Quantifying the effect of autonomous adaptation to global river flood projections: Application to future flood risk assessments

Supplementary Materials

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Vulnerability data
In this study, we used historical vulnerability data by Tanoue et al (2016), who estimated historical vulnerability according to a modified version of equation (2) in the main text (Section 2), \[ \text{vulnerability} = \frac{\text{consequences}}{\text{potentially affected exposure}} \], with reported country-level flood consequences (fatalities and economic losses) by the Emergency Events Database (EM-DAT) \((\text{consequences})\) and modeled potentially affected flood exposure. The historical vulnerability data contained 2403 flood events for the period ranged from 1960 to 2013. The EM-DAT, provided by the Centre for Research on the Epidemiology of Disasters (CRED), provides country-level information on reported fatalities and economic losses with regard to natural disasters reported by various sources, such as UN agencies, insurance companies, and press agencies. The EM-DAT uses quantitative thresholds (10 fatalities and over 100 people affected) as the minimum entry criteria (Kron et al 2012), suggesting that events with a relatively smaller magnitude are not recorded. A 5-arc minute (approximately 10 km at the equator) gridded population data set was obtained from the History Database of the Global Environment (HYDE) version 3.1 (Goldewijk et al 2010). For the gridded Gross Domestic Product (GDP) map, the gridded population data were multiplied by the nominal GDP.
per capita of the World Bank database (World Bank 2016). The GDP values were deflated and converted to US$ at purchasing power parity (PPP) values (base year 2005).

For future population/GDP distribution estimates, we created a globally gridded population and GDP data maps, as projected under Socioeconomic Shared Pathways (SSPs). We assumed that the distribution of population in each country based on the distribution in the HYDE population data of 2005 would be invariant from 2005 to 2100, while the country-total population varied according to the population projection for each SSP obtained from the International Institute for Applied Systems Analysis (IIASA) model (IIASA 2013). According to the method of Ward et al (2013), we evenly allocated country-specific GDP to the 5-arc minute (approximately 10 km at the equator) gridded map. Maps were created for three SSP scenarios. Because the IIASA data has an interval of 10 years, we linearly interpolated the original IIASA data in time to create annual datasets.

Global hydrological and inundation modeling

For inundation simulation, we used the Catchment-based Macro-scale Floodplain (CaMa-Flood) model (Yamazaki et al 2011), which is a global river and inundation model, with
a horizontal resolution of 0.25° (approximately 30 km at the equator) and a daily output time interval. The model implemented a one-dimensional flow equation (a local inertial equation) to calculate water level, inundation area, and depth. The river network map was delineated from 3-arc seconds (90 m) SRTM3 Digital Elevation Model (Farr et al 2007) and a flow direction map, HydroSHEDS (Lehner et al 2008). The river channel width and height is determined either from the Global Width Database for Large Rivers (Yamazaki et al 2014) or by an empirical equation using averaged upstream runoff. The CaMa-Flood model integrates runoff input along a river network and explicitly represents flood extent and depth in addition to river discharge along river channels based on the sub-grid topographic parameters. The validity of the CaMa-Flood model has been discussed in several studies (Yamazaki et al 2011; Hirabayashi et al 2013; Tanoue et al 2016). The tidal effect is not incorporated in the CaMa-Flood model. The retrospective inundation simulation, which has been performed by Tanoue et al (2016), was used in the flood exposure calculation for the historical period. The runoff input to CaMa-Flood for the retrospective simulation was obtained from an off-line land surface model simulation, with the minimal advanced treatments of surface interaction and runoff (MATSIRO) model (Takata et al 2003) with groundwater representations (Koirala et al 2014) forced by bias
corrected Japanese 55-year reanalysis climate data (Iizumi et al. 2017). Runoff data from historical general circulation model (GCM) simulations were also used for historical inundation simulations. In the future simulation, runoff data were obtained from the outputs of the GCMs for four Representative Concentration Pathways (RCPs; Table S2). Flood exposure was calculated annually based on the annual maximum inundation area. Therefore, we did not account for the occurrence of multiple floods at the same location in a single year, or for other flood characteristics like inundation depth, flood velocity, and inundation duration.

