Effect of climate change and urbanisation on flood protection decision-making

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Abstract
The changing climate and the rapid urbanisation may alter flood severity and influence the decision-making process for flood management. In this study, a Multi-Criteria Decision Analysis (MCDA) framework for optimal decision-making in flood protection is developed and applied to a central flood-prone basin of Jakarta, Indonesia. Specifically, the decisions are on levees corresponding to protection under different rainfall return periods (RP), considering climate change and associated uncertainties, urbanisation, and evolving socio-economic features of the flood plain. Three cases were studied to analyse future (year 2050) conditions (i) future rainfall/current urban, (ii) current rainfall/future urban and (iii) future rainfall/future urban. Future climate change projections from the NASA Earth Exchange are used to obtain information about changes in rainfall, whereas Landsat derived imperviousness maps along with the population projections are used for future urban conditions. Annual Expected Loss, Graduality, upgrade Construction cost and Net-Socio-Economic Vulnerability Index are the criteria used in the MCDA. It is found that climate change has a higher impact compared to urbanisation on the flood protection decisions. For the basin studied, the extreme future case of increased rainfall and urbanised conditions have the optimal decision in levee protection level corresponding to 250 years RP under current rainfall which corresponds to ~60 years RP under future rainfall.

KEYWORDS
annual expected loss, climate change, flood protection, graduality, MCDA, urban projections

1 | INTRODUCTION

Flooding is the most prevalent natural disaster causing billions of dollars of loss each year worldwide. The flood risk is expected to change due to climate change (Hirabayashi et al., 2013; IPCC, 2007), urbanisation (Jongman, Ward, & Aerts, 2012; Muis, Güneralp, Jongman, Aerts, & Ward, 2015) and socio-economic changes (Jongman et al., 2015). Jongman et al. (2012) reported that the global population exposure to a 100-year return period (RP) flood will increase by 31% from 2005 to 2050. Arnell and Gosling (2016) indicated that climate change alone drives a 187% increase in flood risk. For the Southeast Asia region, particularly Indonesia, large increases in flood frequency are projected (Budiyono, Aerts, Tollenaar, & Ward, 2016; Hirabayashi...
et al., 2013). Levees, reservoirs (for flood storage and diversion), flood zoning, and land use planning are the common mitigation practices for flood risk reduction. The decision-making process on future flood protection measures mainly involves projections of changing climate (via rainfall projections), urbanisation (via changes in basin parameters and thus flood hazard) and evolving socio-economic levels (i.e., exposure and thus the risk). Such projections and their associated uncertainties increase the complexity of the decision-making process. A more recent study by Convertino, Annis, and Nardi (2019) suggested a conceptual decision-making tool for choosing the best combination of flood control structures by using flood size distribution. While the study indicated that the decision tool is capable of (or extendable to) assessing environmental (taken as flooded area), economical (agricultural loss, urban loss) and social (death, injuries) impact via criteria (or sub criteria), the case study was performed solely with the flood size distribution (environmental criteria) and socio-economic factors were not analysed. Development of a flood protection decision framework accounting for climate change, urbanisation and evolving socio-economic factors along with their uncertainties in current and future conditions will facilitate the decision makers and policy makers on their flood protection decisions and with such decisions being more resilient to future changes. This study specifically addresses such a changing future along with uncertainties in flood protection decision framework in the context of levee protection plans defined via rainfall RPs.

Future rainfall projections from the Global Climate Models (GCMs) or Regional Climate Models (RCMs) involve large uncertainty (Chen, Brissette, & Leconte, 2011; Daksiya, Mandapaka, et al., 2017; De Paola, Giugni, Pugliese, Annis, & Nardi, 2018; Mandapaka & Lo, 2018; Muis et al., 2015), which often gets amplified when propagated through a flood modelling framework. The uncertainty arises from the greenhouse gas emission scenarios/pathways assumed, GCMs or RCMs used, and the downscaling techniques adopted. Although various research methodologies are reported to address such uncertainties, they tended to separately analyse uncertainties as arising from each GCM (Prudhomme, Jakob, & Svensson, 2003), emission scenarios (Kron, 2005), downscaling techniques (Khan, Coulibaly, & Dibike, 2006) with further issues of non-stationarity and uncertainty across GCMs (Sunyer, Madsen, Rosbjerg, & Arnbjerg-Nielsen, 2014). Uncertainties from rainfall projections and the impacts of climate change on the flood predictions have also been studied (Alfieri et al., 2017; Hirabayashi et al., 2013; Kay, Jones, & Reynard, 2006; Mishra et al., 2018; Ward et al., 2014; Wing et al., 2018) but has not been incorporated in a quantitative decision-making analysis involving flood protection infrastructure.

