

Key Points:

- Global flood risk assessment at different warming levels based on ensemble climate projections
- At 4°C warming 70% of the world population and GDP will face increase in flood impact over 500%
- Projected changes in flood risk are largest in Asia, America, and Europe

Supporting Information:

- Supporting Information S1

Corresponding author:

L. Alfieri, lorenzo.alfieri@jrc.ec.europa.eu

Citation:

Alfieri, L., B. Bisselink, F. Dottori, G. Naumann, A. de Roo, P. Salamon, K. Wyser, and L. Feyen (2017), Global projections of river flood risk in a warmer world, *Earth's Future*, 5, 171–182, doi:10.1002/2016EF000485.

Received 20 OCT 2016

Accepted 21 DEC 2016

Accepted article online 26 DEC 2016

Published online 14 FEB 2017

© 2016 The Authors.

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

Global projections of river flood risk in a warmer world

Lorenzo Alfieri¹, Berny Bisselink¹, Francesco Dottori¹, Gustavo Naumann¹, Ad de Roo¹, Peter Salamon¹, Klaus Wyser², and Luc Feyen¹

¹European Commission, Joint Research Centre, Ispra, Italy, ²Rosby Centre, Swedish Meteorological and Hydrological Institute, Norrköping, Sweden

Abstract Rising global temperature has put increasing pressure on understanding the linkage between atmospheric warming and the occurrence of natural hazards. While the Paris Agreement has set the ambitious target to limiting global warming to 1.5°C compared to preindustrial levels, scientists are urged to explore scenarios for different warming thresholds and quantify ranges of socioeconomic impact. In this work, we present a framework to estimate the economic damage and population affected by river floods at global scale. It is based on a modeling cascade involving hydrological, hydraulic and socioeconomic impact simulations, and makes use of state-of-the-art global layers of hazard, exposure and vulnerability at 1-km grid resolution. An ensemble of seven high-resolution global climate projections based on Representative Concentration Pathways 8.5 is used to derive streamflow simulations in the present and in the future climate. Those were analyzed to assess the frequency and magnitude of river floods and their impacts under scenarios corresponding to 1.5°C, 2°C, and 4°C global warming. Results indicate a clear positive correlation between atmospheric warming and future flood risk at global scale. At 4°C global warming, countries representing more than 70% of the global population and global gross domestic product will face increases in flood risk in excess of 500%. Changes in flood risk are unevenly distributed, with the largest increases in Asia, U.S., and Europe. In contrast, changes are statistically not significant in most countries in Africa and Oceania for all considered warming levels.

1. Introduction

Globally, almost 1 billion people live in floodplains [Di Baldassarre *et al.*, 2013]. Close access to fresh water resources provides drinkable water, fertile lands, protection barriers, and navigable corridors. Yet, it increases the exposure to river flooding caused by extreme weather events. Societies have always strived to minimize the impacts of floods by reducing their vulnerability through a variety of flood mitigation measures including physical barriers, retention basins and early warning systems, among others [ABI, 2003; Woodward *et al.*, 2011; Alfieri *et al.*, 2016]. Since the early years of human settlements, actions to reduce vulnerability commonly occurred only after catastrophic events have hit [Wind *et al.*, 1999; Kreibich and Thielen, 2009; Zurich, 2014; Jongman *et al.*, 2015]. Yet, the intensification of the hydrological cycle due to global warming and increasing exposure raise growing concerns on future floods and their impacts on economy and health.

At the 21st Conference of the Parties (COP21) held in Paris in 2015, 195 countries joined forces to produce the first-ever global and legally binding climate agreement. The agreement aims to strengthen the global response to the threat of climate change [UNFCCC, 2015]. A key point of the agreement is a joint effort to keep the increase in the global average temperature to well below 2°C above preindustrial levels and to pursue efforts to limit the temperature increase to 1.5°C. Those goals appear in contrast with the latest observed trends recording global warming in the range of 1°C [GISTEMP Team, 2016; JMA, 2016] and a relentless increase toward the target levels. Scientists are now, more than ever, urged to investigate and quantify the socioeconomic impacts of natural hazards under different degrees of global warming. Realistic impact estimates with the related uncertainty are key to inform international organizations, governments, reinsurance companies, and the Intergovernmental Panel on Climate Change (IPCC), to support climate policy making, disaster risk reduction, and international agreements on climate mitigation.

Recent works in the field of global flood risk assessment have estimated the global population [Hirabayashi *et al.*, 2013; Arnell and Gosling, 2014] and gross domestic products (GDP) [Jongman *et al.*, 2012; Winsemius

et al., 2013, 2016; *Ward et al.*, 2014] exposed to river flooding in the present climate and under future climatic changes. Yet, key impact indicators such as direct and indirect flood losses have not been explicitly estimated so far in global-scale analyses. Moreover, available estimates of people and assets exposed often rely on simplifications and assumptions needed to enable a global-scale assessment including regions where data are scarce or unavailable. Novel research efforts have pushed forward the understanding and the mapping of global flood hazard [*Sampson et al.*, 2015; *Dottori et al.*, 2016], exposure [*Freire et al.*, 2015], and vulnerability [*Huizinga and De Moel*, 2016; *Scussolini et al.*, 2016], finally enabling process-based modeling of river flood risk at global scale under present and future climate conditions.

In this research, we developed and applied a framework for global flood risk assessment based on a meteorological-hydrological modeling chain coupled with state of the art maps of flood depth, exposure and vulnerability. We used climatic projections from seven downscaled general circulation models (GCMs) to estimate changes in the expected damage and population affected by river floods under specific warming levels (SWLs) of 1.5°C, 2°C, and 4°C as compared to the preindustrial levels. Results are aggregated by country, river basin, continent, and global land surface, while the agreement of the ensemble projections is assessed through dedicated statistics.

Sections 2 and 3 illustrate data and methods used. Key results showing changes in precipitation, flood hazard, and flood risk are included in Section 4 while a complete overview of countries and river basins can be found in the Appendix S1, Supporting Information. Results are discussed in Section 5, together with some concluding remarks on their relevance and limitations.

2. Data

Key input to the flood risk assessment is the meteorological forcing data for the present and future climate. We used a set of seven climate projections with high concentration scenario (i.e., RCP 8.5) produced with EC-EARTH3-HR v3.1 [*Hazeleger et al.*, 2012, see Appendix S1] by the Swedish Meteorological and Hydrological Institute. Downscaled projections are obtained by forcing EC-EARTH3-HR with sea surface temperature and sea-ice concentration from seven GCMs as boundary conditions, yet preserving the original global extent. Forcing data are taken from seven independent driving GCMs produced within the Coupled Model Intercomparison Project Phase 5 shown in Table 1. The benefits of downscaling the original models output with EC-EARTH3-HR are to increase and level out the spatial resolution, from their original grids—different for each forcing model—to 0.35°, leading to an improved characterization of extreme events and comparable statistics among different models.

