Evaluation of future flood risk in Asian megacities: a case study of Jakarta

Nurul Fajar Januriyadi¹, So Kazama², Idham Riyando Moe³ and Shuichi Kure⁴
¹Graduate School of Environmental Studies, Tohoku University, Japan
²Department of Civil Engineering, Tohoku University, Japan
³Ministry of Public Works and Housing, Indonesia
⁴Department of Environment and Civil Engineering, Toyama Prefectural University, Japan

Abstract:

The purpose of this research is to assess the future flood risk in rapidly urbanizing cities under climate change. A flood inundation model and a flood damage costs model were employed to project the future flood risk. We employed the combinations of eight global climate models (GCMs) and three representative concentration pathways (RCPs) for precipitation to represent the climate change. Land-use change and land subsidence information were employed to represent the urban development effects. The expected annual damage costs (EADC) were also calculated to explain the severity of the flood risk. In addition, a global approach was used to estimate the asset values by comparing the common parameters (e.g. gross domestic production (GDP) or population). As a result, the combination of climate change and urban development amplified the mean future flood risk by 322% to 402% in 2050, with a 95% confidence interval. The results also show a large uncertainty of the future flood risk due to the future scenarios. These findings will assist policymakers in determining the investment for future flood prevention and mitigation.

KEYWORDS damage cost; flood inundation model; land-use change; land subsidence; climate change

INTRODUCTION

Over the last two decades, the increasing frequency of hydrometeorological disasters has threatened human lives. Flooding is identified as the most frequent disaster that affects lives and property in vulnerable areas (Wahlstrom and Guha-Sapir, 2015). In the global climate models (GCMs) of coupled model intercomparison project phase 5 (CMIP5), extreme precipitation will increase for tropical regions in the future (Scoccimarro et al., 2013). On the other hand, the projected urban area will grow by 66% in 2050 (United Nation, 2014), which could lead to an altered percentage of urban area that would increase the area of the impervious zone. This condition could amplify the direct runoff (Leavesley et al., 1983; Legesse et al., 2003). Additionally, the growth in population causes an increase in water demand that is supplied by surface or groundwater. Excessive groundwater extraction leads to a declining ground elevation (Galloway and Burbey, 2011; Shen and Xu, 2011). Therefore, climate change and urban development can potentially amplify the future flood risk in rapid urbanization areas.

Several studies have noted that climate change, land-use change, and land subsidence are significant drivers of the increase in flood risks. Globally, the average flood risk will potentially increase due to a warmer Earth (Milly et al., 2002; Hirabayashi et al., 2008, 2013) because climate change increases the value of extreme precipitation in some regions (Min et al., 2011; Scoccimarro et al., 2013; Asadieh and Krakauer, 2015). On the other hand, some pieces of evidence have shown that land-use change could amplify the flood risks (Bradshaw et al., 2007; Nirupama and Simonovic, 2007). Additionally, land subsidence contributes to the increase in flood inundation areas (Svytski et al., 2009; Moe et al., 2016b). Many cities in developing countries are facing a rapid growth in urbanization, which causes an increase in impervious areas, which create obstacles for improving the capacity of rivers or canals and cause the lowering of the ground elevation due to land subsidence. Consequently, the increase in direct runoff, the limited capacity of the rivers and the lower ground surface elevation leads to an increase in the frequency of flood events with higher magnitudes.

The severity of floods can be expressed by the flood damage costs, which are representative of flood risks. The World Bank reported that the total damage costs that were caused by the 2010 Pakistan flood were 855 billion Pakistan rupees or equal to 5.8% of Pakistan’s gross domestic production (GDP) in 2009/2010 (World Bank, 2010). Several types of research studied spatial flood damage costs that integrated flood inundation and exposure maps (Kazama et al., 2009; Tezuka et al., 2014). Projecting future flood risks is needed to evaluate whether the current adaptation measures are appropriate or not for facing future conditions. Budiyono et al. (2016) estimated the future flood damage costs in Jakarta using future scenarios. They considered a change in land-use for Jakarta, which alters the exposure assets but also amplifies the flood magnitude. Additionally, one of the obstacles for calculating the damage costs is the lack of information about land-use asset values. The local government does not provide some...
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Therefore, we used a global approach for estimating the asset values that are required to sufficiently make up for the lack of information by collecting those data from other countries. Subsequently, we collected the common parameter (e.g. GDP or population) of each country from the World Bank website.