The uncertainty in future projections of urban extent, land-use patterns and flood plain basin parameters (e.g., roughness, imperviousness etc.) further impacts the uncertainty in flood risk analysis for future time periods. There have been recent studies employing urban growth models and urban cover projections to estimate the impact of urbanisation in flood risk (Budiyono et al., 2016; Huong & Pathirana, 2013; Mishra et al., 2018). To the author’s knowledge, there are few reported works that systematically analysed different uncertainties affecting a hydro-system (Evans et al., 2006; Wheater & Evans, 2009). While uncertainties in rainfall forecasting and climate change projections are widely studied, uncertainty due to changing basin parameters and changing socio-economic factors are rarely incorporated in flood risk studies (e.g., Evans et al. (2006)). For example, Cabrera and Lee (2020) developed a framework to generate a flood risk map using Multi-Criteria Decision Analysis (MCDA). MCDA with six criteria is used to combine flood hazard map with population density; however, climate and land use changes and their effect on the decision-making process are not assessed. Mishra et al. (2018) assessed the impacts of climate change and urbanisation on flood events for the Ciliwung River in Jakarta, but the study does not assess flood protection/mitigation measures in a decision-making analysis framework. Ward et al. (2014) conducted a detailed probabilistic flood risk assessment using ensembles of climate model projections from both GCM and RCMs; however, urbanisation and socio-economic factors were not analysed in the study. Further, the social and economic features of a flood plain largely determine the exposure level to a flood hazard and need to be accounted for in flood mitigation decisions. A number of vulnerability indices have been developed based on selected past flood events for example, PVI, FVI and Social Vulnerability Index, (Balica, Douben, & Wright, 2009; Cardona, 2006; Connor & Hiroki, 2005; Ignacio, Cruz, Nardi, & Henry, 2015; Tascón-González, Ferrer-Julià, Ruiz, & García-Meléndez, 2020). However, these are often noted for their possible duplicative effects, and unequal importance with many variables having only minor impact, unavailability and data collection difficulties (Balica & Wright, 2010; Birkmann, 2013). Further, while they facilitate comparison of flood vulnerability across study areas, they are not readily applicable in engineering flood protection assessments. Thus, there is a need to systematically incorporate these factors and relevant uncertainties in flood loss assessment and decision-making on flood protection measures.
In this work variabilities arising from GCMs and urbanisation are incorporated and their impact on flood protection decision-making is studied for a flood-prone central plain of Jakarta, Indonesia. Specifically, flood protection measures are assessed in a decision-making framework at current (taken as year 2009) and future (year 2050) conditions accounting for climate change, urbanisation and evolving socio-economic factors. Three cases are analysed comprising: (i) future rainfall/current urban conditions, (ii) current rainfall conditions/future urban and (iii) future rainfall/future urban conditions to study their impacts on flood protection decision making. The decision-making framework, which was first developed by Daksiya, Su, Lo, and Cheung (2015) and Daksiya, Su, et al. (2017) is extended here to account for future conditions. This framework adopts a MCDA with Annual Expected Loss (AEL), Graduality (G) and Net Socio-economic Vulnerability Index (Net SEVI), along with levee upgrade construction cost (C) used as criteria to analyse alternative flood levee protection plans. The criteria are further calculated to reflect the changed future conditions of the cases. In particular, a methodology using change factor is developed to incorporate GCM variability and urban projections into the decision-making framework.

2 | BACKGROUND OF FLOOD PROTECTION MCDA FRAMEWORK AND APPLICATION

MCDA is widely used across disciplines and particularly in the field of water resources planning and management covering water policy evaluation, strategic planning and infrastructure selection (Abrishamchi, Ebrahimian, Tajrishi, & Marinho, 2005; Cabrera & Lee, 2020; Porthin, Rosqvist, Perrels, & Molarius, 2013; Raju & Vasan, 2007; Young, Younos, Dymond, Kibler, & Lee, 2010). The flood protection decision framework adapted here was first developed by Daksiya et al. (2015) and improved in Daksiya, Su, et al. (2017) to account for socio-economic factors. Criteria of AEL and G as key measures of flood severity, Net SEVI as a measure of socio-economic vulnerability and further reflecting population distribution and economic productivity, and levee upgrading cost C were used in the MCDA as described in Section 2.2. Sensitivity of the MCDA decision/result on criteria weights was evaluated in Daksiya, Su, et al. (2017), for which the decision maker has further flexibility to adjust criteria weights to better reflect local priorities. This decision framework involves flood modelling including hydrology and hydraulic simulations, and the MCDA outranking PROMETHEE technique (Brans, 1982; Brans, Vincke, & Mareschal, 1986) to assess different levee options for a central basin in Jakarta as shown in Figure 1. The levee protection levels in Daksiya, Su, et al. (2017) ranged from Plan 0 (current level) to Plan 5, where the levee plans are defined to protect against different peak flows corresponding to rainfall RP (Table 1). Thus Plan 1 is defined to have protection up to 50-year rainfall RP in both the rivers. Ciliwung with West Banjar Canal (WBC) and Cengkareng are protected up to 50-year and 100-year rainfall RP, respectively in Plan 2 and swapped in Plan 3 while Plan 5 had 250-year RP in Ciliwung with WBC and Cengkareng rivers. In this study, a further plan Plan 6 (Table 1) with protection up to 400-year RP rainfall in both Ciliwung and Cengkareng rivers is included as an increase in the flood severity is expected when climate change and urbanisation impacts are considered.

2.1 | Flood modelling for Jakarta

The Jakarta flood model was first developed by Lo and Chen (2013) and used in recent studies for flood risk assessment under current conditions (Daksiya et al., 2015; Daksiya, Su, et al., 2017). The model uses the Hydrologic Engineering Centre (HEC)-Hydrologic Modelling System (HMS) version 4.2 and River Analysis FIGURE 1 Study area of Jakarta central basin and catchment area showing rainfall gauge stations and NEX-GDPP grids used, and the three urbanisation regions (upstream, midstream and DKI Jakarta (Daerah Khusus Ibukota or Special Capital Region)) adopted.
TABLE 1 Levee protection plans for Central basin of Jakarta. Note the lower reach of the Ciliwung river merges with the West Banjar Canal (WBC)

| Alternative | Description |
|-------------|-------------|
| Plan 0      | Current level |
| Plan 1      | Protect up to 50-years return period (RP) rainfall (Cengkareng and Ciliwung/WBC) |
| Plan 2      | Protect Ciliwung/WBC up to 50-years RP rainfall & Cengkareng up to 100-years RP rainfall |
| Plan 3      | Protect Ciliwung/WBC up to 100-years rainfall & Cengkareng up to 50-years RP rainfall |
| Plan 4      | Protect up to 100-years RP rainfall (Cengkareng and Ciliwung/WBC) |
| Plan 5      | Protect up to 250-years RP rainfall (Cengkareng and Ciliwung/WBC) |
| Plan 6      | Protect up to 400-years RP rainfall (Cengkareng and Ciliwung/WBC) |

System (RAS) version 4.1 for hydrologic and hydraulic modelling of two major rivers, Ciliwung and Cengkareng (Figure 1). Overflow from these rivers create flooding of the central plan that includes large commercial areas of Jakarta.

