

Modelling river flood risk for the whole continental US

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(With lots and lots of help from Niall Quinn, Chris Sampson, Andy Smith, Ollie Wing and Jeff Neal)



www.fathom.global

The problem – US flood river risk



- Substantial losses each year
 - Average annual damage 1903-2014 = ~\$5Bn
 - (NWS data for river flood, not including coastal events, actual losses at 2014 prices)
 - ~100 fatalities a year on average, with no trend over the same time
 - Significant social disruption
- National Flood Insurance Programme costs \$190M p.a. and is \$25Bn in debt
- Recent events have raised public awareness of the issue

US Flood losses – National Weather Service data



Flood modelling

- Over the last 20 years remote sensing has revolutionized flood modelling
 - From early work at reach scales with LiDAR data
 - to global data sets enabling continental and global models at <100m resolution





Whole US model

- DEM from US National Elevation Dataset (NED)
- 30m resolution
- All river channels explicitly represented
- Boundary conditions from regional flood frequency analysis of rainfall and flow
- Includes US Army National Levee Dataset
- 10 return periods from 5 to 1000 years







Validation – Memorial day, Houston 2015



- 1984 properties defined as being inundated with flood waters.
- Event magnitude estimates range from 100-500 year event depending on exact location.
- Hit rate of 70% and 91% for the 100 year and 1000 year hazard layers respectively.

Layer	Captured	Missed	Hit Rate %	
20YR	683	1301	34	
100YR	1391	593	70	100-500YR observed
1000YR	1818	166	91	

Global model validation: FEMA

- An amalgamation of local studies carried out by FEMA to determine the 1 in 100-year flood extent
- Re-sampled to 90m resolution
- Unexamined areas: both declared and undeclared
- Lack of headwater area coverage problematic
- Analysis performed in Google Earth Engine



Over prediction ?











Global model validation: FEMA

Hite Rate = 81%

84% for catchments >80 km²

86% for 'high quality' FEMA data at all scales

CSI = 59%

Köppen-Geiger zones

Temperate = 84% Arid = 73% Continental = 78%



Catchment-scale validation: USGS 1D models

- Isolated local modelling studies – usually a few kilometres of a single stream
- 10 sites with 100-year simulations
- 3 further sites with events of varying magnitude



LOCATION	HIT RATE (%)
Albany, GA	93.8
Columbus, IN	83.3
Greenville, SC	99.7
Hattiesburg, MS	93.7
Lincolnshire, IL	81.8
Minneapolis, MN	91.0
Ridgewood, NJ	88.6



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LOCATION	HIT RATE (%) 1 in 10	
Harrisburg, PA	95.1	



LOCATION	HIT RATE (%) 1 in 500	
Killbuck, OH	94.3	



Basics of risk calculation



- Hazard
 - Flooded area
- Exposure
 - Value of buildings within floodplain
 - Number of people
 within floodplain
 - Vulnerability
 - Potential damages

Hazard data



 ~30m resolution flood hazard model of CONUS (Wing *et al.*, 2017)

Wing, O. E. J. *et al.* (2017), Validation of a 30 m resolution flood hazard model of the conterminous United States, *Water Resour. Res.*, 53, 7968–7986, doi:10.1002/2017WR020917.

Socio-economic data



- EPA EnviroAtlas dasymetric population map
- Assigns 2010 census populations to 30m pixels based on land-use and slope

Socio-economic data



- FEMA National Structure
 Inventory
- Information on over 100M buildings in the CONUS:
 - Location
 - Value
 - Type
 - Number of storeys
 - Presence of basement

Socio-economic data



- National Land Use
 Database (Theobold, 2014)
- Indicates developed areas across the CONUS

Theobold, D. M. (2014), Development and Applications of a Comprehensive Land Use Classification and Map for the US, *PLOS ONE*, 9(4), e94628, doi:10.1371/journal.pone.0094628.

Future projections



EPA (2016), Updates to the Demographic and Spatial Allocation Models to Produce Integrated Climate and Land Use Scenarios (ICLUS) Version 2. EPA/600/R-16/366F, National Center for Environmental Assessment, Washington, DC.

- EPA Integrated Climate and Land Use Scenarios (ICLUS) project
- Projects population and land use change up to 2100:
 - SSP2 = tracks US census projection
 - SSP5 = high growth case

Vulnerability functions



- Simple relationship between water depth and % damage to an asset obtained from USACE
- Specific function for each building type when used with FEMA NSI

Future vulnerability functions



- Simple relationship between water depth and % damage to an asset obtained from USACE
- Generalised curve used
 for ICLUS projections



• Present-day

Return Period	Exposure (millions)	Exposure (%)
1 in 50	33.5	11.0
1 in 100	40.8	13.3
1 in 500	61.4	20.0
FEMA (1 in 100)	13.0	4.2
Aqueduct (1 in 100)	15.7	5.1



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www.floods.wri.org

Winsemius, H. C. *et al.* (2013), A framework for global river flood risk assessments, *Hydrol. Earth Syst. Sci.*, 17, 1871–1892, doi:10.5194/hess-17-1871-2013.

Ward, P. J. *et al.* (2013), Assessing flood risk at the global scale: model setup, results, and sensitivity, *Environ. Res. Lett.*, 8, doi:10.1088/1748-9326/8/4/044019.