The objective of this study is to assess the future flood risk in rapid urbanization cities under climate change. Jakarta was selected for this discussion because it not only experiences many floods but is also a suitable example for describing the change in flood risk for future scenarios. A flood inundation model and a flood damage costs model were used to evaluate the future flood risks. Additionally, a global approach was proposed for estimating the asset values.

STUDY AREA

Jakarta is located in the northwestern part of Java Island, which borders West Java and Banten provinces, as shown in Figure 1. Jakarta’s river basin lies between 106°45'E and 107°00'E and 6°05'S and 6°50'S, and the altitude varies from 0 to 2985 m. The Jakarta population increased by two-fold from 1971 to 2015, with the present density more than 15 thousand people per km². The Indonesia statistic agency (BPS) also recorded an increase in population for Jakarta’s neighboring provinces of West Java and Banten by 20% and 31%, respectively, from 2000 to 2010. The increase in the population would continue due to people tending to stay in the center of economic activities. Abidin et al. (2011) investigated the land subsidence rates in Jakarta from 2002 to 2010. They found the land subsidence rate was different at several locations in Jakarta; the northern part of Jakarta has a high land subsidence rate especially in the northwestern part, which reaches approximately 11 cm per year.

In this section, we explain the analyses that were used in this study. Figure S1 shows the workflow of the analysis in this study, which consists of three components (i.e. flood inundation as the hazard, asset values as the exposure and the depth-damage function as the vulnerability).

Flood inundation model

This study used a flood inundation model of Jakarta that was developed by Moe et al. (2016a, 2016b, 2017). The model was employed to simulate the flood under some scenarios: land-use change, land subsidence and climate change. Varquez et al. (2017) applied SLEUTH to Jakarta under the RCP8.5-SSP3 scenario for projecting the land-use change, which was employed in this study. SLEUTH is an acronym for slope, land use, exclusion, urban extent, transportation, and hillshade. SLEUTH simulates urban dynamics using four growth rules: spontaneous new growth, diffusive growth and the spread of a new growth center, organic growth, and road-influenced growth. Each type of growth is applied sequentially during each cycle and is controlled by five coefficients: diffusion, breed, spread, slope resistance, and road gravity (Clarke et al., 1997). Furthermore, a land subsidence rate map was drawn based on the land subsidence rate information from Abidin et al. (2011) and the coordinates of the station information from Djaja et al. (2004). We also used the kriging interpolation method, which was confirmed by Murakami et al. (2006) as a reliable method for land subsidence purposes. The land subsidence rate was used for linearly projecting the future land surface by 2050, which represents the land subsidence impact. Additionally, we assess the climate change impact utilizing the precipitation of GCMs, which were corrected for the bias to the observed precipitation.
Bias correction

This study used the daily precipitation data from eight GCMs and three emission scenarios (i.e. RCP 2.6, RCP 4.5 and RCP 8.5) to assess the impact of climate change in the future. Table I shows the list of the GCMs used in this study. We also used the daily precipitation data from 5 nearby stations that were recorded from 1985 to 2010, as shown in Figure 1. First, we used the nine closest grids of GCMs with the study site (e.g. as shown in Figure S2) to downscale the resolution of the GCMs by using the inverse distance weighting (IDW) interpolation method at a latitude and longitude resolution of 30 arc-seconds or approximately 1 km × 1 km as shown in Figure S3. The interpolated GCMs spatially show varied precipitation over river basin, which depends on the original resolution of GCMs. The lower GCMs resolution has lower variability in precipitation values over river basin.

The precipitation data of the GCMs have a bias in frequency and intensity compared with the observation data. Some studies applied the quantile mapping bias correction method for reducing the bias of the observation and GCM precipitation data in intensity and frequency (Boé et al., 2007; Lafon et al., 2013). We calculated the empirical cumulative distribution function (CDF) for the downscaled historical GCMs and observation, as shown in Figure S4. Figure S4 shows that the observation CDF values are higher compared with the CDF values of the GCMs, particularly for the quantile of 99%. The GCM precipitation data were corrected according to the inverse of the CDF of the GCMs with observation distribution parameters (Equation 1). $X_{GCM}$ is the daily precipitation of the GCM both historically and in the future (mm), and $X_{GCM\_Corrected}$ is the daily precipitation after correcting the bias. $CDF_{Obs}$ is the inverse CDF of the observed precipitation, and $CDF_{GCM\_His}$ is the CDF of daily historical GCMs.

$$X_{GCM\_Corrected} = CDF_{Obs}^{-1}(CDF_{GCM\_His}(X_{GCM})) \quad (1)$$

Moreover, we divided the time range into three categories: present, near-future and far-future. The present is the precipitation that occurred from 1985 to 2010, which was recorded by the observation station. The near-future and far-future represent the precipitation conditions of the GCM data. The near-future represents the precipitation value of the GCMs from 2011 to 2050, while the precipitation value for the far-future is from 2051 to 2100. Furthermore, we calculated the return period precipitation for each time range using the log-Pearson 3 method (Bobée, 1975).