Observed daily rainfall data were obtained from Institute of Water Resources, Bandung, Indonesia for Ciliduk, Priuk, Halim and Depok stations (see Figure 1). The rainfall frequency analysis employed Log Pearson type III (LP3) distribution fits for the combined daily rainfall data from Ciliduk, Halim and Priuk stations over a period of 23 years (1984–2006). Rainfall data from these three stations were combined using station-year method to produce a longer record of 69 years, this assuming spatial homogeneity across the stations that are in proximity. The point-scale precipitation needs to be converted to areal scale to obtain a design rainfall event. This conversion is typically achieved using the Areal Reduction Factor (ratio of areal precipitation to the point precipitation).

In this study, the observed rainfall was uniformly distributed over the river basin with an Area Reduction Factor of 0.75 derived from Boerema (1925) and used in Partner_For_Waters (2007). Temporally the daily rainfall data was distributed to hourly with the 24-hr soil conservation services (SCS) type 1A distribution (U.S. Department of Agriculture, 1973). While hourly rainfall curves are developed under consulting programs (Partner_For_Waters, 2007), these curves are not publicly reported. Rather we have used the SCS Type 1A curve as it is the closest to the reported distribution for Jakarta amongst the four SCS curves as based on 3 hourly maximum rainfall amount and the time to peak. The imperviousness percentage was calculated based on land-use type information from Dinas Pekerjaan Umum - Public Works Department (DPU) for the year 2009 value, and the Digital Elevation Model was from Dinas Pekerjaan Umum Jakarta (DPU, Public Works Agency). The discharge values from HEC-HMS were provided as input to the HEC-RAS to simulate water level in the rivers. Two HEC-RAS runs were used. The first allowed the determination of the overflow from the main rivers via a weir formula applied to the riverbanks. Then, a second HEC-RAS run was performed driven with this overflow together with flow from the local rainfall. The resulting inundation extent and depth was mapped with ArcGIS. Flood loss was benchmarked using a ~2 km² area of the Cengkareng basin that was flooded during the February 2007 flood event and extrapolated to the central basin based on population distribution via per capita loss calculated for the flooded area and depth-damage curves from Lo and Chen (2013). Loss curves as shown in Figure 2 were generated for the daily rainfall for the range of 100–350 mm/day. The developed flood model was calibrated with the recorded water level from DPU for the earlier February 2007 and February 2002 flood events with percentage difference in peak flow of ≤5.4% and ≤7.1% for the two events as measured at Katulampa, Depok and Manggarai stage stations (see Figure 1; Daksiya, Su, et al., 2017). There are extensive studies on hydrology and hydraulic model uncertainties and its impact on flood inundation mapping (Ahmadisharaf, Kalyanapu, & Bates, 2018; Annis, Nardi, Volpi, & Fiori, 2020; Apel, Merz, & Thieken, 2008; Bates, Pappenberger, & Romanowicz, 2014; Dimitriadis et al., 2016; Rafiei Emam, Kappas, Fassnacht, & Linh, 2018). However, in this study our focus is on uncertainties from rainfall projections rather than model uncertainty.

2.2 Criteria in MCDA-PROMETHEE

Criteria of AEL, G, C and Net SEVI are selected based on Daksiya, Su, et al. (2017) for use in MCDA-PROMETHEE flood protection decision-making framework. Except for C which depends solely on the levee height (i.e., plan) and calculated using construction cost estimates from Cho, Frangopol, and Ang (2007), the other criteria incorporate uncertainties in the rainfall arising from the frequency analysis. Thus, the AEL is the damage expected to occur in any given year, obtained as the integral of the loss $L_T$ at each RP $T$ of rainfall multiplied by the $T$-year rainfall probability given by the LP3 probability density function $f(R)$, that is, $AEL = \int L_T f(R) dR$. However, $L_T$ has uncertainty arising from rainfall frequency analysis.
which is expressed as the integral of random loss $l_T$ multiplied by the probability of rainfall occurrence $f_T(R_T)$, that is, $L_T = \int l_T f_T(R_T) dR_T$ (see Daksiya, Su, et al. (2017) for more details). Substitution of $L_T$ into the $AEL$ integral equation leads to the following double integral and its discrete double summation analogue (Equation 1). In this study, the inner (outer) summation in Equation (1) is obtained using $N = 10$ $(M = 7$ RPs)$\text{ discrete intervals.}$ The $N$ and $M$ values used here provided convergence for $AEL$ calculation.

$$AEL = \int \left( \int l_T f_T(R_T) dR_T \right) f(R) dR$$

$$\approx \sum_{j=1}^{M} \left( \sum_{i=1}^{N} l_{ij} f_T(R_{ij}) \Delta R_T \right) f(R_j) \Delta R$$

Graduality $G$ was developed by De Bruijn (2004) as a resilience indicator which measures the progressive-ness of flood loss, that is, the slope of the discharge-loss curves which differ for different flood protection levels. Specifically, $G$ quantifies the deviation of the percentile discharge vs percentile loss from a linear relation as normalised by the maximum difference of 200 (Equation (2)). $G > 1$ indicates that the deviation is smaller which is preferred. Daksiya, Su, et al. (2017) modified $G$ to account for rainfall uncertainty by taking the difference using the relative increase in the expected discharge ($Q$) to the relative increase in expected loss ($E_{\text{Loss}}$) (both expressed in percentile terms), as shown in Equation (2). Here $K$ of 7 discrete intervals, that is, RPs are used.

$$G = 1 - \frac{\sum_{k=1}^{K} |\Delta E_{\text{Loss}} - \Delta Q_k|}{200}$$

The social economic vulnerability index developed by Daksiya, Su, et al. (2017) is adapted here to capture the social and economic features under current and future conditions. This can be readily used in decision making tools to analyse alternative engineering solutions. The SEVI development in Daksiya, Su, et al. (2017) involved seven variables as selected from an initial list of 15 by consideration of information content and data availability, and with Pearson correlation test applied to remove duplicative variables. The relative importance of the selected variables is further estimated using a gradient vector confirming that the final variables have almost equal importance, and thus minimal duplicative effects. The finalised SEVI is defined as the summation of vulnerabilities from both social and economic components. The social component is assessed using population density, population growth and literacy rate while the economic component uses the per capita gross regional domestic product, unemployment, local and foreign investment and percentage monthly expenditure for insurance and taxes. Data for these variables were collected from Badan Pusat Satistik (BPS) (Statistics Indonesia), the Indonesian governmental agency publishing annual national account statistics (BPS, 2005–2015a; BPS, 2015b). Socio-economic features $Net\ SEVI$ are accounted in the decision framework via two criteria as related to the flooded area ($Net\ SEVI_{A_i}$) and the flood depth ($Net\ SEVI_{D_j}$). The $Net\ SEVI_{A_i}$ (subscription i indicating the specific levee plan) is represented by the population ratio for inundated area multiplied by SEVI for each
district $m$ that overlapped spatially with the central plan (Equation [3]). It is noted that there are five such districts and district specific SEVI$_m$ are separately computed. The ratio of expected overflow to expected discharge at the river mouth multiplied by SEVI gives Net SEVI$_{Di}$ (Equation [4]).