To define inundation depth and extent for simulated river flood events, we make use of the global flood hazard maps developed by *Dottori et al.* [2016] for six return periods between 10 and 500 years under present climate conditions. These raster maps define the flood depth in rivers with an upstream drainage area larger than 5000 km² in all continents except Antarctica, covering 73% of the considered continental area along 1.9 million km of rivers [*Dottori et al.*, 2016]. They were produced at 30 arc-second resolution (~1 km at the equator) with a two-dimensional hydrodynamic model designed to ensure an accurate representation of flow processes in the river network and in the flood plains. *Dottori et al.* [2016] and *Alfieri et al.* [2013] assessed the performance of the flood hazard maps and of their underlying global streamflow climatology, considering several river basins, flood events and more than 600 river gages across the globe.

Population data were taken from the Global Human Settlement Layer Global Population Grids [*Pesaresi et al.*, 2013; *Freire et al.*, 2015]. It includes estimates for the year 2015 and it was derived by upscaling the original product at 250-m resolution, to 30 arc-second resolution.

Further datasets used in the risk assessment include the FLOPROS [*Scussolini et al.*, 2016] global database of FLOod PROtection Standards; land use from the GlobCover 2009 [*Bontemps et al.*, 2011]; and damage functions by *Huizinga and de Moel* [2016]. The latter describe the relation between inundation depth and the corresponding direct economic damage per unit surface, through piece-wise linear functions. Damage curves were defined through literature searches and dedicated surveys to collect flood damage data in several countries from six continents [*Huizinga and De Moel*, 2016]. Functions were then defined for five sectors including residential, commercial, industrial, infrastructures, and agriculture. Country-specific functions per sector have been derived by multiplying the maximum unit damage per country by linear step-functions defined at continent level [*De Moel et al.*, 2016].

Table 1. Climate Projections Downscaled With EC-EARTH3-HR and Corresponding Year of Exceeding 1.5, 2, and 4°C Warming

	Forcing Model	Ensemble Member	Data Availability	1.5°C	2°C	4°C
1	IPSL-CM5A-LR	r1i1p1	1971–2120	2015	2030	2068
2	GFDL-ESM2M	r1i1p1	1971–2100	2040	2055	2113
3	HadGEM2-ES	r1i1p1	1971–2125	2027	2039	2074
4	EC-EARTH	r12i1p1	1971–2100	2019	2035	2083
5	GISS-E2-H	r1i1p1	1971–2130	2022	2038	2102
6	IPSL-CM5A-MR	r1i1p1	1971–2100	2020	2034	2069
7	HadCM3LC	r1i1p1	1971–2100	2003	2020	2065

SWLs not included in the model simulations are in bold.

3. Methods

In this work, all hydrological variables are modeled through three levels of grid resolution, so to optimize the tradeoff between information content and computing resources needed (Figure 1):

1. A global hydrological model was set up at 0.5° resolution (~55 km at the equator) to run 130+ years (see Table 1) of daily climatic projections for seven independent models, and estimate changes in flood magnitude and flood frequency under climate change.
2. A streamflow climatology was produced with a global hydrological model run in continuous mode over 34 years at daily temporal resolution [Alfieri *et al.*, 2013]. Spatial resolution used is 0.1° (~11 km at the equator).
3. Flood hazard maps at 30 arc-second (~1 km at the equator) were derived from the global streamflow climatology for six selected return periods. Details on methods, output, and validation against regional maps are given by Dottori *et al.* [2016].

The proposed framework for global flood risk assessment is based on two key components: (1) estimation of the potential impacts of flood events with magnitude corresponding to the six selected return periods under present climatic conditions and (2) estimation of the magnitude and frequency of extreme flood events in the present and future climate. Those are described in the following sections.

3.1. Potential Flood Impacts

We derived maps of potential population affected and potential damage for six flood return periods ($T_F = 10, 20, 50, 100, 200$ and 500 years) under present climatic conditions. Impact maps at 30 arc-second resolution are obtained by combining global flood hazard maps by Dottori *et al.* [2016] with exposure data in the form of population density and land use, and with vulnerability information expressed by the flood damage functions. Potential population affected are estimated by overlaying population density and flood hazard maps, assuming population to be affected for any positive flood depth. Potential damage maps are generated for each of the five sectors (i.e., residential, commercial, industrial, infrastructures,

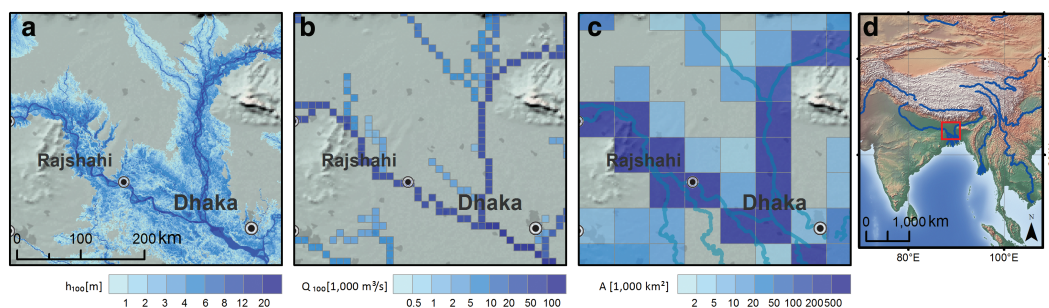


Figure 1. The three levels of spatial resolution considered—illustrative example for the Ganges–Brahmaputra confluence in Bangladesh (d). Panels show the 1 in 100 year flood depth at 30'' (a), 1 in 100 year peak discharge at 0.1° (b), and upstream area of the river network at 0.5° (c).

and agriculture) by combining inundation depth with the damage functions and with maps of percent land use pertaining to each sector, derived from the GlobCover at 10-s (~300 m) resolution. Maps of potential impact per sector were aggregated at the resolution of the hydro-climatic forcing of 0.5° using a physically based approach proposed by *Alfieri et al.* [2015], which assigns flooded areas to the grid point of the causative inflow hydrograph at coarser resolution. In this case, flood polygons were first aggregated at 0.1° resolution of the flood hydrographs and then upscaled to 0.5° according to the drainage direction.

3.2. Projections of the Frequency and Magnitude of River Floods

Daily streamflow simulations at 0.5° resolution were produced with the Lisflood model [*van der Knijff et al.*, 2010; *Burek et al.*, 2013, see Appendix S1] forced by seven climatic projections starting in 1971, using temperature, precipitation and potential evapo-transpiration as input variables. The latter was estimated using the Penman-Monteith equation calculated with daily mean temperature, wind speed, relative humidity and solar radiation as input. For each grid cell and climate projection, we fitted a Gumbel extreme value distribution on the series of 30 discharge annual maxima between 1976 and 2005, with the method of L-moments [*Hosking*, 1990]. Significance of the analytical curves was assessed by bootstrapping, using 1000 repetitions for each fit. A Peak Over Threshold (POT) routine was used to select flood events simulated in the present and future climate. To this end, we first calculated the return period of simulated discharges for the available time windows by inverting the analytical Gumbel distributions. High-flow events above natural bank full conditions are defined as the set of contiguous discharge values with return period larger than 2 years [e.g., *Carpenter et al.*, 1999]. Then, high-flow events with maximum return period larger than the local value of flood protections are considered as flood. Note that the output of such analysis is not the quantitative streamflow estimation, but rather the timing and magnitude of simulated flood events. Hence, the use of the raw model output in place of bias corrected alternatives is a suitable option for the impact assessment. On the other hand, this avoids a number of issues affecting bias corrected climate scenarios, namely, (1) breaking the physical links between the atmospheric variables; (2) strong influence of the quality and resolution of the observational dataset on the output product; (3) bias-corrected datasets are often associated with a decrease in model resolution; (4) questionable benefits of the bias correction for extreme events [*Ehret et al.*, 2012; *Thiemeß et al.*, 2012; *Muerth et al.*, 2013; *Huang et al.*, 2014].