In practice, because the accuracy of GCMs is not sufficient for flood risk estimation (due to limitations in spatiotemporal resolution and the inevitable biases), the absolute magnitude of runoff data from the GCMs may not be able to replicate inundation depth reliably under flooding conditions. Therefore, these GCM-derived runoff biases should be removed (Ikeuchi et al. 2015). In this study, we obtained relative change of future flood magnitude as a return period of annual maximum flood depth for each GCM and obtained corresponding inundation depth from retrospective simulation for the return period to remove GCM runoff biases, assuming that the inundation depth derived by the retrospective simulation has less biases. We first estimated the Gumbel distribution parameters of annual maximum inundation depth data derived from
historical GCM simulations and a retrospective simulation for the period of 1960–2005. Then, using these parameters, we converted the annual maximum inundation depth in both historical and future simulations to the return period. Finally, we converted the GCM-derived return period to the inundation depth estimated with the Gumbel parameters of a retrospective simulation. The above procedure enabled us to correct for GCM-dependent biases. Bias-corrected annual maximum inundation depth data were downscaled to a 5-arc minute horizontal resolution (approximately 10 km at the equator) following the method of Tanoue et al (2016), who validated modeled river discharge using the observed daily river discharge at 87 gauging stations obtained from the Global Runoff Data Centre (GRDC 2014). They confirmed that the observed and modeled annual mean, maximum and extreme (corresponding to a 100-year return period) discharge within the period 1960–2010 had high correlation coefficients of 0.90, 0.83, and 0.73, respectively. They also compared the modeled downscaled inundation area with the satellite-derived flooded area around Bangladesh and showed good reproducibility. Here, we assumed that bankfull discharge is equal to flood magnitude of two-year return period, with the inundation depth below this level assumed to not represent flooding (Ward et al 2014).
Model Validation Method

We validated the accuracy of the modeled flood consequences by comparing the EM-DAT reported damage, which was classified as the “hydrological group”. In the historical period, the initial value of the vulnerability model was derived from the 1960–1980 average and the initial year in the model was set to 1980. We created a historical vulnerability scenario for the period of 1980–2013. The validation compared 1990–2010 average flood consequences to check the reproducibility of the absolute modeled consequences and the Spearman’s correlation of 1980–2013 global-sum flood consequences for evaluating the long-term trend reproducibility. We also conducted a qualitative assessment of the historical vulnerability reproducibility by comparison with the results of Tanoue et al (2016). The number of countries reported in the EM-DAT differed from year to year because flooding did not occur every year in a corresponding country. Therefore, in the validation, we set the number of countries in the modeled flood consequences to be equal to that in the EM-DAT from year to year.

We also conducted a country-by-country comparison of flood consequence estimations by comparing estimated historical flood consequences with and without autonomous adaptation with the reported flood consequences in the EM-DAT. We calculated the 1990–2005 average
flood consequences from model estimates and the EM-DAT, and then compared differences between the EM-DAT and estimates with and without autonomous adaptation. We classified the results into three categories: “Improved” indicated that the difference with autonomous adaptation was smaller than that without autonomous adaptation, “No change” indicated that the difference between with and without autonomous adaptation were the same, and “Worsened” indicated the opposite of “Improved”.

Model validation results

We validated the modeled vulnerability with respect to the historical vulnerability data. Overall, our modeled vulnerability successfully reproduced the decreasing trends shown in historical vulnerability, and the magnitudes of modeled vulnerability were consistent with the historical values (Figures S1, S2 and S3). For validation, the number of countries used for the historical flood consequence modeling was set to the same number as that of the EM-DAT (Figure S4). The Spearman’s correlation coefficient for the relationship of historical global fatalities from 1980 to 2013 between EM-DAT and our estimation was 0.404 (p = 0.018). The relatively low correlation coefficient may be due to the extremely large number of fatalities in
the EM-DAT database associated with landslide, such as events in Venezuela in 1999. Whilst our model could capture the long-term variation in the reported flood fatalities.