Here an SEVI$_i$ calculated for the whole Jakarta province is used as the overflow is not district distinct.

$$Net\ SEVI_{Al} = \sum_{m=1}^{5} \frac{\text{Population in expected inundated area}_{i,m}}{\text{Total population}_m} \times SEVI_m$$

$$Net\ SEVI_{Di} = \frac{\text{Expected over flow to the central basin}}{\text{Expected discharge at the mouth}} \times SEVI_i$$

The AEL, G and Net SEVIS are used as criteria in the MDCA-PROMETHEE decision framework which ranks the seven levee plans by calculating a net outranking index. The outranking index measures how much a particular plan is preferred over others as well as how much other alternatives are preferred over the particular plan. The levee plan with highest net outranking index then becomes the best alternative. Readers are referred to Daksiya, Su, et al. (2017) in which MCDA-PROMETHEE is described in detail.

## 3 | FUTURE PROJECTIONS

### 3.1 | NEX-GDDP rainfall projections

The NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset presents 0.25° resolution climate projections from 21 GCMs of Coupled Model Inter-comparison Project Phase 5 (CMIP5) (NEX-GDDP, 2015; Thrasher, Maurer, McKellar, & Duffy, 2012). The dataset contains precipitation, and minimum and maximum temperature time series for historical climate projections from 21 GCMs of Coupled Model Inter-comparison Project Phase 5 (CMIP5) (NEX-GDDP, 2015; Thrasher, Maurer, McKellar, & Duffy, 2012). The dataset contains precipitation, and minimum and maximum temperature time series for historical time period 1961–2000 and the future time period 2031–2070 (covering 20 GCMs) are used. The time period of 2031–2070 is considered to represent the midyear 2050. The GCM ACCESS1-0 is not considered in the analyses due to its unrealistic annual maximum rainfall values (~1,000 mm/day) for the region. The rainfall frequency analysis is carried out using LP3 probability distribution and daily rainfall values for different RPs obtained for historical and future time periods. Figure 3 illustrates the variation of daily rainfall as a function of RP for the grid cell containing stations Halim and Depok for the time period 2031–2070 under both RCP scenarios. The inter-model variability (uncertainty) in future rainfall projections from 20 different GCMs can be readily observed in Figure 3.

We employed a change factor (CF) approach to quantify the change in daily rainfall extremes between the two time periods. Specifically, the CF is defined as the normalised change in the daily rainfall extremes from a historical to future time period. The CF for each GCM ‘g’ at the T-year RP is calculated with the normalised difference in the daily rainfall $R$ following Equation (5). The daily rainfall projections from NEX-GDDP dataset is used to calculate the CF for the period from historical (1961–2000) to future (2031–2070) for RCP 4.5 and 8.5 separately and for the three grids covering the four stations (Ciliduk, Priuk, Halim and Depok) in the study area.

$$CF_{TG} = \left[ \frac{R_{TF,g} - R_{TH,g}}{R_{TF,g}} \right]$$

where:

$CF_{TG}$: temporal CF of GCM g for T-year RP.

$R_{TF,g}, R_{TH,g}$: future (F), historical (H) daily rainfall from GCM g at T-year RP.

The variability across GCMs is reflected in the CFs. Here, an expected CF at each T-year RP (denoted as $CF_T$) is defined as a weighted sum over the CFs from the 20 GCMs (Equation [6]). The distance from the median raised to power $d$ is used as a weightage ($W_{TG}$) for GCM ‘g’ (Equation (7) as based on the inverse distance method (Caers, 2011). A constant value of unity is added to the denominator to avoid infinite values for the weights. Three different $d$ values of 0.5, 1 and 2 are tested and
found to have minor effect on expected change factor $CF_T$ as shown in Figure 4. Thus, $d$ is set to 1 hereafter. The $CF_T$s for three grid cells covering Ciliduk, Priuk, Halim and Depok stations are then averaged to yield a constant value over the region.

$$CF_T = \sum_{g=1}^{20} CF_{T,g} \times W_{T,g}$$  \hspace{1cm} (6)

$$W_{T,g} = \frac{1}{\sum_{g=1}^{20} \left( \frac{1}{|CF_{T,g} - \bar{CF}_{T,g}| + 1} \right)^T}$$  \hspace{1cm} (7)

where

$W_{T,g}$: weightage of GCM $g$ at RP $T$  
$CF_{T,g}$: median of $CF_{T,g}$ over GCMs at RP $T$

3.2 | Urban projections

Landsat Surface Reflectance Climate Data Record (Landsat CDR) (https://earthexplorer.usgs.gov/) is used in this study for land cover classification for Jakarta. Landsat 4–5 Thematic Mapper (TM) covering the period of 1989–2000 and 2004–2009 (data was unavailable for 2001–2003) and Landsat 8 Operational Land Imager (OLI) for later years of 2013, 2015 and 2017 are used. Note that the Landsat Enhanced Thematic Mapper (ETM) (2010–2012) data are not considered due to its short time span and incomplete coverage for the study region. Cloud free images are selected from each year for the analysis. Images for years 1989 and 2017 are shown in Figure 5 as illustration with green showing the urban area and red vegetation. It is readily seen that the urban area has grown steadily over 1989–2017 with the whole DKI (Daerah Khusus Ibukota or Special Capital Region) region being almost fully urbanised in 2017.

