EGU2020-10507

Impact-based early warning for pluvial floods

NH9.6 Natural hazard event and cost assessment for risk reduction and climate adaptation

Viktor Rözer, Aaron Peche, Simon Berkhahn, Yu Feng, Lothar Fuchs, Thomas Graf, Uwe Haberlandt, Heidi Kreibich, Robert Sämann, Monika Sester, Bora Shehu, Julian Wahl, and Insa Neuweiler

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Introduction

- **Pluvial (or surface water floods) are caused by rainstorms over urban areas, where the rainfall intensity exceeds the capacity of the urban drainage system**

- **Pluvial floods have caused severe damage in recent years in many cities around world**

- **Pluvial floods are different from other flood types (such as river flooding or storm surges):**
  - Can cause flooding in areas not obviously flood prone (e.g. far away from any water bodies)
  - Often caused by fast moving highly localized convective storm cells (even in smaller cities one neighborhood can be flooded while other neighborhoods stay dry)
  - Short early warning lead times (up to a few hours)
  - Structural flood protection (levees, dams etc.) often not viable (no well-defined source of flooding, such as a river, reservoir or the sea)

Motivation

Why impact-based forecasting of pluvial floods?

- **Current warning systems for pluvial floods are in most areas limited to severe weather warnings with limited information:**
  - Expected amount of rainfall and/or rainfall intensity
  - Affected areas (districts or regions)
  - ▸ **Information often not sufficient to decide when, where and how to prepare for a pluvial flood event (for private households, businesses and emergency responders)**
- **Impact-based forecasting systems can help to improve warnings by providing information on areas that are expected to flood alongside the expected impacts (e.g. inundation depth, direct damage to buildings)**