Exposure assets valuation

Initially, the 2009 land-use map consists of 21 categories provided by the government of daerah khusus ibukota (DKI) Jakarta (DKI Jakarta, 2012). For simplicity, this study reclassified the land-use categories into five categories: agriculture, manufacturing, service, housing, and others. The agriculture represents paddy field, crop field, and livestock. Manufacturing is the land-use that relates to industrial activities. Service consists of wholesale and retail trade, government services, and personal services such as education and healthcare. Housing is the residential sector and includes two categories: planned and unplanned housing. Others consist of the infrastructure, green area, and uninhabited land. The asset value of this study comes from two sources: first, data are collected from the government official website for either BPS or the ministry of agriculture. The agriculture asset data comes from the ministry of agriculture and the tax income comes from BPS. Second, estimates are made by using common parameters. In addition, the building values are estimated using the land and building taxes income of each urban village in Jakarta, which is available in the annual report of BPS Jakarta for the district level (see in Text S1).

To estimate the asset value using common parameters, we collected the asset value data from the house content, manufacturing, and service sectors. The house content assets includes the furniture assets inside the house and the assets of the vehicle. We collected the average value of the net household wealth of four countries: Australia, Japan, the United Kingdom and the United States. Furthermore, those data were divided by the average house area of each country, and we therefore obtained the house content value per m². Additionally, we collected the nonbuilding asset value of the manufacturing and service sectors. Those asset data were divided by the number of employees in each sec-

Table I. List of GCMs

| No | Model | Resolution Lat x Long | Developer |
|----|-------|------------------------|-----------|
| 1  | CNRM-CM5 | 1.4° x 1.4° | Centre National de Recherches Meteorologiques / Centre European de Recherche et Formations Avancées en Calcul Scientifique (CNRM/CERFACS) |
| 2  | IPSL-CM5A-LR | 1.9° x 3.8° | Institut Pierre-Simon Laplace |
| 3  | GFDL-ESM2M | 1.5° x 2.5° | Geophysical Fluid Dynamics Laboratory |
| 4  | MPI-ESM-LR | 1.8° x 1.9° | Max Planck Institute for Meteorology (MPI-M) |
| 5  | MIROC-ESM-CHEM | 2.8° x 2.8° | Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology |
| 6  | CanESM2 | 2.8° x 2.8° | Canadian Centre for Climate Modelling and Analysis |
| 7  | CSIRO-Mk3-6-0 | 1.8° x 1.9° | Commonwealth Scientific and Industrial Research Organization / Queensland Climate Change Centre of Excellence (CSIRO-QCCCE) |
| 8  | HadGEM2-AO | 1.3° x 1.9° | National Institute of Meteorological Research |
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After collecting the asset data, we collected the common parameter of each country from the World Bank website. We analyzed the relationship between the asset values to the common parameters. Using a multilinear regression method, the house content values can be estimated using equation 2. Figure 2 (c) shows a good agreement between the estimated assets and the collected assets, which is indicated by the correlation coefficient (R) value of 0.94. In addition, Figure 2 (a) and (b) show the scatter plot of GDP and the asset values for the manufacturing and service sectors, respectively, which have R values of 0.93 and 0.70. The R value indicated that there is a strong relationship between the asset value and the GDP of each sector. Therefore, we proposed the rational equation to estimate the asset value for the manufacturing and service sectors, as shown by equations 3-1 and 3-2.

\[ HC = 0.06GDP - 9.53P + 2663 \]  
(2)

\[ \left( \frac{Asset_M}{known} \right)_{Estimated} = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{GDP_M}{known} \right)_{Estimated} \times \left( Asset_M \right)_{known} \]  
(3-1)

\[ \left( \frac{Asset_S}{known} \right)_{Estimated} = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{GDP_S}{known} \right)_{Estimated} \times \left( Asset_S \right)_{known} \]  
(3-2)

where \( HC \) is the asset value of the house content (USD/m²), \( GDP \) is the total gross domestic product (billion USD) and \( P \) is the population in millions. \( Asset_M \) and \( Asset_S \) are the nonbuilding assets per employee for the manufacturing and service sectors, respectively (USD). \( GDP_M \) and \( GDP_S \) are the sectorial gross domestic product (billion USD) for the manufacturing and service sectors, respectively, and \( N \) is the number of known data.