The interactive supervised classification tool from ArcGIS 10.0 is used to categorise five land cover classes comprising urban, bare land, water body and vegetation and with a further class of cloud. The Maximum Likelihood (ML) classification technique is employed, and the ArcGIS tool uses all seven available Landsat bands. The ML classification is a statistical approach for pattern recognition with the probabilities of a pixel falling into the land cover classes calculated and the pixel assigned to the class with the highest probability (Rawat & Kumar, 2015; Tso & Mather, 2009). The accuracy of classification depends on the quality of the training samples. Here each of the land-cover classes are trained with ~100 samples for each year.

The urban area is extracted from the classified layer annually over the period of 1989–2017. It is noted that the urban area is uniformly spread over the downstream...
Jakarta basin while the upstream areas are significantly less urbanised and show negligible growth in urbanisation. Thus, the urban extent is studied using three regions defined as upstream, midstream and DKI Jakarta as shown in Figure 1. The Ciliwung catchment south of the Katulampa ‘bottle neck’ is considered upstream, the DKI Jakarta region considered downstream, and area in between midstream. The percentage urban area is calculated for each year and for all three regions (Figure 6). There are expected fluctuations in the time series mainly due to data quality (as images are not completely cloud-free) and subjectivity in the classification process. Further the urban extent from Landsat 8 for the years 2013–2017 is scaled based on the Landsat 4–5 TM derived upstream average urban extent value of 0.64% and assuming a negligible change in this value over years 1989–2009. Such an adjustment is needed to account for difference in the classification outcome (i.e., increased urban area) due to the different bandwidth characteristics in the Landsat 8 OLI sensor. A similar difference between Landsat TM and OLI values is also reported in Poursanidis, Chrysoulakis, and Mitraka (2015).

Urban area fractions are next parameterized using the equation

\[
U_t = (89.9 - U_{1989}) \left(1 - e^{-\alpha(t-1989)}\right) + U_{1989} \tag{8}
\]

where \(U_t\) is the percentage urban area at year \(t\). The equation has a lower bound of \(U_{1989}\) (i.e., in year 1989) and an upper bound of 89.9%, this being the highest district-level urban extent percentage observed in year 2017 in the downstream DKI region. It is assumed that this value of 89.9% represents the saturation level for urban extent, and used as a priori upper bound in Equation (8) for future years, this being consistent with reported Jakarta city Planning projection (Budiyono et al., 2016). Different type of curves which can accommodate upper and lower bounds are tested and the exponential curve with an upper bound Equation (8) was chosen as the best fitting curve. Equation (8) is used to obtain future urban area projections of the midstream and downstream regions. The upstream region showing little or negligible changes in urban extent (maximum of 4.4% from Figure 6) is kept constant at current 2009 condition.

The hydrology model HEC-HMS requires the percentage impervious area in each of the sub-basin as an input. The percentage impervious area of the basin is assumed to follows the percentage urban area. Hence, the percentage impervious area over 2009 to 2050 is calculated using the linear relationship Equation (9) for the sub-basins falling in DKI Jakarta \([D]\) and midstream \([M]\) regions.

\[
U_t = (89.9 - U_{1989}) \left(1 - e^{-\alpha(t-1989)}\right) + U_{1989} \tag{8}
\]
\[ [I_i^{2050}]_{D,M} = [(U_i^{2050} - U_i^{2009}) + I_i^{2009}]_{D,M} \]  

(9)

where

\( I_i^{2050}, I_i^{2009} \): percentage impervious area in the year 2050, 2009

\( U_i^{2050}, U_i^{2009} \): percentage urban area in the year 2050, 2009

The hydrology and flood model for Jakarta central basin is then exercised for the 2050 urban conditions reflected as the revised percentage imperviousness. Figure 7 shows the loss values for daily rainfall with the range of 100–350 mm/day under the projected 2050 urban condition. Compared to the loss curves for current (year 2009) condition shown in Figure 2, the loss curves under future 2050 urbanisation conditions are higher and steeper resulting in higher loss for the same daily rainfall values. Overflow conditions also started to occur at all levee plans at smaller rainfall values.

4 | CRITERIA DEVELOPMENT AND MCDA FRAMEWORK

The variation in rainfall due to climate change is expected to influence loss modelling and flood protection decisions. We incorporated the impact of GCM variability within the MCDA decision framework by re-computing the criteria \( AEL, G \) and \( Net \ SEVI \) separately for RCP 4.5 and 8.5, and with the \( CF_T \) calculated in Section 3.1 applied to the observed station data to obtain future projected point rainfall projection. In this the \( T \)-year RP rainfall for the future time period is calculated by multiplying observed rainfall at each of the four rain gauge stations and assuming that temporal changes of the daily rainfall at the point and areal (grid) scales are the same.

Three separate cases are next considered comprising (i) future rainfall/current urban, (ii) current rainfall/future urban and (iii) future rainfall/urban conditions to analyse in the MCDA framework. The loss values for the case (i) (i.e., future rainfall/current urban conditions) are obtained from the curves shown in Figure 2 using the future rainfall values and with criteria \( AEL, G \) and \( Net \ SEVI \) calculated using the procedure described in Section 2.2. Note that the inner summation in Equation (1) for \( AEL \) is replaced by corresponding loss value for future expected rainfall. This is because the variability in future rainfall projections is already accounted in the form of expected CF. A similar approach is applied for recalculating \( G \) and \( Net \ SEVI \). Jakarta population projection from Hoornweg and Pope (2013) for the year 2050 is used in the criteria calculations as 2050 is the midyear of this study’s future time period 2031–2070. The \( Net \ SEVI \) under future conditions accounts for both urbanisation and population growth in the inundation area. While effects of projected social and economic variables as affecting urbanisation over decadal scales are lacking, such urbanisation as affecting flood vulnerability is captured via projected changes in river basin roughness. Note that the basin parameters other than population are kept at current condition (i.e., 2009 land cover) while analysing the Case 2 of future rainfall/current urban conditions.