3.3. Projections of Flood Risk at SWLs

The socioeconomic impact of river floods in the present and future climate is assessed by linking every simulated flood event to its potential damage and population affected, by applying linear interpolation between the six modeled return periods (see Section 2.2). The approach based on POT enables a more accurate estimation of the flood frequency, as it accounts for all flood events exceeding flood protections in any given place, potentially even more than one per year. Accordingly, impacts are counted independently for each flood event, either consecutive or in different seasons/years. This is consistent with a framework assessing the direct impacts of floods, which by definition occur during the physical contact of the flood water with the exposed assets, and end as the inundation recedes [*Penning-Rowsell et al.*, 2005; *Merz et al.*, 2010]. Results are aggregated over four time horizons of 30 years each: a baseline scenario between 1976 and 2005, and three future scenarios centered on the year of exceeding the three SWLs of 1.5°C, 2°C, and 4°C for each of the seven models (Table 1). Given the inherent low frequency of flood events, impact values simulated for each grid cell are aggregated at different spatial levels to increase their robustness. Spatial aggregations were performed by country, continent (Russia was considered as a separate continent, being the world's largest transcontinental country), global land surface and large river basins with area in excess of 500,000 km² (see Figure S1). The agreement of country aggregated estimates from an ensemble of seven climatic projections is assessed with the Student's *t*-test on the projected changes in impact between the baseline and each SWL.

This research aims to explore changes in flood risk at different warming levels, independently from when those occur. Hence, we did not include the effect of socioeconomic changes such as projections of population, GDP, or land use. Impact estimates refer to population estimates of 2015 and damage in EUR at Purchasing Power Parity in 2010 values.

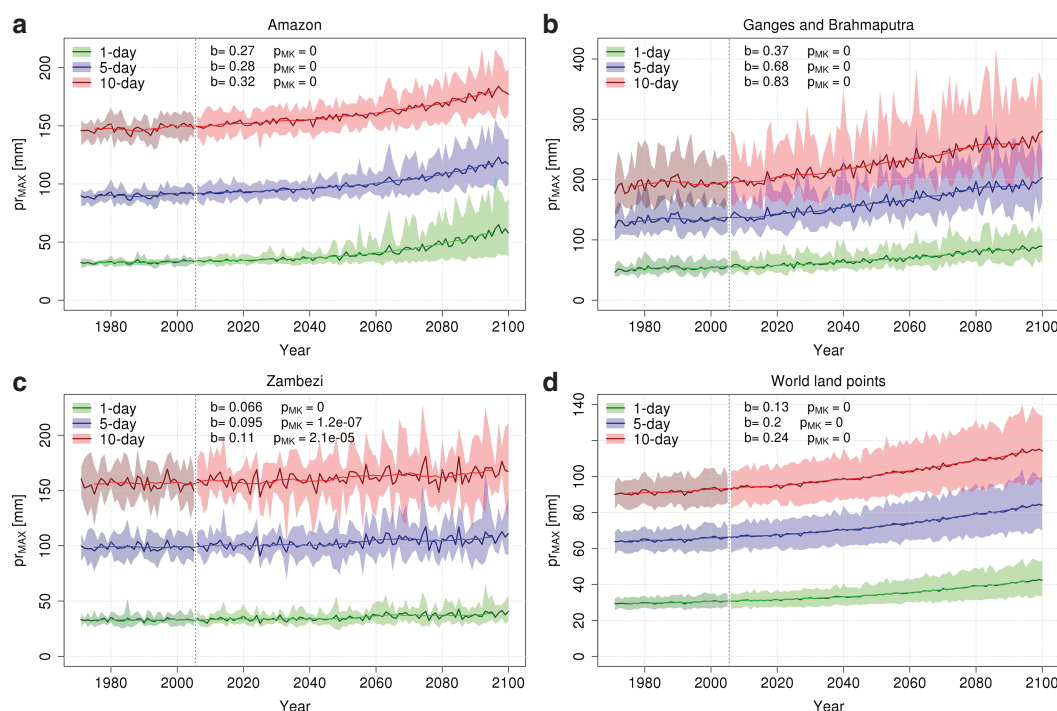


Figure 2. Multimodel ensemble projections of annual maximum precipitation over 1, 5, and 10 days under RCP 8.5. Three panels show zonal averages for the Amazon (a), Ganges and Brahmaputra (b), and Zambezi (c) river basins. The fourth panel (d) refers to all world land points except Antarctica. Statistics on each panel show the slope b of the linear regression (in mm/yr) and the p -value for significance of the Mann–Kendall test for trend.

4. Results

4.1. Trend in Precipitation Extremes

We analyzed trends of extreme annual precipitation cumulated over durations of 1, 5, and 10 days, in 37 world's largest river basins (see Figure S1). Those are useful nonparametric indicators complementing the assessment of the future flood hazard. Climate projections point toward an intensification of the hydrological cycle, with the vast majority of river basins projected to experience more extreme precipitation events over durations typically associated with large-scale floods. The average trend of the ensemble was assessed through linear regression while the statistical significance was tested with the Mann–Kendall statistics for monotonic trends [Mann, 1945; Kendall, 1975]. Results are shown in Figure 2 for three river basins and for the World's land surface, while 34 more river basins are shown in the Appendix S1. An increasing trend of maximum daily precipitation is projected for all river basins, with significance level exceeding 95% (i.e., $p_{MK} < 0.05$) in all cases except that of the Okavango. Over longer accumulations trends remain mostly positive despite becoming weaker in arid regions. Trends of 10-day maxima are significantly increasing for 32 of 37 basins, unchanged for the Colorado and the Australian's Murray–Darling and Eyre Lake, and significantly decreasing in the Okavango and Orange, in Southern Africa. Under high-end climate change, projections for the entire land surface indicate *virtually certain* ($\sim 100\%$ confidence) increase of annual precipitation maxima, with average rates between 0.13 (1-day) and 0.24 (10-day) mm/yr.

