Real-Time Prediction of Pluvial Floods and Induced Water Contamination

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ICUD-0098 Real-time prediction of pluvial floods and induced water contamination in urban areas

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Summary

A forecast model for pluvial floods and their consequences is developed. It consists of the components: (1) short-term rainfall forecast using multiple data sources, among which are also Social Media and Volunteered Geographic Information (VGI) data; (2) a detailed 1D sewer and 2D surface flow model; (3) an Artificial Neural Networks-based flooding model for fast prediction of flooded areas; (4) a 3D subsurface model for saturated and variably saturated subsurface flow coupled with the 1D/2D model; (5) a particle based transport model for fast prediction of travel paths and times of contaminants after spill; and (6) a pluvial flood damage estimation model. The surface topography is based on a Digital Terrain Model refined by a Mobile Mapping Lidar.

Keywords

flooding, pluvial floods, real-time forecast, water contamination, crowd

Introduction

Extreme rainfall leads to failure of drainage systems and flooding of the surface. A cascading potential damage is the accidental release of hazardous substances, which may endanger groundwater and surface water quality. We are developing a pluvial forecast model for rainfall, related flow, flow paths and times of contaminant transport in the sewer system, on the surface and subsurface and rapid damage estimation for the city of Hannover. Additional information about extreme rainfall and/or flooding is collected via mobile phone apps and analysing tweets. The structure of the pluvial flood forecast model consists of different sub-models, as shown in Fig. 1.

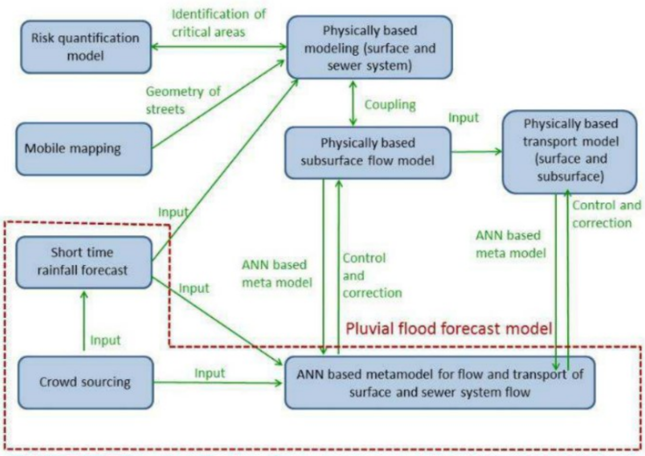


Fig. 1. *Structure of the pluvial flood forecast model.*

Short Time Rainfall Forecast

Accurate estimates of rainfall intensities with high spatial and temporal resolution are crucial for predicting flows and issuing adequately pluvial flood warnings. Radar data are used nowadays as a rainfall product for the urban models to distinguish, track and predict the movement of rainfall storms (Achleitner et al., 2009; Li et al., 1995). Nevertheless, the estimation and prediction of rainfall quantities from radar data still suffers from high errors (Seo et al., 1990). In this regard, the objective of this sub-project is to improve the rainfall quantification for pluvial flood now casting by 1) achieving a better representation of the rainfall field through merging different types of rainfall data sources, 2) developing a new forecast model for the city of Hannover with improved lead-time and 3) addressing the issue of uncertainty via ensemble members.

The present study is focused on the improvement of the precipitation estimates by merging radar and gauge data with a special focus on extreme events. Different techniques applied from hourly to daily durations have been investigated to merge appropriately the high spatial resolution of radar with the high accuracy of station data (Goudenhoofdt and Delobbe, 2009; Rabiei and Haberlandt, 2015). So far, only a few studies have investigated the merging on fine temporal resolution for urban flood forecasting (Berndt et al., 2014; Wang et al., 2013). To investigate the benefit of merged in contrast to single rainfall data on 5 min time steps, three methods combining radar and gauge data are implemented here: mean field bias correction, quantile mapping based bias correction and conditional merging. Tab. 1 illustrates the methods used and their temporal window of combining station and radar intensities.

The study area is the Hannover radar range where data from 79 DWD gauges and radar station are available in 5 min time steps for the period 2006-2012. C-band radar data are provided by DWD as raw reflectivity with an azimuth angle of 1° and are converted to rainfall intensities according to the DWD Z-R relationship ($Z=256R^{1.42}$) (Riedl, 1986; Seltmann, 1997). The merging methods are tested by split sampling over 80 pre-selected events and compared against raw radar data and kriging interpolation of stations. The performance criteria are calculated per station and event for time steps with rainfall intensities higher than a defined threshold. Since the study focusses on forecasting, the methods are implemented online where only past time steps are used as information for merging and the raw radar data are corrected by applying a simple clutter and erroneous beam correction as described in Berndt et al. (2014).