The difference in \( AEL, G \) and \( Net \ SEVI \) criteria values between the future and current conditions as calculated for each levee plan is used as additional criteria in the MCDA. The difference in criteria logically represents degradation in \( AEL, G \) and \( Net \ SEVI \) and thus they

\[ \text{FIGURE 7} \quad \text{Flood loss values for daily rainfall with 2050 projected urban conditions} \]
are used as addition criteria to be minimised in the MCDA. The five criteria from the current condition \((AEL, G, C \text{ and } \text{Net SEVI})\) and four criteria as the difference between future and current criteria values \((\Delta AEL, \Delta G \text{ and } \Delta \text{Net SEVI})\) are used as the final nine criteria in MCDA.

Similarly, the MCDA criteria were re-computed for the two future urban condition cases using the updated loss curves (Figure 7). The seven levee plans were analysed with PROMETHEE-MCDA for the two future urban cases comprising firstly current rainfall/future (year 2050) urban extent, and future rainfall/future (year 2050) urban extent. The latter case comprising future rainfall and future urban extent represents the most severe case but reflects the future conditions closest.

5 | RESULTS AND DISCUSSION

5.1 | Impact of climate change

The CFs for the period from 1961–2000 to 2031–2070 were calculated for 20 GCMs in NEX-GDDP data as shown in Figure 8 for the \(CF_T\) computed using Equation (6) for RCP 4.5 and 8.5. Under RCP 4.5, CF is decreasing with increasing RP for the grid cells covering Halim, Ciliduk, and Depok, while it is flatter for the grid cell covering Priuk with the exception at longer RPs where it shows a slight increase. We next used the average of CFs from the three grid cells to project the observed rainfall values to the future period of 2031–2070. The resulting percentage increase in 50, 100 and 250-year RP rainfall are shown in Table 2. For example, the 100-year RP rainfall is expected to increase by 7.5 and 16.2% under RCP 4.5 and RCP 8.5, respectively. As a sensitivity test, instead of averaging the grid-based CF, we also obtained a single CF for the entire study region by pooling all data at the four stations using the station-year method. This sensitivity analysis showed that the percentage increases in projected daily rainfall are very close to those obtained using the average CFs (Table 2).

Daily rainfall values projected via average CFs under RCP 4.5 and 8.5 are compared against the current rainfall values for different RPs as plotted in Figure 9. The 250 mm/day rainfall which is ~400-years RP at current condition is projected to be at a reduced 100-years RP in year 2050 under the RCP 8.5 projection.

The criteria values under current and future rainfall are summarised in Table 3 where current urban extent is used. The increased flood severity due to climate change (RCP 4.5 and RCP 8.5 projections) is reflected via large increases in the \(AEL\). For example, \(AEL\) shows 177% and 275% increases for Plan 0 under RCP 4.5 and RCP 8.5, respectively (See Table 3). Similarly, large percentage changes in \(G\), and \(\text{Net SEVI}\) are seen due to climate change when compared to their original values. The projected increased population in the inundated area which also increased due to the increased overflow under future rainfall accounted for the drastically changed \(\text{Net SEVI}\) values. The \(\text{Net SEVI}_A\) shows 58and 96% increases under RCP 4.5 and RCP 8.5 respectively for Plan 0. \(\text{Net SEVI}_D\) shows 56 and 39% reduction which is due to the expected overflow to expected discharge ratio used (see Equation (4)), with this ratio being reduced for Plan 0 under future rainfall conditions. Conversely, this ratio increases for RCP 8.5 cases under Plans with higher protection levels, that is, Plans 5 (16% increase) and 6 (62% increase) (see Table 3).

As stated in Section 4, the difference in the criteria values \((\Delta AEL, \Delta G \text{ and } \Delta \text{Net SEVI})\) are used to analyse the future condition cases. The \(AEL\) and \(\text{Net SEVI}_A\) are increased and \(G\) and \(\text{Net SEVI}_D\) are decreased for this future condition (future rainfall/current urban condition) of Table 3. Note that all criteria are minimised except \(G\) in the MCDA-PROMETHEE as applied to the seven alternative levee plans with resulting outranking values shown in Table 4. Here higher net outranking index become the better alternative.
As seen, Plan 3 (Ciliwung/WBC up to 100-years & Cengkareng up to 50-years RP rainfall discharges) is the best option with rainfall under RCP 4.5 climate projection (Table 4). Plan 2 is the second best and Plan 0 is the worst option. The best plan moves even further towards higher protection levee under RCP 8.5, where Plan 4 is the best and Plan 3 second best. Plan 0 remains as the worst option. Under current rainfall condition Plan 2 is the best plan for higher protection levee with Plan 3 (Plan 4) being the best under RCP 4.5 (RCP 8.5).

That the best plans are moving to higher levee protection levels is due to the increased severity of flood as driven by the increased rainfall and which is observed from Table 3. The criteria $\Delta AEL$ and $\Delta G$ became dominant over the upgrade construction cost $C$ resulting in this shift of the best plan to higher protection levels. Plan 0, the current levee system is the worst option in this future condition as well as in the other two further conditions where the criteria $AEL$ is high compared to other plans. It is noted that the uncertainty as incorporated into the criteria values can be sensitive to the choice of the confidence interval used in the LP3 fits (i.e., the 99.7% confidence level used, see Section 2.2). This is tested using a 90% confidence interval and for the current condition case. The maximum percentage change over the individual criteria values while substantial at 51.4% has the resulting net outranking values being comparable with a maximum percentage change of 2.9% when compared to using the larger 99.7% confidence interval. This stability or reduced sensitivity to the confidence interval used is due to the net outranking values being calculated from the difference in the criterion value across the plans and normalised with preference function (normal distribution used here).