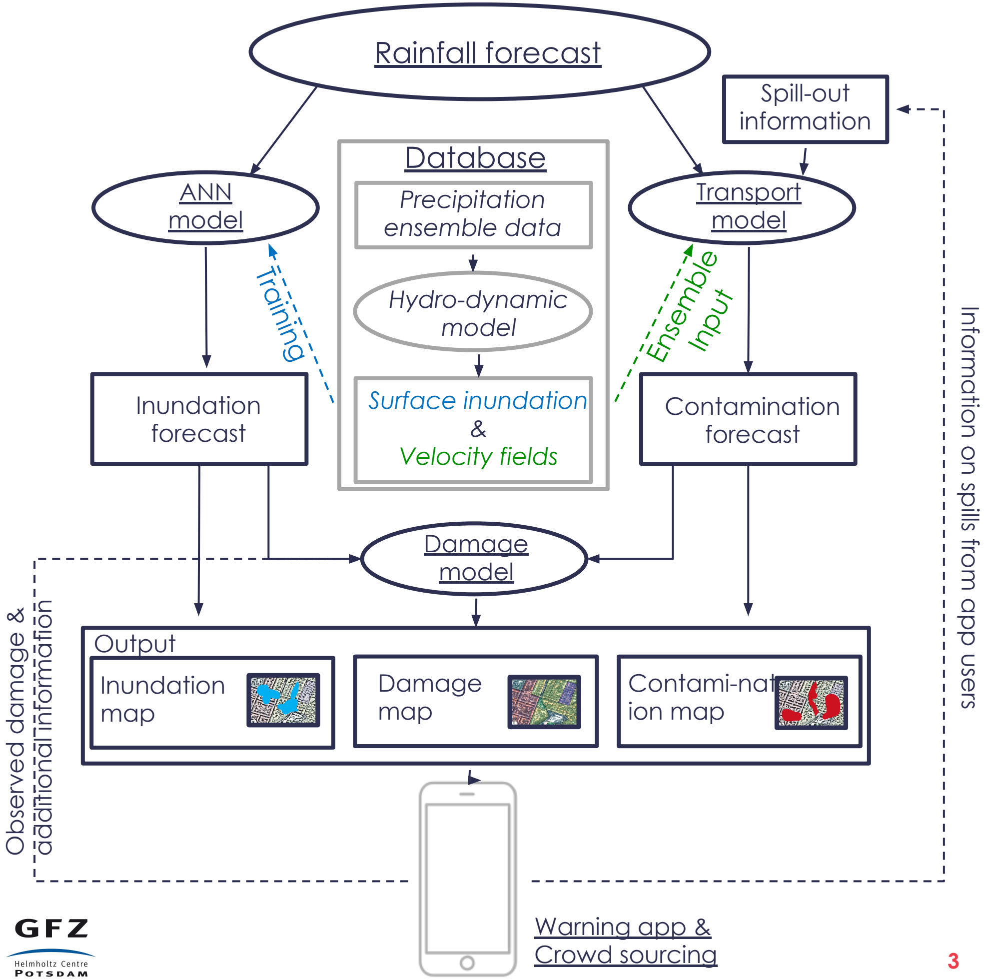
Challenges

- ▸ **Short lead time of rainfall forecast vs. long calculation times of hydro-dynamic models**
- ▸ **High uncertainties regarding flooded areas, magnitude and impacts**

Impact-based forecasting & early warning framework

(click on model components for details)

- **Model chain containing:**
  - Short-term rainfall forecast module
  - Inundation model
  - Contaminant transport model
  - Damage model
- **Database model containing pre-calculated surface inundation and flow velocity fields (used for training artificial neural network (ANN) inundation model)**
- **Two-way warning & crowdsourcing app:**
  - Shows impact-based forecasts
  - Collects volunteered geographic information (VGI) to improve forecasts



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Model application

Pluvial flood event Hannover, Germany

- Hindcast of pluvial event on June 22 2017 in Hannover, Germany (20 mm of rain in 20 minutes)
- Pluvial flood event caused widespread disruption in Hannover with over 500 fire runs reported
- Application of entire forecast model chain (except crowd sourcing and warning app, which was not yet operational by the time of the event)
- Comparison and validation of each model component against observed data to analyze sensitivity and forecasting skill


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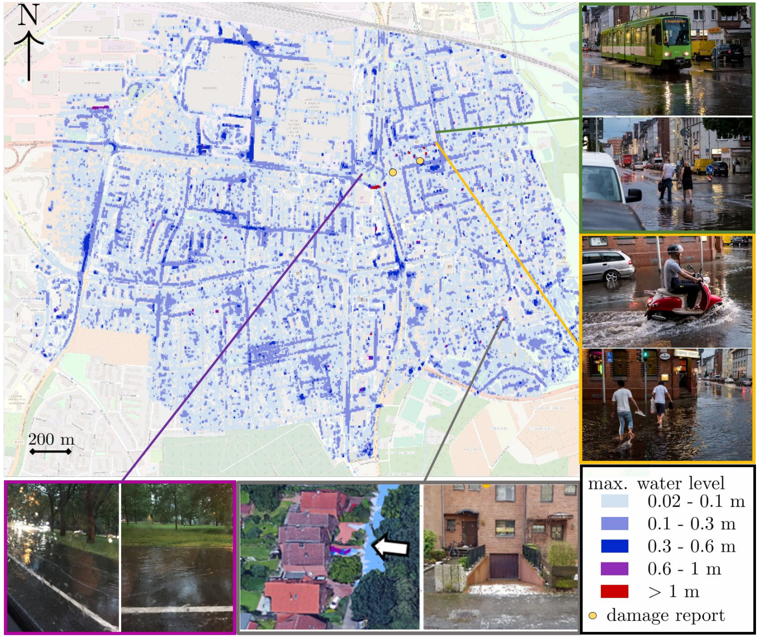
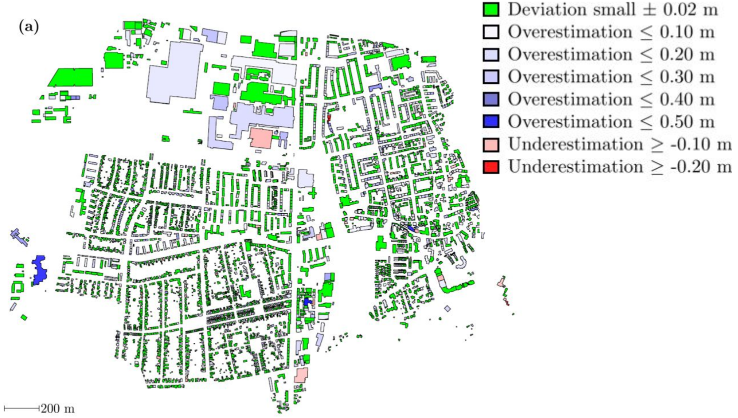
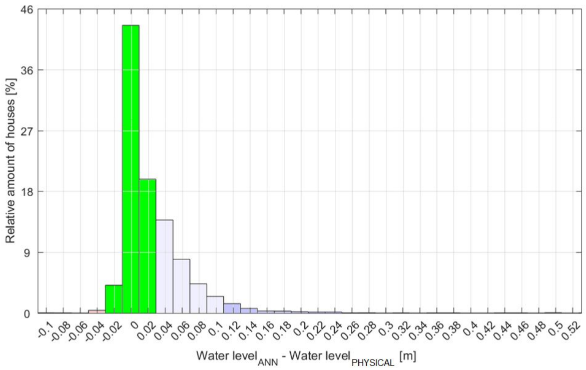
Results