Tab. 1. *Description of the products and merging methods used for the fine temporal (5 min) and spatial (1 km^2) resolution of rainfall intensities*[*1]*.*

Methods	Time window	Symbol
Raw radar data (ref.)	-	RR
Ordinary kriging interpolation of gauge data (ref.)	-	OK
Mean field bias of raw radar data	60 min	MFB
Quantile mapping based bias correction of raw radar data	180 min	QQ
Conditional merging of smoothed radar and gauge data	15 min	CM1
Conditional merging of MFB corrected radar and gauge data	60 min	CM2
Conditional merging of QQ corrected radar and gauge data	180 min	CM3

[*1]Readers are guided to Berndt et al., (2014), Rabiei and Haberlandt (2015) and Seo et al. (1999) for further description of the methods.

From Fig. 2 it is visible that not all of the methods have an advantage towards the single data source. All the three performance criteria show that the conditional merging based on smoothed radar data (CM1) outperforms the other merging methods. Fig. 3 illustrates the benefit of using CM1 towards the single data sources RR (green) and OK (blue). Compared to radar data, the use of CM improves considerably the RMSE and the BIAS by 20%, however decreases the correlation by 0.2. The application of CM smoothens the radar information both in time and space before merging, resulting so in a lower correlation. Compared to the use of OK as well, the CM improves the performance of RMSE, BIAS and even correlation by respectively 15%, 20% and 0.25. The results show clearly the advantage of the selected merging method CM1 towards the single data source. This gives way to the application of the merging on forecasting and investigating how the merging improves the estimation of the existing forecast algorithms.

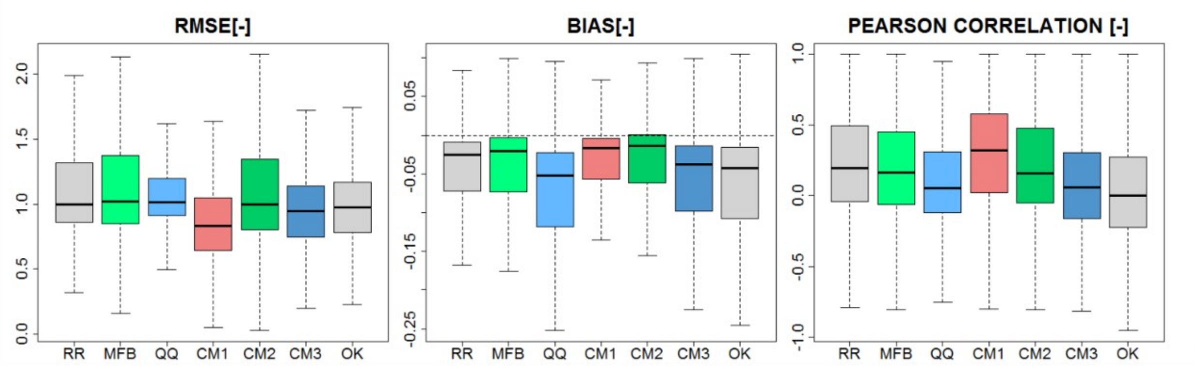


Fig. 2. *The RMSE -normalized root mean square error (left), normalized bias (middle) and Pearson correlation (right) of the selected merging methods applied online. Boxplots represent station temporal errors for time steps higher >= 0.2 mm/5 min for all the events.*