4.2. Flood Statistics at SWLs

We analyzed the statistics of simulated flood events to detect significant changes in the flood hazard at SWLs. Figure 3 compares the empirical recurrence interval of simulated events with their theoretical values as derived by the corresponding analytical distributions. Flood events are aggregated by continent and include all seven models, so to increase the sample robustness and enable the analysis of extremely rare events in the order of 1 in 10,000 years. All floods peaks are transformed into their return periods using the analytical curves derived for the baseline scenario. The empirical frequency of simulated events over different classes of magnitude is then compared to the theoretical frequency, assuming independence of

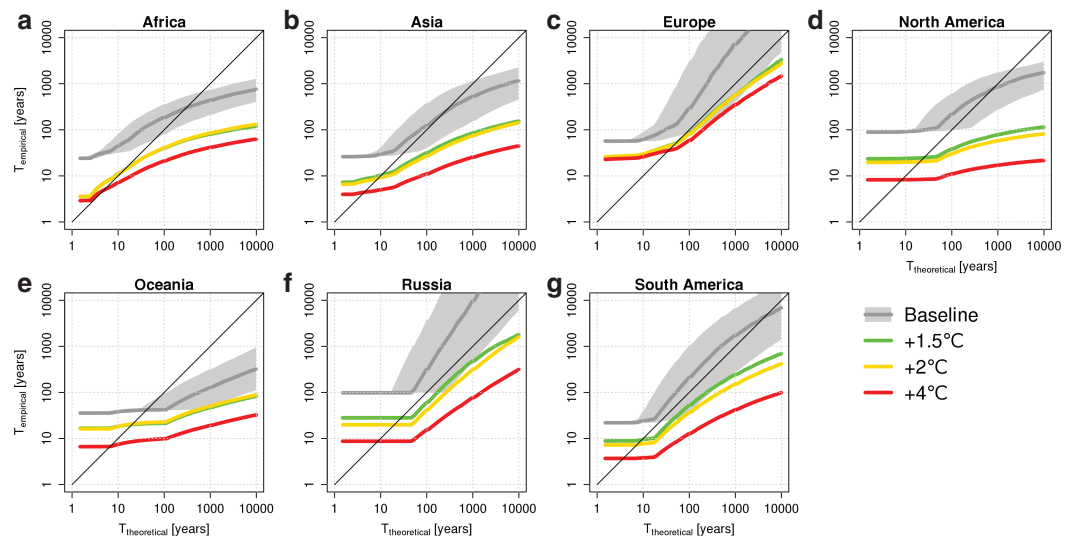


Figure 3. Empirical recurrence intervals, in years, of simulated flood events per continent in the baseline and at SWLs. 95% confidence bands are shown in grey for the baseline window. (a) Africa, (b) Asia, (c) Europe, (d) North America, (e) Oceania, (f) Russia, (g) South America.

the data samples. In the ideal case, the grey lines of the baseline scenario would match the 1:1 line. However, lines tend to flatten for low theoretical return periods thanks to the effect of flood protections preventing floods to occur. Similarly, empirical lines tend to loose steepness for increasing return periods, due to the autocorrelation of the flood magnitude along the drainage network, as previously noted by *Jongman et al.* [2014] in a large-scale assessment.

Graphs indicate a significant increase in the frequency of extreme events for all SWLs. This appears as a decrease in the future recurrence interval of simulated floods with the same intensity as in the baseline. As an example, in Africa, events with a present theoretical return period of 100 years were simulated to occur on average every 185 years (95% confidence interval within 80 and 360 years). These figures are projected to drop to 1 in 40 years at 1.5°C and 2°C and 1 in 21 years at 4°C warming, implying that protection standards will need to be upgraded to ensure the same statistical level of protection. In North America, most regions are presently protected to the 1 in 100 year flood, though at 4°C warming these standards will only withstand up to the 1 in 10 year flood. On average, red lines indicating changes at 4°C lie well below those of milder warming levels for all continents except that for Europe, where similar changes are expected for all warming levels.

4.3. Global Projections of Flood Risk

Flood impact was derived for each simulated flood and then aggregated over different temporal and spatial scales to achieve robust statistics for the present and future climate. Annual ensemble projections of damage and population affected till 2100 are shown in Figure 4, while Table 2 shows the modeled flood impact in the baseline scenario (i.e., 1976–2005) disaggregated by continent and economic sector. Impact values simulated over past events cannot be compared directly with observed figures, as the historical scenario of climate projections does not reproduce the day-to-day history of the observed climate but rather a coherent evolution of the atmosphere under a specific climatic forcing. Yet, simulated scenarios reproduce skillfully the magnitude of the socioeconomic impact of observed river floods over large spatial and temporal aggregations. Central estimates of global flood risk in the baseline scenario total 54 million people affected and 58 billion EUR (75 billion USD) of damage per year. Estimates of population affected compare well in magnitude with observed data, reporting 81 million (1975–2001) and 109 million (1995–2015) people per year [*Jonkman*, 2005; *UNISDR and CRED*, 2015]. Larger uncertainty affects official figures on global flood losses, where reported 29 billion USD per year (1980–2014) [*Munich Re*, 2015] are in contrast with the supposedly more realistic estimates of 104 billion USD per year by the Global Assessment Report [*UNISDR*, 2015; *UNISDR and CRED*, 2015], the latter pointing out that only 35% of weather-related disasters include information about economic losses.

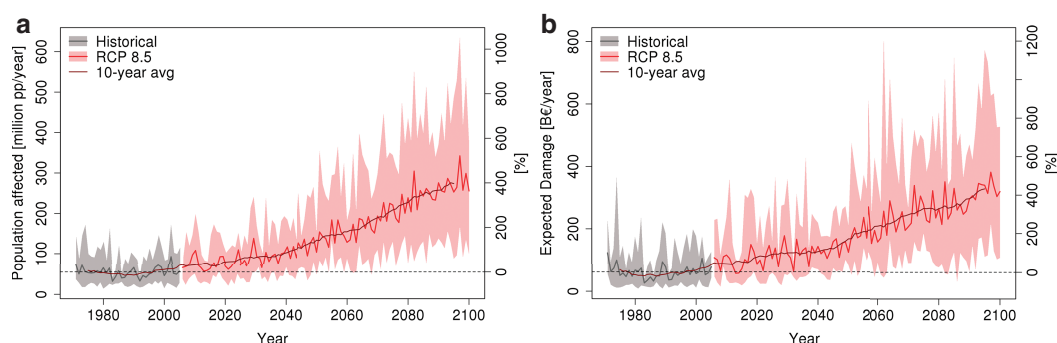


Figure 4. Projected population affected (a) and expected damage per year (b) under RCP 8.5 and relative change from the baseline scenario. Multimodel mean, spread and 10-year running mean of worldwide aggregated figures.

Table 2. Modeled Population Affected and Damage for Each Continent in the Baseline Scenario (Ensemble Mean), Together With Sector Disaggregation of Damage.

	Population Affected (millions/yr)	Damage					
		(B€/yr)	Agriculture (%)	Residential (%)	Commercial (%)	Infrastructure (%)	Industrial (%)
Africa	16.5	6.5	13	36	33	0	17
Asia	35.0	35.9	7	39	32	1	21
Europe	0.5	4.6	1	45	32	1	21
North America	0.8	1.8	2	46	27	6	20
Oceania	0.1	4.9	1	48	32	0	19
Russia	0.2	3.2	1	43	34	0	22
South America	1.1	1.5	7	39	31	1	22

Simulated impacts in the baseline are largest in Asia and Africa, which together account for 95% of people affected and 73% of the economic damage. The sectoral analysis shows that residential damages represent up to half of the total losses, followed by commercial and industrial impacts. Agricultural damage often takes a minor proportion, though it reaches 13% in Africa and 7% in Asia and South America. The damage share by sector did not change significantly in the future scenarios (not shown), due to the assumption of constant land use and population density. Under a high-end climate scenario, global flood impacts are projected to rise at an average rate of 2.4 million people and 3 billion EUR per year, exceeding a fourfold increase in flood risk by the end of the century due to climate change only.