### 5.2 Impact of urbanisation

The 21 years of Landsat data during the period of 1989–2017 were used to classify the land cover classes of urban, bare land, vegetation and water body as described in Section 3.2. The urban areas for the midstream and DKI Jakarta (downstream) regions were parameterized using Equations (8) and (9) with final forms shown in Equations (10) and (11), and plotted in Figure 6. The projected percentage urban extent for the year 2030 (2050) for DKI Jakarta and midstream areas are 81.0% (86.8%) and 42.5% (54.3%), respectively. Budiyono et al. (2016) reported that the urban area extent in DKI Jakarta in 2009 was 82.4% and projected to reach to 84.9% in 2030, as based on Jakarta’s city planning. The Landsat based projections obtained here for DKI Jakarta are therefore comparable with Budiyono et al. (2016) with a projected value of 81.0% in 2030.
TABLE 3 Criteria values for seven alternative levee plans—effect of rainfall under current urban (2009) extent

| Levee systems | Current conditions | Future rainfall and current urban conditions | RCP 4.5 | RCP 8.5 |
|---------------|--------------------|---------------------------------------------|---------|---------|
|               | C (million US$)    | AEL (million US$) | G       | Net SEVI_A | Net SEVI_D | AEL (million US$) | G       | Net SEVI_A | Net SEVI_D | AEL (million US$) | G       | Net SEVI_A | Net SEVI_D |
| Plan 0        | 0.0000             | 14.5678          | 0.9383  | 0.0071      | 0.0561      | 40.2986          | 0.8301  | 0.0111      | 0.0249      | 54.5955          | 0.8101  | 0.0139      | 0.0344      |
| Plan 1        | 9.5091             | 3.2973           | 0.7268  | 0.0023      | 0.0133      | 9.8481           | 0.6085  | 0.0040      | 0.0060      | 18.3945          | 0.7106  | 0.0077      | 0.0110      |
| Plan 2        | 13.4272            | 2.9560           | 0.7175  | 0.0021      | 0.0103      | 9.0475           | 0.6085  | 0.0037      | 0.0046      | 16.8564          | 0.7010  | 0.0071      | 0.0083      |
| Plan 3        | 42.5927            | 2.6471           | 0.7061  | 0.0014      | 0.0093      | 8.0648           | 0.6085  | 0.0025      | 0.0041      | 14.9069          | 0.6828  | 0.0045      | 0.0075      |
| Plan 4        | 46.5108            | 1.4945           | 0.6167  | 0.0012      | 0.0066      | 4.5402           | 0.5049  | 0.0020      | 0.0028      | 9.6278           | 0.6364  | 0.0036      | 0.0061      |
| Plan 5        | 92.4034            | 0.5183           | 0.5908  | 0.0003      | 0.0018      | 1.7634           | 0.3972  | 0.0006      | 0.0008      | 4.0908           | 0.5057  | 0.0011      | 0.0021      |
| Plan 6        | 192.6381           | 0.3116           | 0.3843  | 0.0001      | 0.0008      | 1.0647           | 0.2479  | 0.0002      | 0.0003      | 3.0788           | 0.4238  | 0.0008      | 0.0013      |
| Standard deviation | 34.1184         | 0.1421          | 5.1600  | 0.0024      | 0.0199      | 8.9103           | 0.0069  | 0.0013      | 0.0111      | 12.7386          | 0.0513  | 0.0022      | 0.0084      |
The urban projections for the year 2050 were then used to update flood simulations. The criteria values are summarised in Table 5 for future urban extent with current and future rainfall combinations. The difference between future and current values in the criteria that is, $\Delta AEL$, $\Delta G$ and $\Delta Net SEVI$s are calculated as explained in Section 4. The large increase in the criteria values in Table 5 reflects the increase in flood severity due to urbanisation and climate change. Urbanisation (i.e., future urban/current rainfall) has stronger effect on the $AEL$ when compared to climate change alone (i.e., future rainfall/current urban) as seen from Table 3 and Table 5. For example, the $AEL$ for Plan 0 shows a 484% increase due to urbanisation alone compared to 275% due to climate change alone under RCP 8.5. The range of G values decreases for future urban conditions under both current and future rainfall (Table 5), that is, larger percentile loss to percentile discharge increase (Equation (2)). It is noted that the changes, that is, $\Delta AEL$, $\Delta G$ and $\Delta Net SEVI$s, rather than the individual values themselves are used as criteria which are equally weighted in the MCDA-PROMETHEE. Thus, the decision will be driven by the difference in the values across the levee plans for each criterion.

The outranking indices with the rank values for the seven plans are listed in Table 6. For the future urbanisation case only (i.e., current rainfall), Plan 2 is chosen to be the best alternative which is identical to the current condition case with socio-economics features reported in Daksiya, Su, et al. (2017). Plan 0 is the least preferred option which is similar to all the current and future cases discussed previously. Comparing Table 4 and Table 6, it is concluded that the impact of increasing rainfall due to climate change has a much greater effect on flood levee plan decision than increased urban/impervious land cover due to urbanisation. This is despite the larger effect of urbanisation on criteria values (e.g., $\Delta AEL$). In this it is noted that the decision-making framework PROMETHEE used here analyses the difference in criteria value amongst the plans (Daksiya, Su, et al., 2017). The urban growth in the midstream is much faster than in DKI Jakarta as the latter is reaching a saturation point. Since the major part of river Cengkareng is in the midstream region, the risk increases rapidly with urbanisation. Thus Plan 4 (protects Ciliwung up to 50-years rainfall) is prioritised over Plan 3 (Ciliwung up to 100-years rainfall) in the Cengkareng basin which is a part of the midstream region. A comparison between all three future condition cases (see Table 4 and Table 5) readily shows the climate change is the key driver pushing the best plan to higher protection levels due to the increased rainfall.

The extreme effect of both future climate (rainfall under RCP 4.5 and RCP 8.5) and urbanisation are clearly reflected in the large change in criteria values ($AEL$, $G$ and $Net SEVI$s) as listed in Table 6. In this extreme scenario of both changing climate and rapid urbanisation, the Plan 5 (protect up to 250-years RP rainfall in Cengkareng and Ciliwung) is selected as the best under both RCPs even though there are large difference in the criteria and outranking values amongst the scenarios. Plan 4 (protect up to 100-years RP in both rivers) and Plan 6 (protect up to 400-years in both rivers) are the second best under RCP 4.5 and RCP 8.5, respectively. Under RCP 8.5 the plan with higher protection level (Plan 6) is chosen as the second-best option than for the case RCP 4.5 due to the increased severity of flood. Plan 0 is the least preferred similar to all the current and future cases discussed earlier. As mentioned in the Section 5.2, Plan 2 is prioritised over Plan 3 due to the rapid urbanisation in the Cengkareng basin which is a part of the midstream region. A comparison between all three future condition cases (see Table 4 and Table 5) readily shows that the climate change is the key driver pushing the best plan to higher protection levels due to the increased rainfall.