In some countries (e.g., Japan, Spain, and the USA for the period of 1990–2013), our mortality rate model tended to yield overestimates due to the relatively high initial value of the vulnerability, which was estimated from the average of the period of 1960–1980 compared to the vulnerability values reported by Tanoue et al (2016). Annual average global potential flood fatalities in our model, for the period of 1990–2010 was 4412, which was slightly smaller than the annual averages of the EM-DAT, of 7230 (Figure S3). Although the average number of fatalities in the EM-DAT was higher than our estimate, this was due to the extremely high number of fatalities in the EM-DAT for 1999 (34,787 persons), which included fatalities due to landslides and flooding in Venezuela (30,005 persons). Average fatalities between 1990–2010, excluding 1999, were 4371 in our model and 5780 in the EM-DAT. Another possible reason for the underestimation was the poor reproducibility of the abrupt vulnerability increase associated with catastrophic flooding events.

The Spearman’s correlation coefficient of the economic loss was 0.616 (p <0.001). Therefore, our model could also successfully reproduce the long-term increasing trend of economic losses.
Annual average global potential flood economic losses in our model, for the period of 1990–2010 was US$10.9 billion, which was slightly smaller than the annual averages of the EM-DAT, of US$16.8 billion (Figure S3).

Figure S1
Examples of historical flood fatalities (upper) and mortality rates (lower) in some selected countries.
Figure S2

Examples of historical flood economic loss (upper) and loss rates (lower). The selected countries are the same as those in Figure S1.

A country-by-country comparison of the flood consequence estimation with and without autonomous adaptation showed that for approximately 100 countries, estimations were closer to the EM-DAT when the effect of autonomous adaptation was included in our model (Table S3). This supports the effectiveness of including autonomous adaptation in flood consequence modeling.
Figure S3

Time series of recorded and historical flood consequences. (a) Time series of flood fatalities. (b) Time series of economic losses. Gray bars represent reported flood consequences, as derived from the EM-DAT. The modeled historical consequence (cyan) was derived from a
retrospective simulation (forced with the bias-corrected reanalysis data). Yellow lines show flood consequences in historical GCM simulations. The number of countries used in the simulation was set to be equal to that in the EM-DAT.

Figure S4

Number of recorded flood disaster events in the EM-DAT.
Figure S5

(Left) Countries included in the EM-DAT. (Right) Countries included in our vulnerability scenarios.

**Time series of future global potential flood consequences**

Figures S6(a) and S6(b) showed the time series of future annual potential global flood fatalities and economic losses, respectively. The combination of SSP1 and RCP2.6, which together represent the most sustainable future projection, had the lowest number of potential fatalities throughout the analysis period and modeled a continuously decreasing trend throughout the 21st century (Figure S6(a) and Table S4). Annual potential global fatalities in 2081 – 2100 (2283 persons) showed a 59% reduction from that in the period of 1991 – 2005 (6641 persons). On the other hand, the combination of SSP3 and RCP8.5, which represents the worst projected climatic and socioeconomic conditions, had the largest number of potential flood fatalities among all of the scenario combinations, with a slightly decreasing trend throughout the period. Annual global potential fatalities in 2081 – 2100 (6505 persons) showed a 0.7% reduction from that in the period of 1991 – 2005. Annual global potential fatalities in
other combinations, such as SSP2 and RCP4.5, fell within those of the least- and most-extreme combinations (RCP2.6 and SSP1; and RCP8.5 and SSP3). Our estimations indicated that the global potential fatality in SSP3 and RCP8.5, by the end of the 21st century, is 2.8 times larger than that of SSP1 and RCP2.6, and the percentage of potential fatalities as a proportion of the global population is higher in SSP3 and RCP8.5 versus SSP1 and RCP2.6.

In the worst climatic and socioeconomic projection (SSP3 and RCP8.5), estimated global potential economic losses were US$14.22 billion on average over the period of 1991 – 2005, monotonically increasing throughout the 21st century until reaching an average of US$129.9 billion for the period of 2081 – 2100 (Figure S6(b)). In the most sustainable future projection (SSP1 and RCP2.6), annual economic losses were projected to increase to US$121.2 billion on average for the period of 2081 – 2100. Although total amounts of potential economic losses in scenarios were close to each other, the proportion of potential economic losses relative to global GDP clearly differed among scenarios (0.0321% in SSP1 and RCP2.6, 0.0547% in SSP3 and RCP8.5). This was due to the effect of vulnerability reductions achieved through autonomous adaptation.
Figure S6

Time series of potential flood consequences. (a) Time series of potential flood fatalities. (b) Time series of potential economic losses. Each symbol shows the annual mean GCM value. The number of countries used in the simulation was set to be equal to that in the International Institute for IIASA model (170 countries).