Damage costs calculation

The damage costs calculation is based on the land-use classification. The depth-damage function of the Japan Ministry of Land, Infrastructure, Transportation, and Tourism (MLIT, 2005) was applied by Kazama et al. (2009) to estimate the flood damage costs across all of Japan. Damage costs in agricultural fields were calculated using the inundated area and the depth of inundation as the main components while considering the price of the rice or crop and the production rate.

\[ DC_{Agr} = \sum_{depth=1}^{5} prd \times Price \times A_{depth} \times DR_{Agr} \]  
(4)

where \( DC_{Agr} \) is the damage costs for agriculture (USD), \( prd \) is the average of the crop or rice production (ton/km²), \( Price \) is the average price of the crop or rice (USD/ton), \( A_{depth} \) is the inundated area for different depth classifications (km²), and \( DR_{Agr} \) is the damage rate value for the agriculture sector based on the water depth.

In the housing sector, the calculation of damage costs includes the building and the house content damage as follows:

\[ DC_{H} = \sum_{depth=1}^{5} A_{depth} (BP \times DR_{B} + HC \times DR_{HC}) \]  
(5)

where \( DC_{H} \) is the flood damage costs for housing (USD) and \( BP \) is the building price (USD/m²), which is different depending on the location. \( DR_{B} \) and \( DR_{HC} \) are the damage rate values for the building and house contents based on the water depth, respectively.

Similar to the housing sector, the manufacturing and services sectors were also calculated for building and nonbuilding asset damage, as follows:
\[ DC_M = \sum_{depth = 1}^5 A_{depth}(BP \times DR_B + Asset_M \times DR_{Asset}) \quad (6-1) \]

\[ DC_S = \sum_{depth = 1}^5 A_{depth}(BP \times DR_B + Asset_S \times DR_{Asset}) \quad (6-2) \]

where \( DC_M \) and \( DC_S \) are the flood damage costs for the manufacturing and service sectors (USD), respectively. \( DR_{Asset} \) is the damage rate value for the nonbuilding asset based on the water depth.

The final step is calculating the expected annual damage costs (EADC). The EADC is a strong indicator for a given area showing how vulnerable it is to flood risk and how much can be gained by implementing, e.g. climate change adaptation measures (Olsen et al., 2015). Olsen et al. (2015) compared the methods for estimating the EADC, i.e. statistical, numerical and analytical methods. They found three methods yield very similar results, and the identified shift in costs occurring at the design return period was more important than the method to calculate the EADC. Furthermore, this study used the numerical method for estimating the EADC (Olsen et al., 2015).

**RESULTS**

This section consists of two subsections. First, we explain the future precipitation conditions due to climate change. Second, we show the potential flood risk under future scenarios that are represented by the EADC comparison.

**Future precipitation**

To evaluate the performance of the bias correction downscaling method, we calculated the return period precipitation (i.e. 2-, 5-, 10-, 25-, 50- and 100-year return period) before and after correcting the biases. Figure S5 shows the comparison of the 50-year return period precipitation before and after downscaling. Subsequently, we calculated root mean square error (RMSE) between return period precipitation of GCMs and observation. We found that the average RSME values of CNRM-CM5 and MIROC-ESM-CHEM for before and after downscaling are varied 31.4 mm (CNRM-CM5, before) to 121.8 mm (MIROC-ESM-CHEM, before) and 17.1 mm (CNRM-CM5, after) to 30.7 mm (MIROC-ESM-CHEM, after). The results show the quantile mapping method succeeds to minimize the error between GCMs and observation.

Furthermore, the correction functions were used to correct the biases of future precipitation. Subsequently, we calculated the return period precipitation for each time range category. For example, Figure S6 shows the comparison of the return period precipitation of three time-ranges for three GCMs with the RCP 8.5 scenario. Moreover, we summarized the change in precipitation due to climate change as shown in Figure 3. The median value increases by 17% and 23% for the near-future and far-future, respectively. The median value of the low-return period precipitation tends to have a larger increase than that of the high-return period precipitation. Furthermore, along with the increase in the median value, the uncertainty also increases due to climate change, which is indicated by a wide-range of maximum and minimum precipitation values. In contrast to the median value, the high-return period precipitation has a larger uncertainty.