It is noted that the current 250-years RP rainfall is shifted to ~60 and ~120-years RP under RCP 4.5 and 8.5,
### TABLE 5  Criteria values of criteria for eight alternative levee plans—effect of future (2050) urban extent

| Alternative levee plans | Current rainfall and future urban condition | Future rainfall and future urban condition |
|------------------------|--------------------------------------------|--------------------------------------------|
|                        | AEL (million US$) | G  | Net SEVI\(_A\) | Net SEVI\(_D\) | AEL (million US$) | G  | Net SEVI\(_A\) | Net SEVI\(_D\) | AEL (million US$) | G  | Net SEVI\(_A\) | Net SEVI\(_D\) |
| Plan 0                 | 85.0685          | 0.8507 | 0.0350          | 0.0448          | 129.0613          | 0.8791 | 0.0544          | 0.0686          | 154.5481          | 0.8259 | 0.0648          | 0.0828          |
| Plan 1                 | 26.7824          | 0.7290 | 0.0139          | 0.0146          | 49.2688           | 0.8056 | 0.0228          | 0.0231          | 66.5103           | 0.7714 | 0.0311          | 0.0334          |
| Plan 2                 | 20.7150          | 0.7343 | 0.0104          | 0.0110          | 33.5725           | 0.7390 | 0.0167          | 0.0171          | 52.1374           | 0.7867 | 0.0237          | 0.0262          |
| Plan 3                 | 22.1480          | 0.7343 | 0.0118          | 0.0117          | 41.3629           | 0.8047 | 0.0199          | 0.0175          | 57.9478           | 0.7974 | 0.0269          | 0.0275          |
| Plan 4                 | 14.4902          | 0.6418 | 0.0077          | 0.0072          | 26.4548           | 0.7307 | 0.0128          | 0.0132          | 40.3704           | 0.7508 | 0.0180          | 0.0194          |
| Plan 5                 | 5.1052           | 0.4909 | 0.0033          | 0.0025          | 11.1876           | 0.5996 | 0.0061          | 0.0048          | 21.1893           | 0.7360 | 0.0097          | 0.0088          |
| Plan 6                 | 3.1210           | 0.4461 | 0.0018          | 0.0013          | 6.1994            | 0.5174 | 0.0034          | 0.0027          | 12.5455           | 0.6268 | 0.0060          | 0.0058          |
respectively (Figure 9). Thus, the suggested levee protection Plan 5 with the protection level of 250-years RP under the future conditions is comparable (in terms of future RP) with the current condition best plans Plan 1 and 2.

### 6 CONCLUSIONS

This study analysed the influence of changing climate, urbanisation, and socio-economic features on the selection of levee options to mitigate the flood risk. The MCDA decision framework, developed by Daksiya, Su, et al. (2017) for analysing flood protection under current conditions is extended to include future climate and urbanisation conditions. The future rainfall projections were obtained using the temporal CF approach under RCP 4.5 and 8.5 emission scenarios while parametric forms of urban projections were derived using Landsat data over 1989 to 2017 and applied for year 2050. In addition, population projections for the year 2050 were used in the study. Three different cases were studied with the decision framework to assess the future conditions. The impact and cost of climate change and urbanisation analysed separately (Cases 1 and 2) and together (Case 3) provide knowledge on the severity of each future scenario and hence facilitates decision making by planners and policy makers. If required to better reflect local priorities, they can later adapt criteria weights in the MCDA decision framework.

Amongst the seven levee protection levels analysed, 50-and 100-years rainfall RP protection level is chosen to be the best protection level for Cengkareng and Ciliwung rivers, respectively under RCP 4.5 but at current urban conditions. Climate change strongly increases the severity of the flood as was reflected by the criteria, AEL, G and Net SEVI. The extreme climate change scenario RCP 8.5 under current urban conditions, have the flood protection levees be set for 100-year rainfall RP for both Ciliwung and Cengkareng rivers. For the scenario where the rainfall is unchanged and urbanisation is included, a lower protection level (50-year and 100-year RP for Ciliwung/WBC and Cengkareng, respectively) is ranked first by the framework compared to climate change only case. Including both climate change and urbanisation together shifted the best plan towards the higher protection level (250-years RP rainfall in both rivers). That changes in climate (rainfall) having a stronger impact compared to urbanisation alone is not unexpected for areas already highly urbanised such as Jakarta.

In terms of further improvements, the rainfall projection could be substituted with dynamically downscaled projection but will require more computational resources. Urbanisation models could further be used to better project the urban extent. The impacts and costs of major river maintenance and improvement works are not included in this study while assessing future changes. These result in changed flood hazard which can be recomputed and propagated in the MCDA framework. However, we noted that initiation of such major works is highly unpredictable as they are driven by political and budgetary considerations. The MDCA framework itself could be improved by adding more levee plan alternatives, or even replacing the MCDA-PROMETHEE decision framework with more recent evolutionary-based approaches that yield non-dominated optimal solutions, known as Pareto optimal solutions (Su, Cheung, & Lo, 2018). This approach treats the levee protection level as a continuously varying design variable to be optimised, rather than as the selection of a best plan amongst a fixed number of alternatives.

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CONFLICT OF INTEREST
The authors declare no potential conflict of interest.

DATA AVAILABILITY STATEMENT
1. Data derived from public domain resources The data that support the findings of this study are available in (repository name) at (URL/DOI), reference number (reference number). These data were derived from the following resources available in the public domain: (list resources and URLs) 2. Data available on request from the authors The data that support the findings of this study are available from the corresponding author upon reasonable request.

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