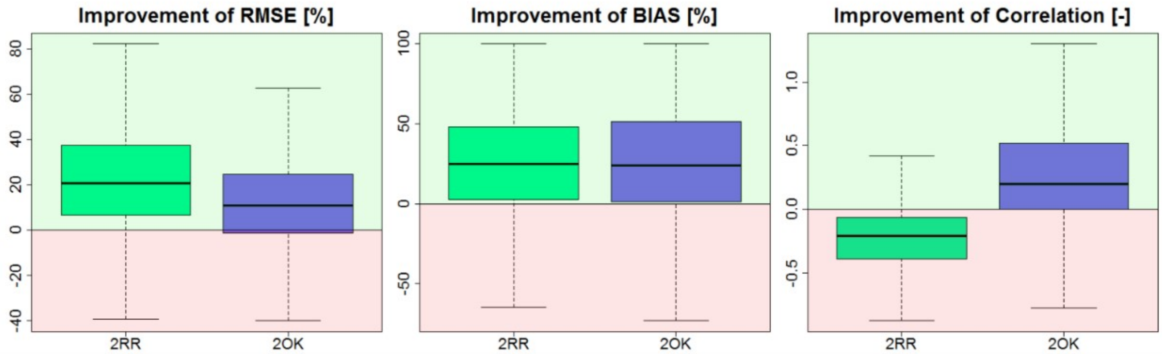
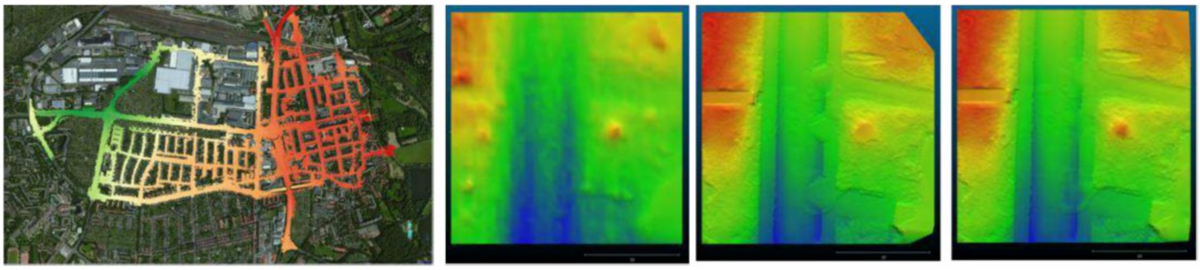


Fig. 3. *Improvement of RMSE (left), bias (middle) and Pearson correlation (right) from comparison of CM1 with radar data (CM1vsRR - green) and with interpolation of station data (CM1vsOK - blue). The boxplots represent improvement of all stations in all the events. The green/red areas of the plot indicate respectively that the CM1 performs better/worse than the single data.*

Modelling Environment for Surface Flow Modelling

A coupled 1D/2D sewer and surface model (HYSTEM-EXTRAN 2D, itwh, 2015) is set up for the entire city using a 50 cm Digital Terrain Model (DTM). For fast forecasting of the flooding, we developed, tested and validated a meta-model based on Artificial Neural Networks (ANN) (Berkhahn et.al. 2017). Simulation times of the meta-model are sufficiently short to forecast pluvial floods.

For the test area in Hannover Oberricklingen, the DTM in the road area is refined to 10 cm by using data from a Mobile Mapping System with a 10 cm resolution. The Mobile Mapping System (MMS) captures very precise 3D-pointclouds in an area of approx. 200 m around the roads, which is accessible by the Laser. The test area has been measured with such a system and a DTM of roads in 10cm resolution [as shown in Fig. 4(a)] was generated using ground filtering algorithms (Wack, 2002). This DTM was merged with the 50cm resolution DTM product from the local land-surveying agency in order to fill the areas not covered by the MMS data. We applied interpolation to smooth unexpected height jumps at connecting borders of two DTMs. In this way, we improved the resolution of a 50cm resolution DTM in the road area to 10cm and achieved at the same time the completeness of data in the test area [Fig. 4(b), 4(c), 4(d)].



(a) (b) (c) (d)

Fig. 4. *Digital Terrain Model (DTM) generated from point cloud measured by the Mobile Mapping System (a). DTM from local land surveying agency in 50cm resolution (b), DTM measured by Mobile Mapping System in 10cm resolution (c) and DTM after merging (d).*

Subsurface Flow Model

For the quantification of pluvial event-driven pipe leakage in an urban system a three-dimensional physically based subsurface flow model (SSFM) was developed. This model calculates saturated-unsaturated subsurface flow, pipe flow and exchange fluxes between defect pipes and the soil.

In order to generate the SSFM, the numerical pipe flow simulator HYSTEM-EXTRAN (itwh, 2015) was coupled with the numerical groundwater simulator OpenGeoSys (Kolditz et al., 2012). That novel shared-memory coupling is based on a time step-wise (non-iterative) updating of boundary conditions and source terms. The coupled SSFM was successfully validated and verified by numerically reproducing results from two transient physical experiments and one steady-state analytical solution.