4.4. Future Flood Risk Per Country at SWLs

Maps of changes in flood impacts per country at 1.5°C, 2°C, and 4°C are shown in Figure 5. A confidence level of 90% is used to display the multimodel agreement. Following the IPCC terminology for likelihood [Mastrandrea et al., 2010], countries with no hatching in the figures are *very likely* to experience significant changes of flood risk. Changes in flood risk appear unevenly distributed, with the largest increases in Asia, U.S., and Europe. On the other hand, projected changes are statistically not significant in most countries in Africa and Oceania for all considered warming levels. Relative changes in population affected (damage) at 4°C warming are projected to exceed 1000% in 15 (16) countries in Central Europe, South Asia, South America, and Japan (confidence = 90%), as compared to that in 1976–2005. Negative changes in flood risk are found in some countries in Europe and Africa, in agreement with the regional assessment on Europe by Alfieri et al. [2015]. Interestingly, only Latvia showed statistically significant negative changes at all SWLs for both impact indicators.

Figure 6 shows the top 20 countries projected to be impacted the most by future floods, ranked by largest impacts at 4°C global warming. Countries 21 to 100 are shown in the Appendix S1, together with a ranking by river basin, while Table S1 show the projected average change in flood risk at SWLs for all considered

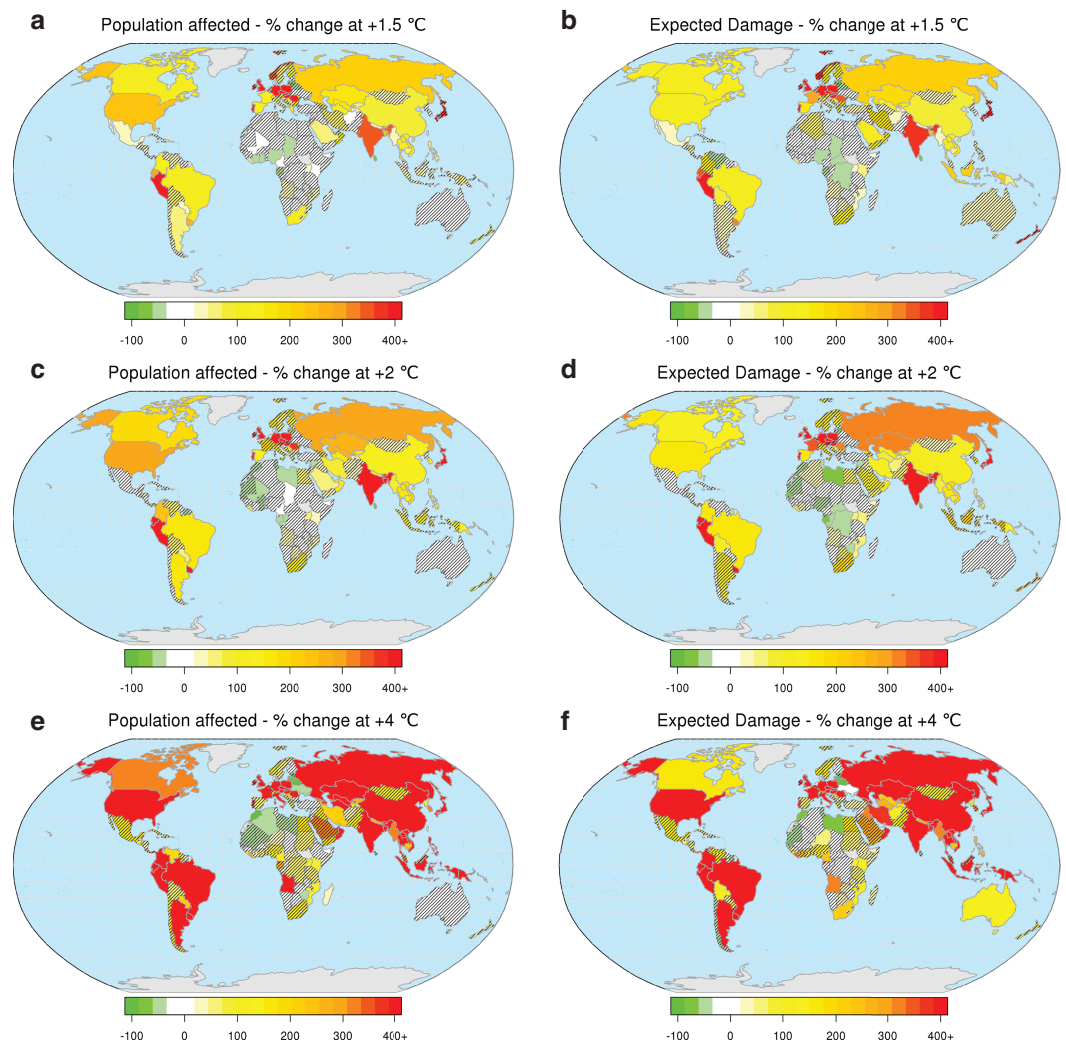


Figure 5. Average change in population affected (a, c, e) and expected damage (b, d, f) per country at SWLs. Hatching indicates countries where the confidence level of the average change is less than 90%.

world countries. Largest absolute impacts are found in China, where current estimates of 9 million people affected and 25 billion EUR damage per year are projected to rise with the global warming, reaching 40 million and 110 billion EUR per year at 4°C warming. A remarkable finding is the more than 20-fold increase in flood risk in India and Bangladesh at 4°C warming, which puts them in the first 3 (8) countries by population affected (damage). Also, in spite of the relatively high standards of flood protections in the EU28 countries, projected increase in flood risk is estimated to place the European Union as a whole as third (fourth) most affected country by expected damage at 1.5°C and 2°C (4°C) warming.

5. Discussion and Conclusions

This research presents a novel framework to explore the socio-economic impacts of a changing climate on the future flood risk at global scale. We used an ensemble of seven high-end climate scenarios as meteorological input and assessed the changes in flood risk under SWLs of 1.5°C, 2°C, and 4°C, considering different spatial aggregations including countries, continents, large river basins and global land areas.

In addition to the climatic uncertainty shown through our analyses, flood impact estimates are affected by other sources of uncertainties pertaining to the different components and datasets used within the modeling chain to represent hazard, exposure, and vulnerability. However, most of those datasets have been validated to some extent against observed or higher resolution data [see Bontemps *et al.*, 2011; Alfieri *et al.*,