Contributions of climatic, socioeconomic, and vulnerability changes to flood consequence
To quantitatively assess the modelization impact of vulnerability improvements, we evaluated the contributions of drivers by applying the method similar to Winsemius et al (2015). The method quantifies contribution rate of climate, socioeconomic and vulnerability change in future (2081 – 2100) from current flood consequences (1991 – 2005). Current flood consequences were calculated under fixing population/GDP to 2005 (the end year of the current flood consequence period) and vulnerability to 2010 (the first year of future vulnerability scenarios),

Figure S7
Flood consequence contributions. Red: changes in climate (2081 – 2100; population/ GDP are fixed at 2005, vulnerability is fixed at the 2010); blue: changing socioeconomic conditions (1991 – 2005; population/ GDP are fixed at 2005, vulnerability is fixed at the 2010); green: changes in vulnerability (1991 – 2005; population/ GDP are fixed at 2005, vulnerability is fixed at the 2090); and yellow: future state (2081 – 2100, population/GDP/vulnerability are fixed at the 2090). The three leftmost columns show the potential fatalities; the three rightmost columns are the potential economic losses. Values are represented as percentage changes from current consequence values.

**Bootstrapping test to evaluate the impact of temperature increase to flood consequences**

To meet the requirement of Paris Agreement Target (UNFCCC 2016), we assess the sole effect of climate change on potential flood consequences. Bootstrapping tests (100,000 bootstrap samples) to estimate the significance of the climate change effect were conducted by fixing the population/GDP to 2005 (the latest year in the HYDE3.1) and vulnerability to 2010 (the initial year of the vulnerability model) since uncertainty range of future flood consequences is sometimes large and hence sensitivity to climate change is not clearly seen in small
temperature range. The bootstrapping test enables us to estimate the uncertainty range of flood consequences and thus to assess the robustness of the increase of flood consequences between situations under different temperature increases. Figure S8 shows bootstrapping results (100,000 bootstrap samples) of potential flood consequences with respect to global temperature increases from pre-industrial levels (1850–1900), left of which shows potential fatalities, and right of which shows potential economic losses (in billion US$). Results in Figure S8 are cases in which population/GDP are fixed to 2005 levels, and vulnerability is fixed to the 2010 levels, and thus show the impact of just climate change. Figure S8a indicates that the potential increase in fatalities, in association with climate change, was robust when the global temperature increased from its current level by +1.5°C (7,035 persons at the upper boundary of the 97.5% confidence interval) or +2.0°C (7,120 persons at the lower boundary of the 2.5% confidence interval). However, the difference in the increase in potential economic losses between the temperature increase of +1.5°C (95% confidence interval between US$14.0 and US$14.6 billion) and +2.0°C (95% confidence interval between US$14.1 and US$14.8 billion) was not significant (Figure S8b). In the extreme case of +4.0°C, both potential flood fatalities and economic losses significantly exceeded the current level of flood consequences.
Figure S8

Bootstrapping results (100,000 bootstrap samples) of potential flood consequences with respect to global temperature increases from pre-industrial levels (1850 – 1900).


**Tables**

| Variables                        | Span                        | Spatial Resolution | Time Resolution | Reference                  | Comments                                      |
|----------------------------------|-----------------------------|--------------------|-----------------|-----------------------------|-----------------------------------------------|
| Bias-corrected                   |                             |                    |                 |                             |                                               |
| JRA-55 GCM runoffs               | Precipitation, Temperature, | Historical (1960-2014) | 0.5° × 0.5°     | 3-hourly                    | Iizumi et al. In preparation                  |
|                                  | Pressure                    | Future (2006-2100)  | depend on GCMs  | 6-hourly                    |                                               |
| HYDE v3.1                        | Runoff                      | Historical (1960-2014) | 5’ × 5’        | yearly                      | Goldewijk et al. 2010                         |
| World Bank GDP                   | Population                  | Historical (1960-2014) | 5’ × 5’        | yearly                      | World Bank 2016                               |
| IIAAS SSP data data              | GDP                          | Future (2010-2010)  | 5’ × 5’        | yearly                      | IIAAS 2013                                    |
| The EM-DAT                       | Mortality, Economic loss    | Historical (1960-2014) | country        | yearly                      | Giha-Sapir et al. 2015                        |
| Flood vulnerability values       | Fatality, Economic loss     | Historical (1960-2014) | country        | yearly                      | Tanoue et al. 2016                            |