Artificial Neural Network (ANN) - Inundation model



- ANN-Inundation model agrees well with observed inundation
- Deviation of ANN-model from hydro-dynamic model (PHYSICAL) in the range -2 to +10cm





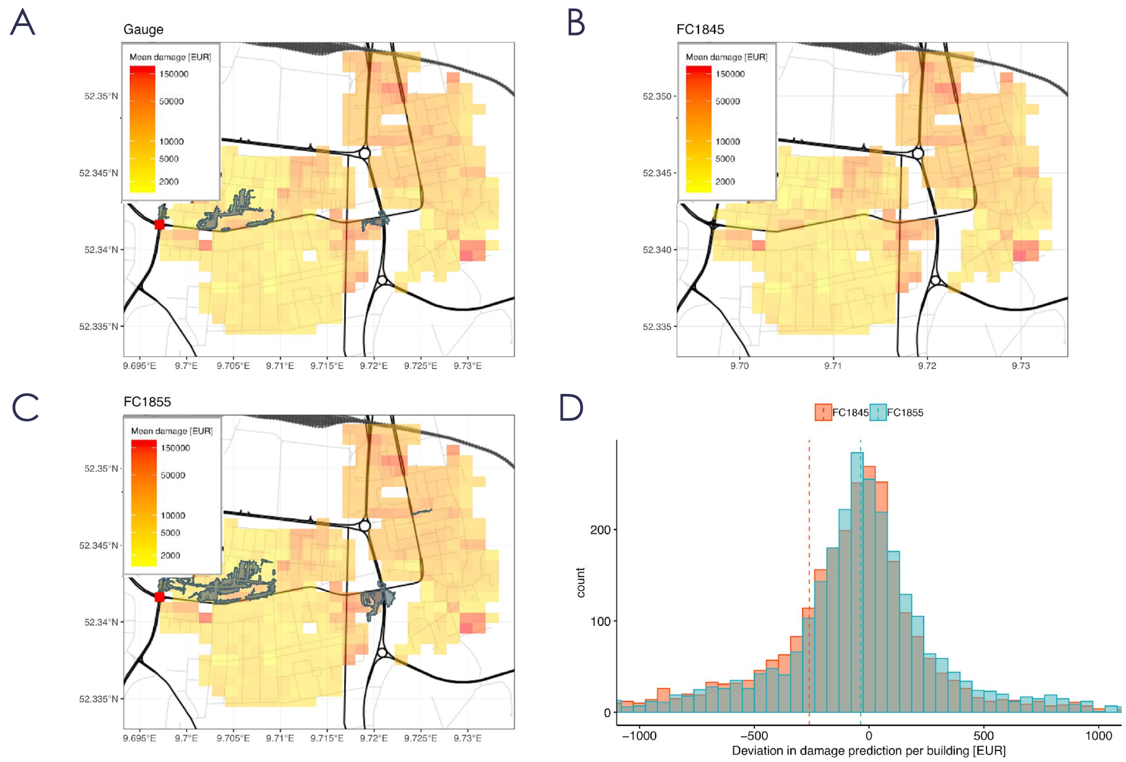
Maximum water depth:
ANN-Inundation model vs. observed