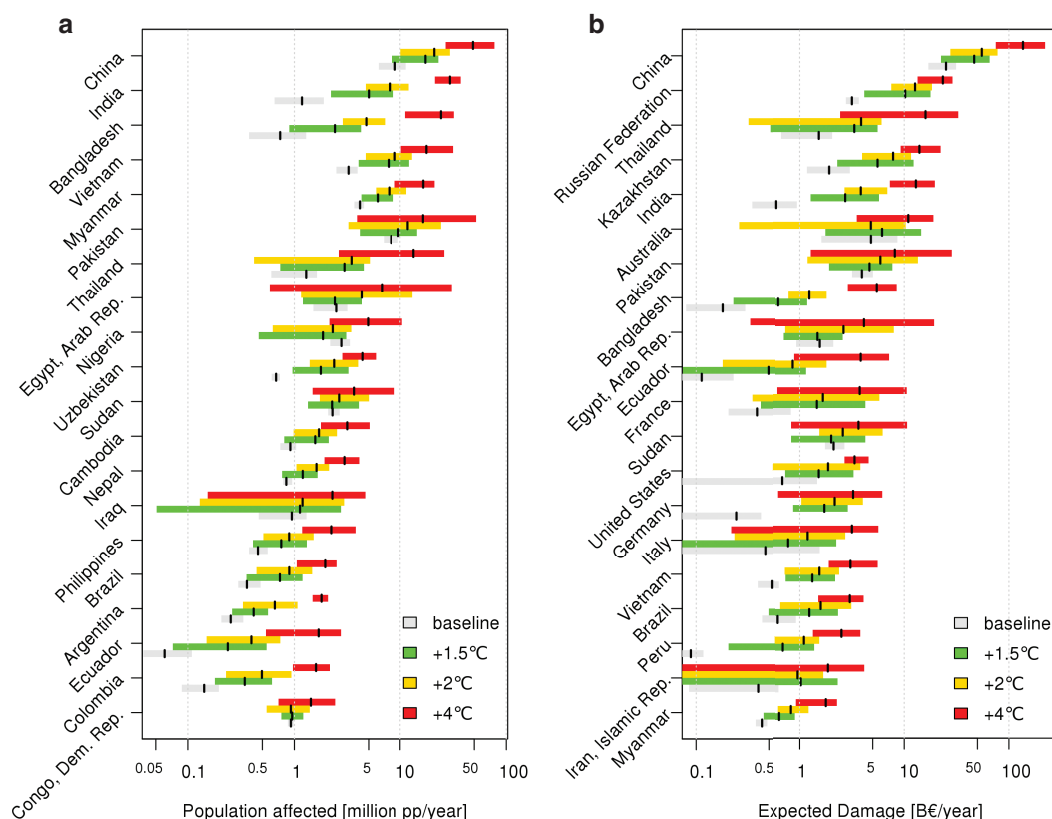


Figure 6. Population affected (a) and expected damage (b) in the baseline and at SWLs (mean value and ensemble spread). Top 20 countries ranked by largest impact at 4°C global warming.

2013; Freire *et al.*, 2015; Dottori *et al.*, 2016; Huizinga and De Moel, 2016; Scussolini *et al.*, 2016]. In addition, the risk assessment framework provided skillful estimates of the global flood impact in the present climate, proving itself as a suitable tool for impact assessment under climate change. Results of this research clearly point out a positive correlation between global warming and global flood risk. Our analyses reveal that the intensification of the hydrological cycle caused by warmer air temperature is linked to more extreme rainfall accumulations in all world regions, particularly over short durations. Flood events with occurrence interval larger than the return period of present flood protections are projected to rise in all continents under all considered SWLs, leading to widespread increase in the flood hazard. Statistically significant increase in flood risk was found in most world regions due to the combination of the future flood hazard and information on global exposure and vulnerability. Our findings indicates that, at 4°C global warming, countries representing 73% of the world population and 79% of the global GDP will *very likely* experience increasing flood risk at an average 580% increase in population affected and 500% increase in damage, as compared to the impact simulated over the baseline period 1976–2005. Such figures reduce to 100% (170%) increase in population affected and 120% (170%) increase in damage for a warming level of 1.5°C (2°C). Projected changes are not homogeneously distributed on the world land surface. Largest increase in flood risk was found in U.S., Asia, and Europe while negative changes were found in only few countries in Eastern Europe and Africa. In contrast, the multimodel projections did not agree on a significant change in flood impacts in several countries in Africa, Oceania, Central America, Northern Europe, and Middle East.

The model framework we used includes unprecedented features for global flood risk applications, which were possible thanks to recent progresses in global datasets on flood hazard, exposure, and vulnerability. Key advances over previous works are:

- An event-based selection of simulated flood peaks, enabling more accurate detection of nonlinear patterns of change in flood frequency and magnitude under nonstationary climate.

- A multiresolution approach, which maximizes the computing power in the representation of different variables and enables the coupling of large datasets. Key example is the use of high-resolution global flood hazard maps to estimate the impact of floods, coupled with 130+ year climatic projections at daily resolution to assess the flood frequency.
- The first global-scale assessment of flood damage, rather than the commonly used exposed GDP, thanks to recent efforts in producing global flood damage functions [Huizinga and De Moel, 2016] and of the release of the first global dataset on flood protections [Scussolini et al., 2016]. Similarly, advances in mapping the global population distribution [Pesaresi et al., 2013] has significantly increased the accuracy in the estimation of population affected by floods.

Findings and implications of this work should be evaluated by considering some underlying modeling assumptions. We assume that impact levels at SWLs are independent of the timing of the warming and of the pathways of the greenhouse gas concentrations. In the presented work, we evaluated impacts on 30-year windows centered on the year of passing each SWL, without considering longer term inertial effect under hypothetical stabilization scenarios corresponding to each SWL. We used RCP 8.5 projections as they normally exceed 4°C warming by the end of the current century, hence all three considered SWLs could be analyzed in the same set of simulations. Despite its limitations, this assumption is commonly accepted by the scientific community and adopted in a number of recent works [Hirabayashi et al., 2013; James and Washington, 2013; Swain and Hayhoe, 2014; Koutroulis et al., 2016]. Also, this research focuses on impacts due to riverine flooding in river sections with upstream area larger than 5000 km², consistent with the underlying inundation maps by Dottori et al. [2016]. Impacts from flash floods, pluvial floods, and coastal floods are not simulated by the impact model.

Results of this research support the recommendations of the Paris Agreement and confirm the urgent need for all World countries to take active mitigation measures to limit global warming and the consequent increase in flood risk. It is worth noting that, even under the most optimistic warming scenario of 1.5°C, we estimate a more than doubling of global flood risk as compared to 1976–2005. This implies that effective adaptation plans must be implemented timely to complement mitigation efforts if we aim to keep flood risk rates within the current levels or below. In addition, socioeconomic drivers are likely to make impacts higher in developing countries and in regions with significant population growth. The increase in flood risk may become unsustainable in regions where the combination of socioeconomic and climatic drivers is particularly adverse, potentially triggering large-scale climatic crises involving conflicts and mass migration.

Acknowledgments

The research leading to these results has received funding from the European Union Seventh Framework Programme FP7/2007-2013 under grant agreement no 603864 (HELIX: High-End cLimate Impacts and eXtremes; www.helixclimate.eu). Authors are also very grateful to Alessandra Bianchi for the GIS support. The EC-EARTH3-HR simulations were performed on resources provided by the Swedish National Infrastructure for Computing (SNIC) at PDC. The data used are listed in the references and their supporting material. Global flood hazard maps are available for download at the url <http://data.jrc.ec.europa.eu/collection/floods>.