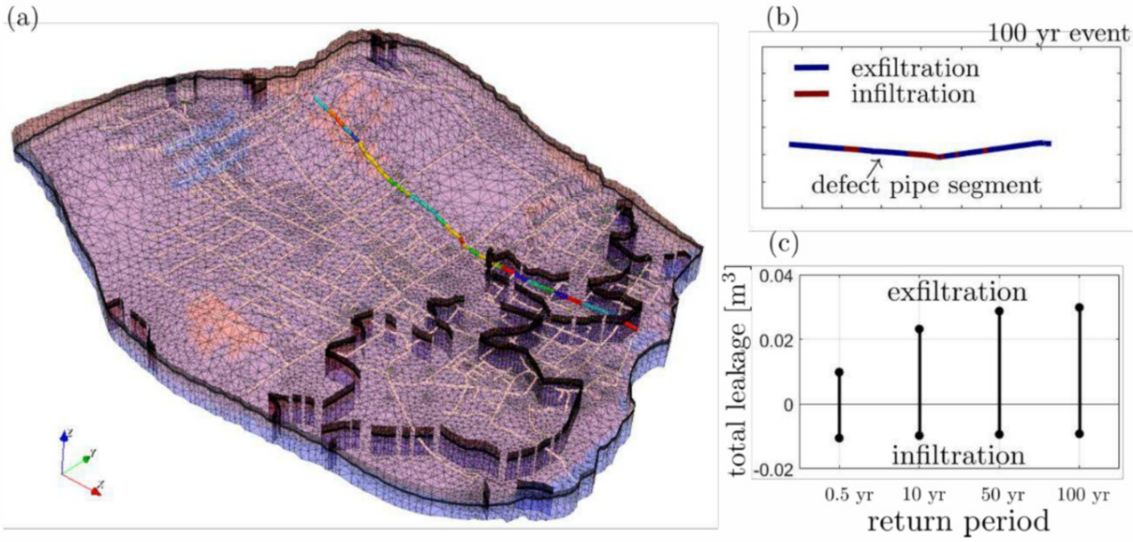


Fig. 5. *(a) Model domain and numerical grid of a catchment scale SSFM simulation. Grey colors indicate the full pipe network, colorful pipes the defect pipe section, the subsurface pressure distribution is given in blueish (positive) and reddish (negative) colors. (b) Exfiltration and infiltration in the defect pipe segment. (c) Total leakage for each simulated event.*

The SSFM was applied to a series of transient problems on different scales: single pipe defects, street scale defects and catchment scale defects. For simulations on a scale bigger than the single defect scale, pipe leakage was up scaled using novel transfer functions derived from numerical simulations. This upscaling enables a significant reduction in computation time.

A visualization of the model domain of a catchment scale simulation is given in Fig. 5 (a). In that model, a series of quadratic standard defects after Karpf (2012) was distributed along the pipes in a hypothetical scenario. Strong pluvial block rain events of 100 year, 50 year, 10 year and 0.5 year return periods (for a city located in northern Germany) and hourly duration were simulated and the total leakage volume was quantified. Fig. 5 (b) shows the locations within the defect pipe segment where pipe water exfiltrated into the subsurface (exfiltration) and where groundwater infiltrated into the pipe segment (infiltration). Fig. 5 (c) shows total leakage in form of exfiltration and infiltration and for each pluvial event.

Particle Based Transport Model

Due to high water levels during pluvial flooding, the risk of mobilization of potentially dangerous substances increases. High precipitation may lead to exceeding the capacity of urban drainage systems, resulting in interaction flow between pipes and surface via manholes and street inlets, so that the transport paths are not necessarily clear. One aim of the project is to develop a real time contaminant spreading forecasting model, which helps civil protection and disaster management authorities to deal with hazardous substances in case that they are spilled during a pluvial flood event. Temporal connections between pipes due to overland flow as well as due to possibly reversed flow directions create complex dynamic flow patterns. The problem for the project is that computation times are long when solute transport is calculated coupled to a hydrodynamic model. Therefore, a particle based transport model for fast prediction of travel paths of contaminants has been set up that is independent of the hydraulic model, but reads in velocities at given time steps. Advection, mixing and dispersion is captured in the model by using a time explicit random-walk approach (Banton et al., 1997).

Particles represent a solute mass in a drainage network after an accidental spill. Assuming that injected substances have a negligible volume, they do not affect the flow field. Also, density effects are neglected. A dynamic flow field, matching the actual heavy rainfall event, is chosen from an assembly of pre-calculated simulations using a Nearest-Neighbor approach (Lall & Sharma, 1996). The selected flow field is used to calculate the advective transport velocity in a one dimensional pipe network. Diffusion and mixing are accounted for with a random jump in each time step, scaled with the square root of a dispersion factor of 2 m^2/s (Schlütter & Mark, 2003). The particle transport model is validated against a finite volume model with very fine spatial and temporal discretization, reproducing a concentration peak in a pipe with a discharge wave after several kilometers. The advantage of this particle model is the easy way to track the path of contaminants. Another benefit is its conservation of mass and the low numerical diffusion, which is essential for a good prediction of solute concentration.