Maximum water depth:
ANN-Inundation model vs. hydro-dynamic model

Results

Contaminant transport and damage model

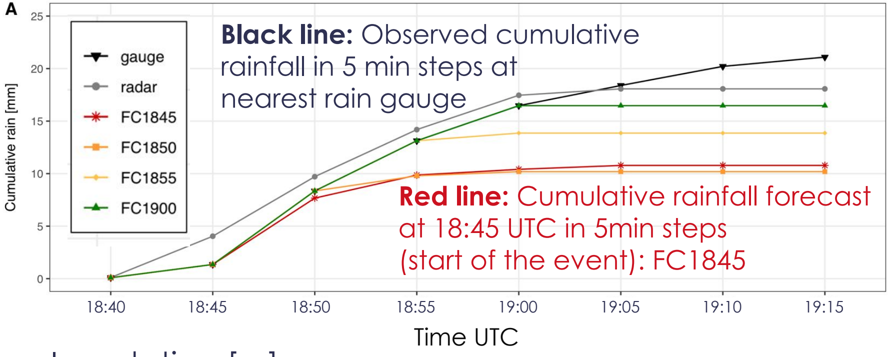
- Damage estimates based on rainfall & ANN inundation forecast (B & C) consistent with results based on observed rainfall (A)
- Slight underestimation of damage per building for earlier forecasts (D)
- Spread of contaminants forecast based (grey areas) on hypothetical oil spill (red square) slightly overestimated compared to observed rainfall and hydro-dynamic model outputs



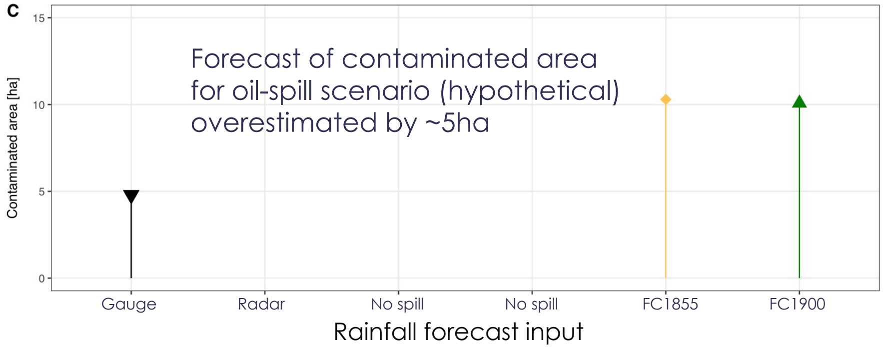
Results

Forecasting skill of rainfall model and subsequent outputs (compared to observed rainfall)

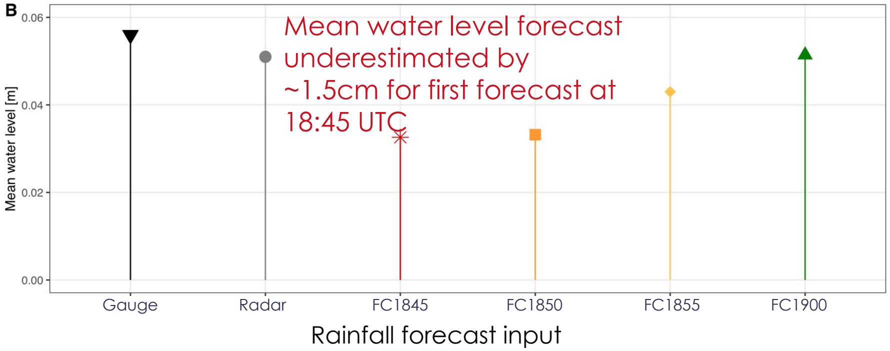
Rainfall [mm]