**Projection of the flood risk**

In this section, we explain the future flood risk under future scenarios (i.e. climate change and urban development). The EADC was used for representing the change in flood risk.

**Urban Development**

The meaning of urban development in this study is the adverse effect of rapid urbanization on the environment (i.e. land-use change and land subsidence). One of the consequences of urbanization is the increasing population in particular areas, which requires more space for the dwelling. This condition could change the land use, where initially the agricultural land or forest become the urban area. Figure 4 shows the change in the EADC due to the land use change and land subsidence. Altering the land-use to be an urbanized zone increases the EADC by 99%. Land subsidence potentially increases the future flood risk, which is indicated by the increase in the EADC by 95%. Moreover, the combinations of land-use change and land subsidence significantly increase the future flood risk more than three-fold, which can be identified by the increase in the EADC by 226%.

**Climate change**

The change in EADC due to climate change and urban
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Figure 4. The comparison of expected annual damage costs (EADC) under urban development scenarios (LU 2050 denotes the land use condition in 2050 and LSub 2050 denotes the impact of land subsidence on the ground surface elevation by 2050)

Figure 5. The projection of expected annual damage costs (EADC) near-future (2011 to 2050) and far-future (2051 to 2100) development is shown in Figure 5. With a 95% confidence interval, climate change alone increases the mean of the EADC for the near-future by 54% to 100%. The maximum and minimum values of EADC are 1874 and 469 million USD, respectively. The far-future has a more severe flood risk and higher uncertainty compared to the near-future, which is indicated by the significant increase in the mean value of EADC by 72% to 127%. The maximum and minimum values of EADC are 2613 and 732 million USD, respectively.

Furthermore, the combination of urban development and climate change significantly increases the future flood risk. The near-future shows that the mean value of EADC increases by 322% to 402%, with minimum and maximum values for EADC of 1754 and 4266 million USD, respectively. Similarly, the far-future shows the mean value of EADC significantly increase by 353% to 445%, with minimum and maximum values for EADC of 2273 and 5434 million USD, respectively. The results identified that the combination of the urban development and climate change could increase the uncertainty of the future flood risks.

DISCUSSION

This study estimated the EADC for the present condition is 707 million USD, which is much higher compared with the estimation by Budiyono et al. (2016). The difference in the results is due to the different methods for estimating the asset value. They assigned the asset value based on the land-use categories (i.e. one land-use category has one asset value). Nevertheless, the asset values are not the same even though there is one land-use category for the different locations. This study used the global approaches to estimate the asset values. Moreover, the asset values in Jakarta are based on not only the land-use categories but also the location of the asset. The asset value was indicated by the difference between building and land tax incomes of urban villages, as shown in Figure S7. This study also estimated the asset value based on the distribution of tax income, which means the estimation of EADC considers not only the land-use categories but also the distribution of incomes. Moreover, Huizinga et al. (2017) collected the worldwide depth-damage functions, which are also employed to estimate the EADC. In addition, the results show EADC values using
the average depth-damage function of Asia and North America of 783 and 858 million USD, respectively. This indicates that the asset value is a dominant factor in calculating the damage costs. Additionally, we compared our results to the government’s estimation of damage cost of the 2013 flood. The government used the quick damage and loss assessment method explained by the Economic Commission for Latin America and the Caribbean (ECLAC) (ECLAC, 2003). Their estimation for the economic losses due to the 2013 Jakarta flood exceeded 7.5 trillion IDR or approximately 0.8 billion USD (World Bank, 2016), whereas our calculation of the 2013 flood damage costs was 3.8 billion USD.

For the single driver, the land-use change slightly increases the future flood risk compared with land subsidence and climate change. The results correspond to Moe et al. (2017) who found that land-use change has a larger increase in the flood inundation areas compared with land subsidence. Conversely, Budiyono et al. (2016) found that land subsidence increased the Jakarta flood risks more than land-use and climate change. However, they considered that land-use change occurred in the exposure or asset. They did not consider the increase in flood magnitude due to the changing land use in the river basin. Nevertheless, the results show each driver potentially increases the future flood risks. Mishra et al. (2018) emphasized that the combination of land-use change and climate change increases the inundation area in the Ciliwung River Basin, which is the main river basin in Jakarta City. Conversely, Budiyono et al. (2016) found that climate change could decrease the median flood risk in 2030 by -46%. The differences in the results are due to a different input of precipitation. They employed the downscaled GCMs of the inter-sectoral impact model intercomparision project (ISI-MIP) with a resolution of $0.5^\circ \times 0.5^\circ$ (Hempel et al., 2013). The data has a limitation with a truncation of extreme values in the precipitation downscaling algorithm (Hempel et al., 2013). This study corrected the percentile bias between nearly all the observation stations and the historical GCMs using the quantile mapping method. Despite giving different results of the climate change impact on future flood risks, both studies found that the uncertainty of the flood risks increases due to climate change.