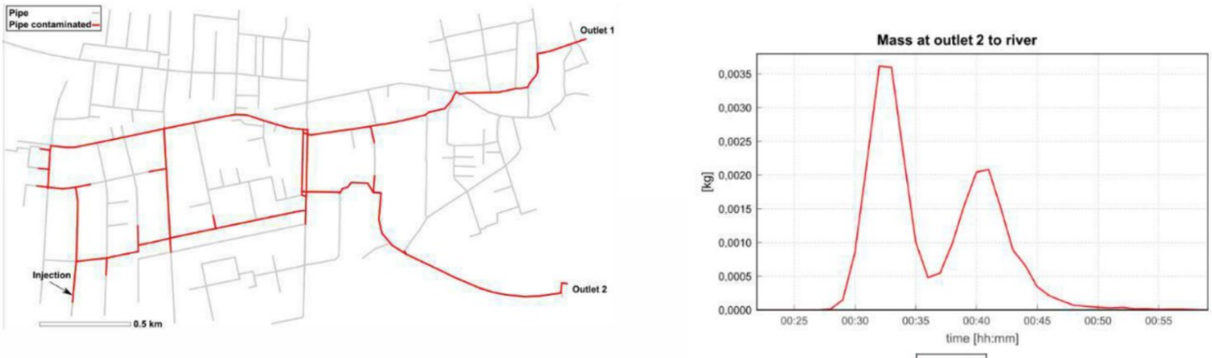


Fig. 6. *Contamination in pipe network and mass spill out breakthrough curve.*

An example of the model is shown above. A scenario spill event was run and the model shows clearly contaminated pipes and a breakthrough curve with two mass peaks at an outlet. These peaks were created by a split at a junction in the pipe system and a later reunion (Fig. 6).

The model is also coupled to a surface flow model to take storage in ponds and transport with overland flow on streets into account. A detailed description can be found in "Lagrangean particle transport model for real-time solute spreading forecasting in an urban drainage system" (Sämann et al., 2017).

Risk Quantification

To quantify the pluvial flood risk, we will combine the flow model with a pluvial flood damage model. We develop a new probabilistic multi-variable damage estimation model based on empirical data. First, a tree-based machine-learning algorithm is used to identify the most important damage influencing factors out of a set of 35 candidate variables. Second, the most important variables are used to derive the pluvial flood damage estimation model by learning a Bayesian Network (BN). By inherently providing quantitative uncertainty information and the possibility to include expert knowledge, the BN damage model is expected to outperform existing approaches in terms of spatial and temporal transfer (Schröter et al. 2014).

Crowd Sourcing for Distributed Data Acquisition

A fast developing method for data acquisition is crowd sourcing, which aims at collecting useful information containing location information from voluntarily users. For collecting crowd-sourcing information, exchanging of necessary information between subprojects and visualizing of the prediction results, we propose a data infrastructure (Fig. 7).