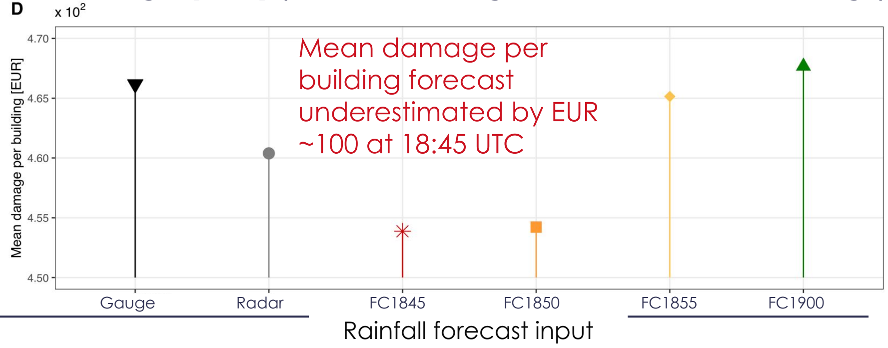
Contamination [ha] (contaminated area)



Inundation [m]



Damage [EUR] (direct damage to residential buildings)



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Results

Computation time of forecasting model chain compared to benchmark models

Model component	Output	Forecast	Benchmark	Comp. time forecast [mm:ss]*	Comp. time benchmark [mm:ss]*
Rainfall forecast	Cum. Rainfall volume [mm]	C-Band Radar merged with 80 gauge stations within a 128 km radius	Closest rain gauge (< 1 km away)	00:40	-
Inundation model	Max. water depth [m]	ANN model using rainfall forecast	Physically based model using benchmark rainfall	00:20	260:00
Contaminant transport model	Contaminated area [ha]	Ensemble of pre-calculated flow fields selected based on forecast rainfall input	Flow field calculated with physically based model with benchmark rainfall	03:30	00:39
Damage model	Damage to building structure (residential) [EUR]	Maximum water depth from ANN model Contaminated area forecast Additional data: building location and type, average household size, flood zones	Maximum water depth from ANN model with benchmark rainfall Contaminated area forecast Additional data: building location and type, average household size, flood zones	0:28	00:17
Total				**04:58**	**260:56**

* On a standard desktop PC

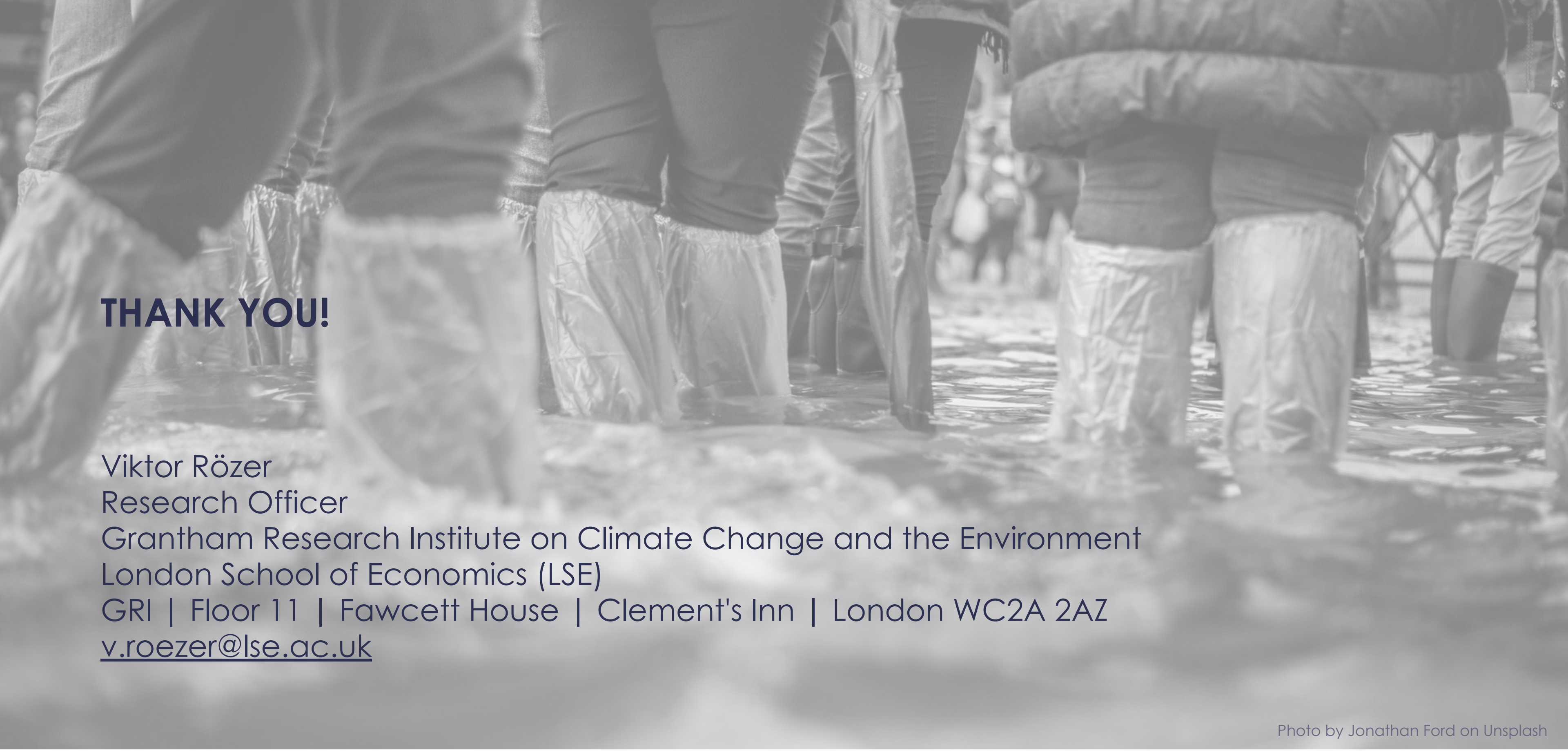
➔ **Computation time of forecast model significantly lower than benchmark model (5 minutes vs. 4.3 hours (!)) with comparable accuracy in outputs**