References

- ABI (2003), *Assessment of the Cost and Effect on Future Claims of Installing Flood Damage Resistant Measures*, Assoc. British Insurers, London, U. K.
- Alfieri, L., P. Burek, E. Dutra, B. Krzeminski, D. Muraro, J. Thielen, and F. Pappenberger (2013), GloFAS – Global ensemble streamflow forecasting and flood early warning, *Hydrol. Earth Syst. Sci.*, 17(3), 1161–1175, doi:10.5194/hess-17-1161-2013.
- Alfieri, L., L. Feyen, F. Dottori, and A. Bianchi (2015), Ensemble flood risk assessment in Europe under high end climate scenarios, *Global Environ. Change*, 35, 199–212, doi:10.1016/j.gloenvcha.2015.09.004.
- Alfieri, L., L. Feyen, and G. D. Baldassarre (2016), Increasing flood risk under climate change: a pan-European assessment of the benefits of four adaptation strategies, *Clim. Change*, 136(3), 507–521, doi:10.1007/s10584-016-1641-1.
- Arnell, N. W., and S. N. Gosling (2014), The impacts of climate change on river flood risk at the global scale, *Clim. Change*, 387–401, doi:10.1007/s10584-014-1084-5.
- Bontemps, S., P. Defourny, E. V. Bogaert, O. Arino, V. Kalogirou, and J. R. Perez (2011), GLOBCOVER 2009-Products description and validation report, Univ. Catholique de Louvain.
- Burek, P., J. van der Knijff, and A. de Roo (2013), *LISFLOOD, Distributed Water Balance and Flood Simulation Model Revised User Manual 2013*, Publ. Off., Luxembourg.
- Carpenter, T. M., J. A. Sperfslage, K. P. Georgakakos, T. Sweeney, and D. L. Fread (1999), National threshold runoff estimation utilizing GIS in support of operational flash flood warning systems, *J. Hydrol.*, 224(1–2), 21–44, doi:10.1016/S0022-1694(99)00115-8.
- De Moel, H., J. H. Huizinga, and W. Szewczyk (2016), Flood damage curves for consistent global risk assessments, *Geophysical Research Abstracts* Vol. 18, EGU2016-14699, 2016. EGU General Assembly 2016.
- De Roo, A., M. Odijk, G. Schmuck, E. Koster, and A. Lucieer (2001), Assessing the effects of land use changes on floods in the meuse and oder catchment, *Phys. Chem. Earth*, 26(7–8), 593–599, doi:10.1016/S1464-1909(01)00054-5.
- Di Baldassarre, G., A. Viglione, G. Carr, L. Kuil, J. L. Salinas, and G. Blöschl (2013), Socio-hydrology: Conceptualising human-flood interactions, *Hydrol. Earth Syst. Sci.*, 17(8), 3295–3303, doi:10.5194/hess-17-3295-2013.
- Diamantakis, M., and J. Flemming (2014), Global mass fixer algorithms for conservative tracer transport in the ECMWF model, *Geosci. Model Dev.*, 7(3), 965–979, doi:10.5194/gmd-7-965-2014.
- Dottori, F., P. Salamon, A. Bianchi, L. Alfieri, F. A. Hirpa, and L. Feyen (2016), Development and evaluation of a framework for global flood hazard mapping, *Adv. Water Resour.*, 94, 87–102, doi:10.1016/j.advwatres.2016.05.002.
- Ehret, U., E. Zehe, V. Wulfmeyer, K. Warrach-Sagi, and J. Liebert (2012), HESS Opinions “Should we apply bias correction to global and regional climate model data?”, *Hydrol. Earth Syst. Sci.*, 16(9), 3391–3404, doi:10.5194/hess-16-3391-2012.

