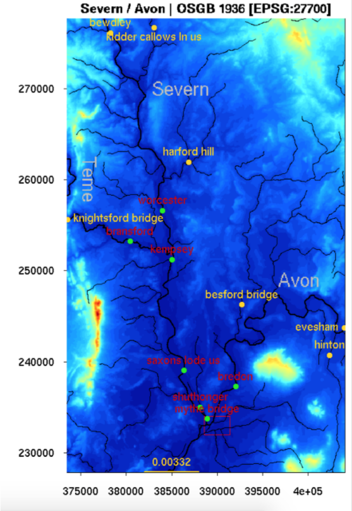
# Urban observations

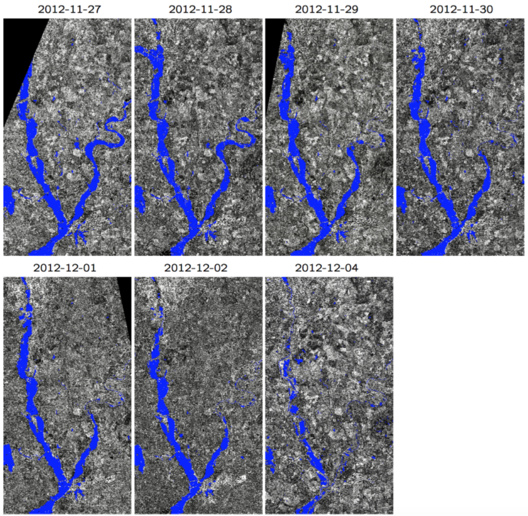

- **river gauges** (sparse in space, frequent in time);
- **SAR satellite images** (frequent in time and space, but have some issues);
- **CCTV cameras** (varied spatial distribution, frequent in time);
- **rivercams** (sparse in space, frequent in time);
- **surface water road sensors** (where available);
- **other crowdsourced data** (e.g. Twitter).

# Assimilation of SAR images




- **Model:** LISFLOOD-FP (2D);
- **Inflow BC:** ensemble from hydrological model;
- **Domain:** 30 x 50 km (75m resolution) ≈ 15000 flooded cells;
- Tributaries: Severn, Avon, ... ;
- **Water Level Observations:** Delivered from 7 COSMO-Skymed overpasses [X-band SAR] in Nov 2012 event.

# Assimilation of SAR images



# Assimilation of SAR images

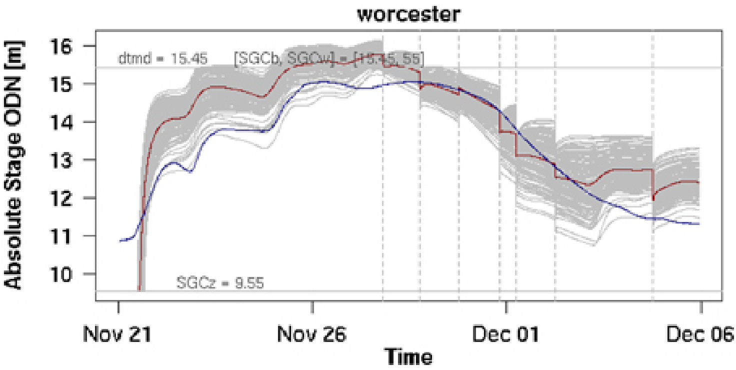



Figure: Water level forecast at Worcester, whose major inflows come from Bewdley (river Severn), Kidder Callows (river Stour), and Harford Hill (river Salwarpe). The plot is for a filter configuration involving along-network localisation and inflow and parameter estimation. Gray lines are the forecast ensemble, the red line is the mean forecast and the blue line is the gauged water level, used here as a reference and not for modelling or assimilation. Vertical dashed lines indicate the times of the CSK overpasses/assimilation. Horizontal lines indicate the bank level (labeled as 'dtmd'), and the mean channel bottom level (labeled as 'SGCz') (after Garcia-Pintado et al., 2015).