Discussion & Limitations

- Accuracy of rainfall forecast needed for impact-based forecasting **not reached before start of the rainfall event** (i.e. **lead times of 5-10 minutes before peak of rainfall event**)
- **Only small deviation** between results based on **measured rainfall compared to forecast** at start of the rain event
- **ANN-inundation model** based on artificial neural networks produces **comparable results to coupled hydro-dynamic model** in a fraction of the time **(< 1 minute compared to several hours**) allowing for inundation forecasts in near real-time
- Effect of reported information on contamination for accuracy of contamination and damage forecasts could not be tested at this stage (mobile app was not yet operational at time of the event)

Conclusions & Outlook

- With structural flood protection for pluvial floods often not being a viable option, **impact-based forecasting and early warning for pluvial floods** can **support efficient emergency response** and **protection of lives and assets**
- **Key obstacles** for impact-based forecasting are **accuracy of rainfall prediction** of fast-moving convective storm cells and **long computation times of physically based hydro-dynamic inundation models**
- Proposed model chain using **radar-based storm tracking and rainfall forecast** with **neural network-based inundation model** allowed for first **reliable impact-based forecast** including contaminated areas and expected damage **5-10 minutes before peak of the rainfall event** (based on case study of real pluvial flood event)
- Early warning lead times still very short, but can support short-term capacity planning for emergency response
- Forecast model chain and app-based early warning system planned to be rolled out for pilot testing stage in Hannover, Germany



THANK YOU!

Viktor Rözer
Research Officer
Grantham Research Institute on Climate Change and the Environment
London School of Economics (LSE)
GRI | Floor 11 | Fawcett House | Clement's Inn | London WC2A 2AZ
v.roezer@lse.ac.uk