Table S1

Datasets used for the flood consequence modeling.
| Models          | RCP2.6 | RCP4.5 | RCP6.0 | RCP8.5 |
|----------------|--------|--------|--------|--------|
| bcc-csm1-1     | ○      | ○      | ○      | ○      |
| CanESM2        | ○      | ○      | ○      | ○      |
| CMCC-CM        | ○      | ○      | ○      | ○      |
| CNRM-CM5       | ○      | ○      | ○      | ○      |
| CSIRO-Mk3-6-0  | ○      | ○      | ○      | ○      |
| GFDL-ESM2G     | ○      | ○      | ○      | ○      |
| Inmcm4         | ○      | ○      | ○      | ○      |
| MIROC5         | ○      | ○      | ○      | ○      |
| MPI-ESM-LR     | ○      | ○      | ○      | ○      |
| MRI-CGCM3      | ○      | ○      | ○      | ○      |
| NorESM1-M      | ○      | ○      | ○      | ○      |

Table S2

GCMs used in this study. Availability of runoff data is indicated.
|                  | Improved | No change | Worsened |
|------------------|----------|-----------|----------|
| Fatality         | 95       | 23        | 43       |
| Economic loss    | 100      | 28        | 33       |

Table S3

Result of a country-by-country comparison of historical flood consequences.
| Fatality (persons) | Current (1991-2005) | Projection | Climate change | Socioeconomic change | Vulnerability change |
|-------------------|----------------------|------------|----------------|----------------------|---------------------|
| SSP1              | RCP2.6               | 2283 (-65.5%) | 6812 (+2.8%)  | 8543 (+28.5%)        | 1890 (-71.5%)       |
|                   | RCP4.5               | 2448 (-63.1%) | 7185 (+8.2%)  | 8323 (+25.3%)        | 1882 (-71.7%)       |
|                   | RCP6.0               | 2706 (-59.3%) | 7952 (+19.7%) | 8544 (+28.7%)        | 1850 (-72.1%)       |
|                   | RCP8.5               | 2895 (-56.4%) | 8551 (+28.8%) | 8323 (+25.3%)        | 1882 (-71.7%)       |
| SSP2              |                     | 6641 (±0.0%) |                |                      |                     |
|                   | RCP2.6               | 3202 (-51.7%) | 6812 (+2.8%)  | 11036 (+66.0%)       | 2037 (-69.3%)       |
|                   | RCP4.5               | 3419 (-48.5%) | 7185 (+8.2%)  | 10756 (+62.0%)       | 2027 (-69.5%)       |
|                   | RCP6.0               | 3831 (-42.3%) | 7952 (+19.7%) | 11047 (+66.3%)       | 2000 (-69.9%)       |
|                   | RCP8.5               | 4073 (-38.7%) | 8551 (+28.8%) | 10756 (+62.0%)       | 2027 (-69.5%)       |
| SSP3              | RCP2.6               | 5081 (-23.3%) | 6812 (+2.8%)  | 15327 (+130.6%)      | 2342 (-64.7%)       |
|                   | RCP4.5               | 5385 (-18.9%) | 7185 (+8.2%)  | 14970 (+125.4%)      | 2328 (-64.9%)       |
|                   | RCP6.0               | 6058 (-8.8%)  | 7952 (+19.7%) | 15359 (+131.3%)      | 2306 (-65.3%)       |
|                   | RCP8.5               | 6505 (-2.0%)  | 8551 (+28.8%) | 14970 (+125.4%)      | 2328 (-64.9%)       |

Table S4

Results of a contribution assessment to potential fatalities. Values in brackets represent percent changes from the current fatalities.
Table S5

Results of contribution assessment to potential economic losses (in billion US$). Values in brackets represent percent changes from the current level of economic losses.

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