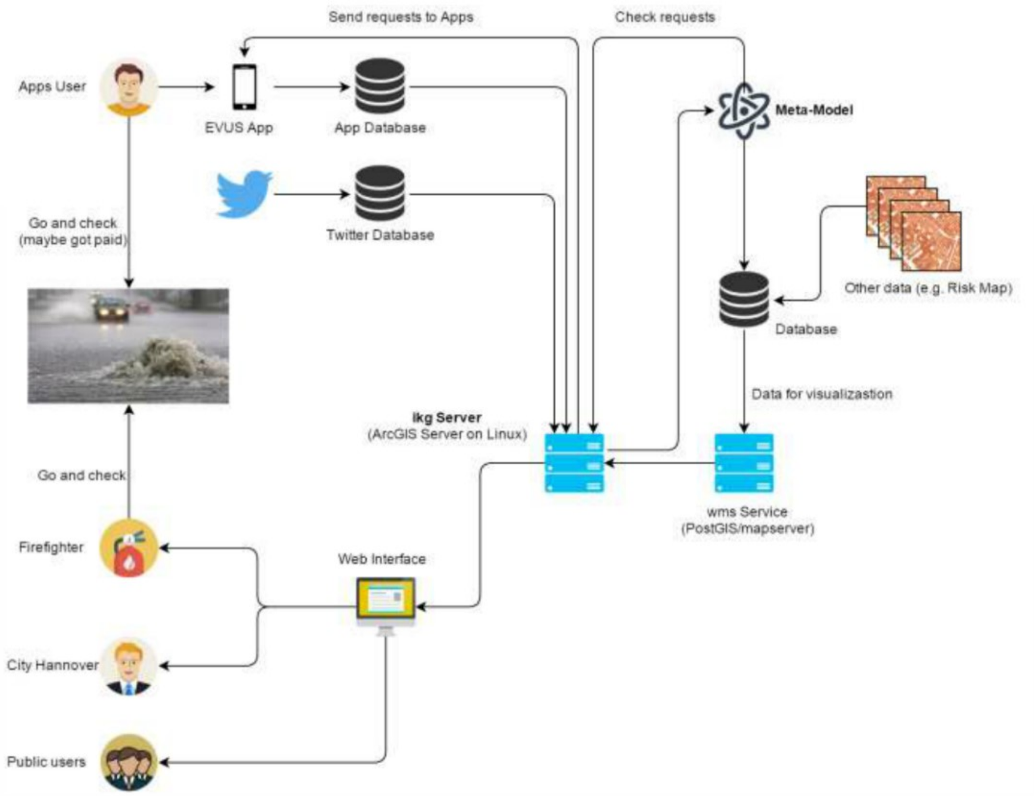


Fig. 7. *Design of data infrastructure for EVUS project.*

Reports from users are collected with two approaches, a participatory approach and an opportunistic approach. For the participatory approach, it requires a conscious and active participation by the users. To this end, we developed a mobile phone app to collect reports from users, which contains their location and our desired information, such as rain intensity, range of inundation area, and occurrence of contaminations (Fig. 8). For the opportunistic approach, information is acquired in a quasi-unconscious and passive manner. Therefore, we developed an approach to identify and localize rainfall events from social media (Feng & Sester, 2017). As Twitter provides access to users' posts in real-time, we developed algorithms based on Natural Language Processing and spatiotemporal clustering to extract rainfall-relevant events from geo-tagged Tweets (Fig. 8).

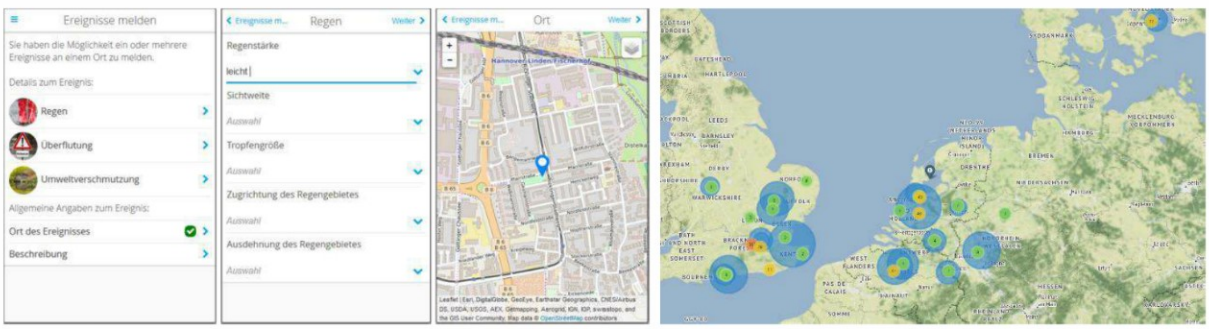


Fig. 8. *the mobile phone app designed for collecting pluvial flood relevant data (Left). Extracted spatiotemporal clusters in west Europe on Jun. 23 2016 (Right Screenshots of).*

The crowd sourcing information then serves as necessary inputs for contaminants movement analysis and short time rainfall forecasting. Finally, the results will be visualized in a web interface and will be made available for city governors, fire fighters and public users in Hannover (Fig. 7).

Conclusions

The model environment has been developed and tested for a sub-catchment. The individual models are developed and will be further tested, enhanced and validated. First experiments with processing of crowd sourcing of rainfall event data have been conducted. Images from social media platforms will be analyzed with Deep Learning approaches to investigate their potential for rainfall event detection. In a next step, the modelling system will be implemented for the entire city of Hannover. The complementation of pluvial flood warning with information about potential flood impacts is an innovative enhancement to better support decision making in emergency management.

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