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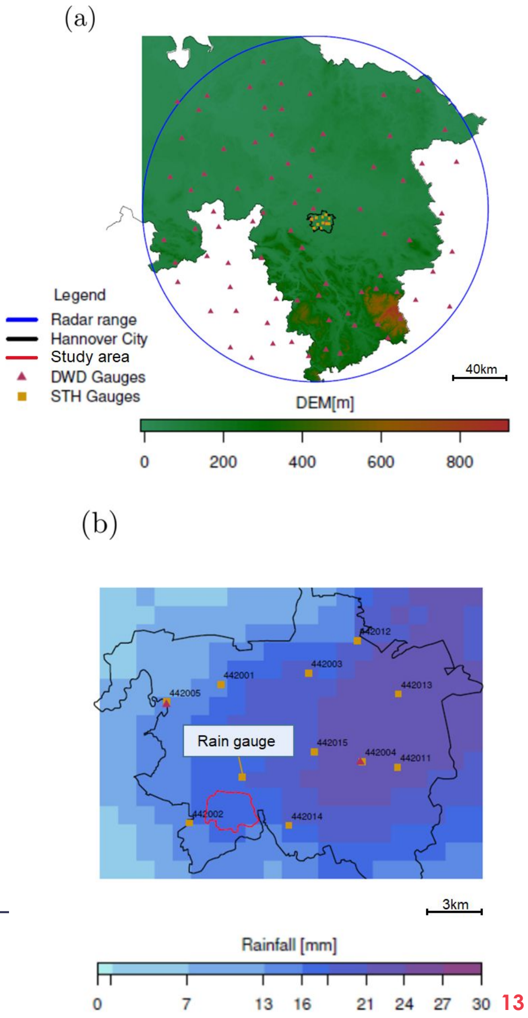
Appendix – Model components

Short-time rainfall forecast

- Based on radar data to track fast moving rain storms
- Radar data is processed for static clutters and very high values based on Berndt, Rabiei & Haberlandt (2014) and transformation of reflectivity into intensities is based on Marshall-Palmer relationship
- Radar data is merged with nearby gauge data to minimize errors
- Rainfall intensity is fed into Hyratrac forecast model (Krämer et al. 2007) to track spatio-temporal development of storm cell
- Rainfall intensities are provided on a Cartesian Plan with 1km^2 grid cells and a temporal resolution of 5 minutes (Shehu & Haberlandt, 2017)



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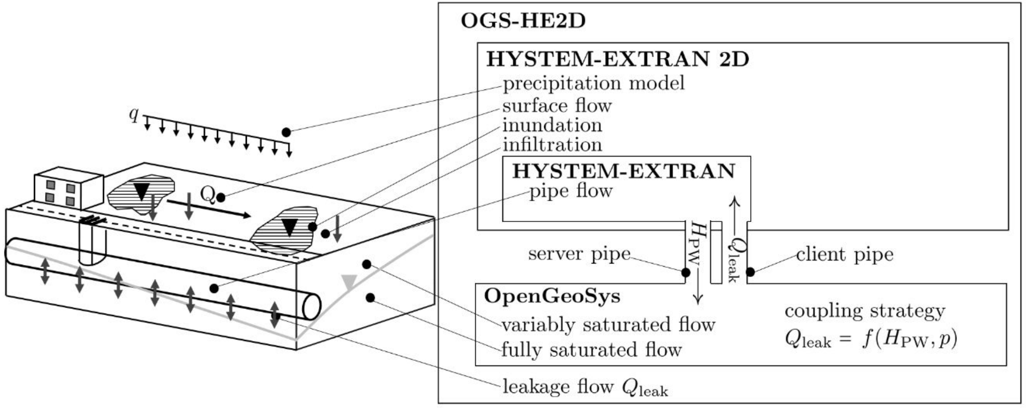
Inundation and flow velocity database

- Coupled physically-based hydrodynamic model representing **surface** and **sub-surface flows**
- Coupled pipe network and 2D surface flow model (HYSTEM-EXTRAN 2D (HE2D))
- High resolution **digital terrain model** with 0.5m spatial resolution



- HE2D model was run with **529 extreme rainfall scenarios** with **return periods of 10 to 100 years** based on gauge measurements from the German Weather Service
- The resulting **529 flood maps** including **maximum water depth** and **flow velocity fields** were stored in the **data base model**
- More details can be found in **Peche et al. (2017)**

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Artificial Neural Network (ANN) urban inundation model

- Stochastic model using a **trained artificial neural network**
- ANN Model was trained **using the 529 flood maps** and the respective **precipitation intensity time series** from the data base model (see previous slide)
- The network processes the data from input to output: time series of precipitation intensities -> maximum water depth
- Model predicts maximum water depth for each **grid cell of a 5m by 5m grid**
- More details on the ANN model can be found in **Berkhahn, Fuchs & Neuweiler (2019)**