- Freire, S., T. Kemper, M. Pesaresi, A. Florczyk, and V. Syrris (2015), Combining GHSL and GPW to improve global population mapping, *Eur. Comm.*, 2015, 2541–2543.
- GISTEMP Team (2016), GISS Surface Temperature Analysis (GISTEMP), NASA Goddard Institute for Space Studies, New York, N. Y. [Available at <http://data.giss.nasa.gov/gistemp/>.]
- Hazeleger, W., et al. (2012), EC-Earth V2.2: Description and validation of a new seamless earth system prediction model, *Clim. Dyn.*, 39(11), 2611–2629, doi:10.1007/s00382-011-1228-5.
- Hazeleger, W., V. Guemas, B. Wouters, S. Corti, I. Andreu-Burillo, F. J. Doblas-Reyes, K. Wyser, and M. Caian (2013), Multiyear climate predictions using two initialization strategies, *Geophys. Res. Lett.*, 40(9), 1794–1798, doi:10.1002/grl.50355.
- Hengl, T., et al. (2014), SoilGrids1km—Global soil information based on automated mapping, *PLoS One*, 9(8), e105992, doi:10.1371/journal.pone.0105992.
- Hirabayashi, Y., R. Mahendran, S. Koirala, L. Konoshima, D. Yamazaki, S. Watanabe, H. Kim, and S. Kanae (2013), Global flood risk under climate change, *Nat. Clim. Change*, 3(9), 816–821, doi:10.1038/nclimate1911.
- Hirpa, F. A., P. Salamon, L. Alfieri, J. T. Pozo, E. Zsoter, and F. Pappenberger (2016), The effect of reference climatology on global flood forecasting, *J. Hydrometeorol.*, 17(4), 1131–1145, doi:10.1175/JHM-D-15-0044.1.
- Hosking, J. R. M. (1990), L-Moments: Analysis and estimation of distributions using linear combinations of order statistics, *J. R. Stat. Soc. Ser. B*, 52(1), 105–124.
- Huang, S., V. Krysanova, and F. F. Hattermann (2014), Does bias correction increase reliability of flood projections under climate change? A case study of large rivers in Germany, *Int. J. Climatol.*, 34(14), 3780–3800, doi:10.1002/joc.3945.
- Huffman, G. J., R. F. Adler, D. T. Bolvin, and G. Gu (2009), Improving the global precipitation record: GPCP version 2.1, *Geophys. Res. Lett.*, 36(17), L17808, doi:10.1029/2009GL040000.
- Huizinga, H. J., and H. De Moel (2016), *Global Flood Damage Functions - Report Tasks 1&2: Review of Existing Data Sources and Global Flood Damage Functions Database*, HKV Lijn in water, Lelystad, Neth..
- James, R., and R. Washington (2013), Changes in African temperature and precipitation associated with degrees of global warming, *Clim. Change*, 117(4), 859–872, doi:10.1007/s10584-012-0581-7.
- JMA (2016), *Global Warming Projection and Climate Change Monitoring*, Tokyo Clim. Center Clim. Predict. Div., Jpn Meteorol. Agency, Tokyo, Jpn..
- Jongman, B., P. J. Ward, and J. C. J. H. Aerts (2012), Global exposure to river and coastal flooding: Long term trends and changes, *Global Environ. Change*, 22(4), 823–835, doi:10.1016/j.gloenvcha.2012.07.004.
- Jongman, B., S. Hochrainer-Stigler, L. Feyen, J. C. J. H. Aerts, R. Mechler, W. J. W. Botzen, L. M. Bouwer, G. Pflug, R. Rojas, and P. J. Ward (2014), Increasing stress on disaster-risk finance due to large floods, *Nat. Clim. Change*, 4(4), 264–268, doi:10.1038/nclimate2124.
- Jongman, B., H. C. Winsemius, J. C. J. H. Aerts, E. Coughlan De Perez, M. K. Van Aalst, W. Kron, and P. J. Ward (2015), Declining vulnerability to river floods and the global benefits of adaptation, *Proc. Natl. Acad. Sci. U. S. A.*, 112(18), E2271–E2280, doi:10.1073/pnas.1414439112.
- Jonkman, S. N. (2005), Global perspectives on loss of human life caused by floods, *Nat. Hazards*, 34(2), 151–175, doi:10.1007/s11069-004-8891-3.
- Kendall, M. G. (1975), *Rank Correlation Methods*, 4th ed., pp., Charles Griffin, London, U. K..
- Koutroulis, A. G., M. G. Grillakis, I. N. Daliakopoulos, I. K. Tsanis, and D. Jacob (2016), Cross sectoral impacts on water availability at +2°C and +3°C for east Mediterranean island states: The case of Crete, *J. Hydrol.*, 532, 16–28, doi:10.1016/j.jhydrol.2015.11.015.
- Kreibich, H., and A. H. Thieken (2009), Coping with floods in the city of Dresden, Germany, *Nat. Hazards*, 51(3), 423–436, doi:10.1007/s11069-007-9200-8.
- Lehner, B., K. Verdin, and A. Jarvis (2008), New global hydrography derived from spaceborne elevation data, *Eos Trans. AGU*, 89(10), 93–94, doi:10.1029/2008EO100001.
- Mann, H. B. (1945), Non-parametric tests against trend, *Econometrica*, 13, 163–171, doi:10.2307/1907187.
- Mastrandrea, M. D., et al. (2010), *Guidance note for lead authors of the IPCC fifth assessment report on consistent treatment of uncertainties*, IPCC, Geneva, Switz., 4 pp..
- Merz, B., H. Kreibich, R. Schwarze, and A. Thieken (2010), Review article “assessment of economic flood damage”, *Nat. Hazards Earth Syst. Sci.*, 10(8), 1697–1724, doi:10.5194/nhess-10-1697-2010.
- Molteni, F., T. Stockdale, M. Balmaseda, G. Balsamo, R. Buizza, L. Ferranti, L. Magnusson, K. Mogensen, T. Palmer, and F. Vitart (2011), *The New ECMWF Seasonal Forecast System (System 4)*, Eur. Centre Medium-Range Weather Forecasts, Reading, U. K..
- Morcrette, J.-J., H. W. Barker, J. N. S. Cole, M. J. Iacono, and R. Pincus (2008), Impact of a new radiation package, McRad, in the ECMWF integrated forecasting system, *Mon. Weather Rev.*, 136(12), 4773–4798, doi:10.1175/2008MWR2363.1.
- Muerth, M. J., B. Gauvin St-Denis, S. Ricard, J. A. Velázquez, J. Schmid, M. Minville, D. Caya, D. Chaumont, R. Ludwig, and R. Turcotte (2013), On the need for bias correction in regional climate scenarios to assess climate change impacts on river runoff, *Hydrol. Earth Syst. Sci.*, 17(3), 1189–1204, doi:10.5194/hess-17-1189-2013.
- Munich Re (2015), *NatCatSERVICE - Loss Events Worldwide 1980 – 2014*, Munich Re, Munich, Germany.
- Penning-Rowsell, E., C. Johnson, S. Tunstall, S. Tapsell, J. Morris, J. Chatterton, and C. Green (2005), *The Benefits of Flood and Coastal Risk Management: A Handbook of Assessment Techniques*, Middlesex Univ. Press, London, U. K..
- Pesaresi, M., et al. (2013), A global human settlement layer from optical HR/VHR RS data: concept and first results, *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, 6(5), 2102–2131, doi:10.1109/JSTARS.2013.2271445.
- Sampson, C., A. Smith, P. Bates, J. Neal, L. Alfieri, and J. Freer (2015), A high-resolution global flood hazard model, *Water Resour. Res.*, 51, 7358–7381, doi:10.1002/2015WR016954.
- Scussolini, P., J. C. J. H. Aerts, B. Jongman, L. M. Bouwer, H. C. Winsemius, H. de Moel, and P. J. Ward (2016), FLOPROS: An evolving global database of flood protection standards, *Nat. Hazards Earth Syst. Sci.*, 16(5), 1049–1061, doi:10.5194/nhess-16-1049-2016.
- Swain, S., and K. Hayhoe (2014), CMIP5 projected changes in spring and summer drought and wet conditions over North America, *Clim. Dyn.*, 44(9–10), 2737–2750, doi:10.1007/s00382-014-2255-9.
- Thiemeß, M. J., A. Gobiet, and G. Heinrich (2012), Empirical-statistical downscaling and error correction of regional climate models and its impact on the climate change signal, *Clim. Change*, 112(2), 449–468, doi:10.1007/s10584-011-0224-4.
- UNFCCC (2015), *Paris Agreement, Conference of the Parties, Twenty-first session (COP21)*, United Nations Framework Conven. Clim. Change, Paris, France.
- UNISDR (2015), *Making Development Sustainable, the Future of Disaster Risk Management: Global Assessment Report on Disaster Risk Reduction 2015*, United Nations Off. Disaster Risk Reduction (UNISDR), Geneva, Switz..
- UNISDR, and CRED (2015), *The Human Cost of Weather-Related Disasters 1995–2015*, United Nations Off. Disaster Risk Reduction (UNISDR) and Centre Res. Epidemiol. Disasters (CRED), Geneva, Switz..

- van der Knijff, J. M., J. Younis, and A. P. J. de Roo (2010), LISFLOOD: A GIS-based distributed model for river basin scale water balance and flood simulation, *Int. J. Geogr. Inf. Sci.*, *24*(2), 189–212, doi:10.1080/13658810802549154.
- Ward, P. J., B. Jongman, M. Kumm, M. D. Dettinger, F. C. S. Weil, and H. C. Winsemius (2014), Strong influence of El Niño Southern Oscillation on flood risk around the world, *Proc. Natl. Acad. Sci. U. S. A.*, *111*(44), 15659–15664, doi:10.1073/pnas.1409822111/-/DCSupplemental.
- Wind, H. G., T. M. Nierop, C. J. De Blois, and J. L. De Kok (1999), Analysis of flood damages from the 1993 and 1995 Meuse floods, *Water Resour. Res.*, *35*(11), 3459–3465, doi:10.1029/1999WR900192.
- Winsemius, H. C., L. P. H. Van Beek, B. Jongman, P. J. Ward, and A. Bouwman (2013), A framework for global river flood risk assessments, *Hydrol. Earth Syst. Sci.*, *17*(5), 1871–1892, doi:10.5194/hess-17-1871-2013.
- Winsemius, H. C., et al. (2016), Global drivers of future river flood risk, *Nat. Clim. Change*, *6*(4), 381–385, doi:10.1038/nclimate2893.
- Woodward, M., B. Gouldby, Z. Kapelan, S.-T. Khu, and I. Townsend (2011), Real options in flood risk management decision making, *J. Flood Risk Manage.*, *4*(4), 339–349, doi:10.1111/j.1753-318X.2011.01119.x.
- Wu, H., J. S. Kimball, H. Li, M. Huang, L. R. Leung, and R. F. Adler (2012), A new global river network database for macroscale hydrologic modeling, *Water Resour. Res.*, *48*(9), W09701, doi:10.1029/2012WR012313.
- Younis, J., S. Anquetin, and J. Thielen (2008), The benefit of high-resolution operational weather forecasts for flash flood warning, *Hydrol. Earth Syst. Sci.*, *12*(4), 1039–1051, doi:10.5194/hess-12-1039-2008.
- Zurich (2014), *Risk Nexus, Central European Floods 2013: A Retrospective*, Zurich, Zurich, Switz.