# Assimilation of SAR images

Garcia-Pintado et al. (2013, 2015) have shown that:

+ It is possible to assimilate SAR images into flood modelling;
+ Joint simultaneous estimation of uncertain parameters improves the forecast;
+ Joint simultaneous estimation of uncertain parameters further stabilises the ensemble-based covariance;
- However, in urban areas SAR images have problems due to building shadows and backscattering which renders large part of SAR observations in urban areas useless.

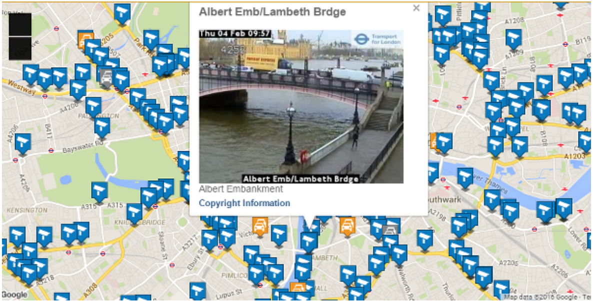
# DARE to use CCTV images to improve urban flood prediction

**Our aim** is to use CCTV images (both traffic and river cameras) to complement SAR observations in urban areas and assimilate them in the model using ensemble methods to improve the flood forecasts in cities.


CSK image of Thames flood west of London on 12/02/2014.

# CCTV observations

All big cities have a dense network of various CCTV cameras including traffic management cameras.




**Selected cities:** London, Bristol, Glasgow, Exeter, Leeds, Newcastle, Tewkesbury.

# Captured surface flooding in London

# Only the beginning...

DARE project has just started and will run till summer of 2021.

There is so much to do:

- complete the observation network;
- test DA + CCTV obs. in a simplified environment using LisFLOOD-FP hydrological model;
- set up DA system with urban hydrological model;
- asses CCTV observation impact using complex system;
- use new SAR delineation algorithm to also test SAR images in urban areas;
- lots more to do...

# Keep up-to-date with DARE blog

For more information and regular updates please visit DARE blog:

http://blogs.reading.ac.uk/dare/

# Free Data Assimilation tools: EMPIRE

**EMPIRE:**
**E**mploying **M**essage **P**assing **I**nterface for **R**esearching **E**nsembles

www.met.reading.ac.uk/~darc/empire/

**EMPIRE is:** a DA system easily connected to any dynamical model.

**EMPIRE uses:** MPI calls to setup communication and transfer data between the model and DA methods.

**EMPIRE is:** continuously developed at UoR.

# Free Data Assimilation tools: SANGOMA

**SANGOMA:**
**S**tochastic **A**ssimilation for the **N**ext **G**eneration **O**cean **M**odel **A**pplications

`http://www.data-assimilation.net/`

**SANGOMA is:** a collection of open source data assimilation tools in both Matlab and Fortran (C compatible) languages including tools for: **diagnostics, analysis methods, perturbations, utilities, transformations**, etc.

The open source code can be found here:

`https://sourceforge.net/p/sangoma/code/HEAD/tree/tools/trunk/`

# Bibliography


1. Cooper E.S., Dance S.L., Garcia-Pintado J., Nichols N.K., Smith P.J. (In preparation) Observation impact, domain length and parameter estimation in data assimilation for flood forecasting.
2. Garcia-Pintado, J., Neal , J., Mason, D., Dance, S. and Bates, P. (2013) Scheduling satellite-based SAR acquisition for sequential assimilation of water level observations into flood modelling. Journal of Hydrology, 495. pp. 252-266.
3. Garcia-Pintado, J., Mason, D., Dance, S. L., Cloke, H., Neal, J. C., Freer, J. and Bates, P. D. (2015) Satellite-supported flood forecasting in river networks: a real case study. Journal of Hydrology, 523. pp. 706-724.