• SSP2 2050

Return Period	Exposure (millions)	Exposure (%)
1 in 50	51.3	13.1
1 in 100	61.2	15.6
1 in 500	86.8	22.2



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Return Period	Exposure (millions)	Exposure (%)
1 in 50	51.3	13.1
1 in 100	61.2	15.6
1 in 500	86.8	22.2

 Changes from presentday (100-year floodplain)



• SSP2 2050

Return Period	Exposure (millions)	Exposure (%)
1 in 50	51.3	13.1
1 in 100	61.2	15.6
1 in 500	86.8	22.2

- Changes from presentday (100-year floodplain)



• SSP2 2100

Return Period	Exposure (millions)	Exposure (%)
1 in 50	63.1	13.9
1 in 100	74.8	16.4
1 in 500	104.5	23.0



• SSP2 2100

Return Period	Exposure (millions)	Exposure (%)
1 in 50	63.1	13.9
1 in 100	74.8	16.4
1 in 500	104.5	23.0

 Changes from presentday (100-year floodplain)



• SSP2 2100

Return Period	Exposure (millions)	Exposure (%)
1 in 50	63.1	13.9
1 in 100	74.8	16.4
1 in 500	104.5	23.0

- Changes from presentday (100-year floodplain)



• Present-day

Return Period	Dev. Area (km²)	Exposed assets (\$tn)	Potential dmg (\$tn)
1 in 50	140,657	4.6	0.9
1 in 100	157,430	5.5	1.2
1 in 500	203,775	8.2	1.9

 100-year developed floodplain = approx. the land area of Georgia



• SSP2 2050

Return Period	urnDev. AreaExposediod(km²)assets (\$tn)		Potential dmg (\$tn)	
1 in 50	174,989	6.9	1.5	
1 in 100	195,981	8.1	1.7	
1 in 500	251,702	11.3	2.7	

 100-year developed floodplain = approx. the land area of S. Dakota



• SSP2 2100

Return Period	rn Dev. Area Exposed od (km ²) assets (\$tn)		Potential dmg (\$tn)	
1 in 50	192,417	8.3	1.7	
1 in 100	215,900	9.8	2.1	
1 in 500	276,956	13.6	3.2	

 100-year developed floodplain = approx. the land area of Kansas



• SSP2 2100

Return Period	turn Dev. Area Exposed riod (km ²) assets (\$tn)		Potential dmg (\$tn)	
1 in 50	192,417	8.3	1.7	
1 in 100	215,900	9.8	2.1	
1 in 500	276,956	13.6	3.2	

 100-year newly developed floodplain = approx. the land area of W. Virginia

Conclusions

- Developed a whole US flood inundation model with skill approaching that local bespoke simulations
- Intersecting simulations with high resolution population data shows exposed population and assets are ~3x higher than previous estimates

University of BRISTOL

- Socio-economic change alone will increase the proportion of US population at risk during the C21st
- Climate change will undoubtedly amplify these effects further
- Now need to move away from 'constant return period in space' hazard layers to properly estimate flood risk

Spare slides

Catchment-scale validation: USGS 1D models

LOCATION	HIT RATE (%)				
	1 in 5	1 in 10	1 in 50	1 in 100	1 in 500
Battle Creek, MI	-	81.9	84.3	88.1	90.7
Harrisburg, PA	-	95.1	92.3	88.7	86.1
Killbuck, OH	78.1	81.8	90.2	91.9	94.3

Traditional flood hazard assessment

- Return period flows from gauge data
- Reach scale hydraulic models
- Large scale hazard maps then 'stitch together' the results of many local studies
 - E.g. FEMA Special Flood Hazard Areas
- Spatially invariant return period assumption breaks down at large scales



Event footprints

- Over large scales the event return period varies in space
 - Known as the 'flood footprint'
- Often ignored in many large scale analyses
- Gauge time series not long enough to sample all possible footprints
- Use conditional stochastic simulation to generate a bigger sample of plausible event footprints



The problem

- For a *T* year return period flow at gauging site *X*, Q_X^T , what is the probability distribution of flow at gauge *Y*, i.e. $Pr(Q_y | Q_X^T)$ for all $Y_{1,2} \dots n$
- Multi-site conditional probability statistical methods are well known, but not previously applied at continental scales for thousands of gauges
 - Cross-correlation between all gauges gives a large compute problem
 - Large climatic differences at continental scales
 - Multiple flood generating mechanisms

Method



Heffernan, J.E. and Tawn, J.A. (2004). A conditional approach for multivariate extreme values. J. *R. Statist. Soc. B*, **66**, Part 3, 497–546.



Gauge preparation



Spatio-temporal dependence



See also poster H21J-1615 by Quinn et al

Spatio-temporal dependence

c. Define dependence structure



See also poster H21J-1615 by Quinn et al

Spatio-temporal dependence

c. Define dependence structure



Generate event catalogues

- Given gauge dependence structure we can simulate event footprints at any given conditioning site
- Need a structure to interpolate over
 - Use HydroBasins Level 8 and 10 units
 - Interpolate gauge return period values to these units
 - Build footprint using pre-computed set of return period hazard layers from the Fathom Global US 30m hydraulic model



Example event footprint



Validation

- Test 1: observed vs. modelled extreme value CDFs
 - For a given CDF quantile (0.5 in this case) does the dependence structure in the synthetic event ensemble match the observations?
- Test 2: Independent events
 - Extract all independent events > 1 in
 5 year return period in USGS record
 - Simulate same record length many times using the stochastic method
 - Mean error in no. of events and no. of gauges hit is <5%



Event animation



Costs of avoidance