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Contaminant transport model

- **Lagrangean particle-based** transport model
- Contaminant mass is represented as **crowd of individual particles** following the flow velocity field
- Mixing and dispersion based on random walk approach, adding a random jump to each particle's kinematics (Ahlstrom et al. 1977)
- Particles can move in **two dimensions on the surface** and in **one dimension in the pipe network**
- **No chemical reaction or deposition** is considered and particles are assumed to be **volume-less** and do not change the flow field to avoid time-consuming re-calculation of flow field
- For the contaminant transport forecast, an **ensemble of pre-calculated flow field** based on similar precipitation events are selected from the **data base model**
- More details in **Sämann, Graf & Neuweiler (2019)** and source code available here

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Damage model

- Damage model estimates expected direct monetary damage to the **building structure of residential buildings**
- **Probabilistic multi-variable damage model** with 6 variables: water level, flood duration, contamination, building type, number of people living in a household and the household's prior knowledge about flooding.
- Model developed specifically for pluvial floods based on **empirical data** on recent pluvial flood events in Germany using a **Bayesian zero-inflated beta model**
- Damage estimated as **predictive distribution** showing the probable range of damage per building (results are then aggregated on a raster grid)
- Damage model uses maximum water depth from **ANN-model** and contamination information from **contaminant transport model**. Additional model inputs come from **publicly available information** (census & OpenStreetMap data)
- More details in Rözer et al. (2019)

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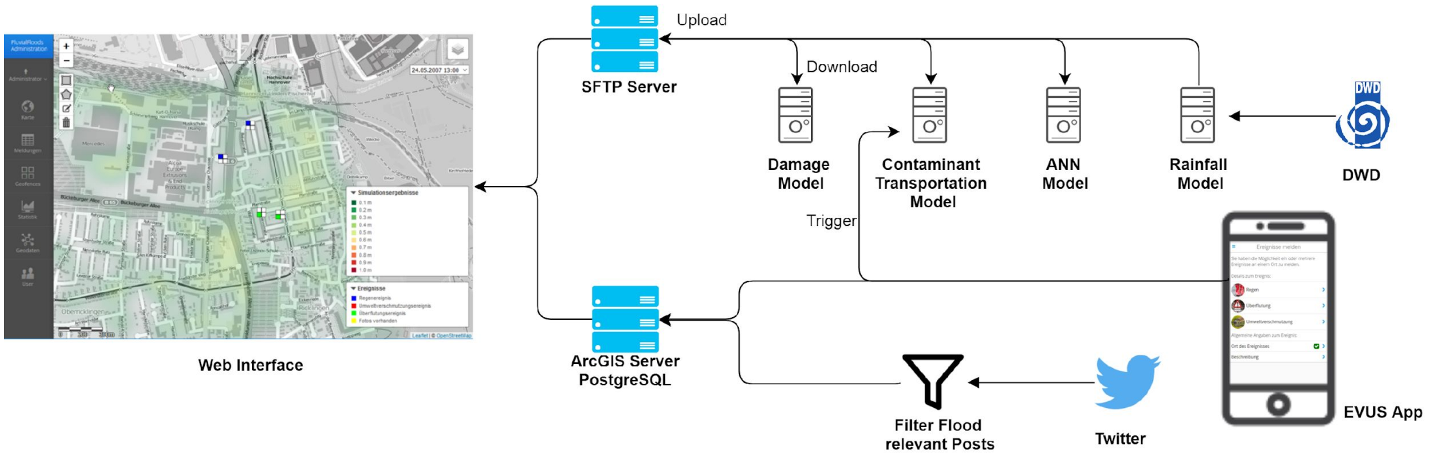
Warning app & crowdsourcing model



- Crowdsourcing model gathers **information from eyewitnesses** to **improve situation awareness** and to **validate outputs** of the forecasting model
- Crowdsourcing model uses **inputs from Twitter** using a filtering algorithm for relevant Tweets (Feng & Sester 2018) and inputs from **users of the mobile warning app** (EVUS)
- **Two-way mobile warning app** allows to **receive warnings** and access information on impacts and allows users to **provide real-time information** to improve model outputs

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