The other megacities also faced a similar problem related to the future flood risks, especially in Southeast Asia countries. In a World Bank report, Pillai et al. (2010) reported the climate change impact on the future flood risk in three Southeast Asia megacities, namely, Bangkok, Manila and Ho Chi Minh City (HCMC). In Bangkok, climate change and land subsidence could increase the 100-year return period flood damage cost by 207% in 2050 (present = 2.72% and future = 8.36% of the regional GDP (RGDP)). Climate change alone tends to increase the 100-year return period flood damage costs by 24% of the RGDP in Manila, where the present damage cost is 3% of the RGDP. Using a different approach, the damage costs for the extreme events in HCMC increase by 16-fold due to climate change. Compared with Jakarta, the 100-year return period flood damage cost is 4.9% of the RGDP and potentially increases by 10% of the RGDP in 2050 due to climate change and urban development. These results show the future flood risks likely increase by 2050 in the megacities of developing countries, especially Southeast Asia countries, due to climate change and urban development. Furthermore, the results show the combination of urban development and climate change significantly increase the flood risk by 322% to 402%. The results correspond to the research performed by Aerts et al. (2014), who found that the future flood risks of New York City increased by 266–1289%. Moreover, Adnan and Kreibich (2016) indicated that Jakarta has a lower flood prevention standard compared to other megacities, including New York City. Therefore, the appropriate adaptation measures, either structural or nonstructural, are required for preventing the increase in future flood risk. Controlling the urbanization could decrease the adverse effect of the land subsidence and land-use change. Furthermore, improving the capacity of current countermeasures is required for anticipating the increased precipitation due to climate change.

Furthermore, the selection of the downscaling method affects the reliability of future projection. This study used a quantile mapping bias correction method to downscale the GCMs data. Based on our analysis, the quantile method could minimize the error between GCMs and observation, which was indicated by the reduction in RSME values. These results corresponded to several climate change impact studies that also used the quantile mapping to downscale the GCMs data. Based on our analysis, the quantile mapping method had another limitation, ignoring the correlation between future GCMs and observation. The quantile mapping can produce negative projection when the correlation future GCMs do not have a strong positive correlation to the observation. In addition, this study used the IDW method to interpolate the precipitation, which considered only the distance effect. The precipitation interpolation should consider the other parameters (e.g. topography condition, sea and lake percentages) for obtaining a better result (Aalto et al., 2013). In summary, even though this study succeeds to assess the change in flood risk due to future scenarios, we still have a limitation in the downscaling method. Therefore, further studies shall consider more sophisticated methods to increase the reliability of future projection.

CONCLUSIONS

A flood inundation model and a flood damage costs model were employed to estimate the change in future flood risk under future scenarios with the consideration of climate change and urban development. Based on the analysis, the combination of climate change and urban development amplified the mean future flood risk with a 95% confidence interval by 322% to 402% in 2050. All drivers could also increase the uncertainty of future flood risks. Moreover, the results show the future flood risk could be more severe and more uncertain in the far-future. The rapid urbanization cities potentially undergo similar problems in

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the future. Controlling urbanization and improving the current flood countermeasures could reduce the potential flood damage cost in the future.

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SUPPLEMENTS

Text S1. Land and building price map
Figure S1. Diagram of the analysis
Figure S2. Example of selected grids of GCMs (MIROC-ESM-CHEM model)
Figure S3. The distribution of mean annual maximum daily precipitation of GCMs after interpolation over river basin
Figure S4. The comparison of spatial CDF for observation and historical GCMs (the red dots are the locations of the observation stations)
Figure S5. The comparison of the 50-year return period precipitation between observation (left-column), original GCMs (middle-column) and downscaled GCMs (right-column)
Figure S6. The comparison of the 50-year return period precipitation between the present (left-column), near-future (middle-column) and far-future (right-column) for three GCMs with an RCP8.5 scenario
Figure S7. Land and building prices in Jakarta in 2013
Figure S8. The comparison between the Lorenz curve of income and land building price

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