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Incorporating Socio-Economic Effects and Uncertain Rainfall in Flood Mitigation

Decision using MCDA

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Abstract

The decision making process in flood mitigation typically involves a number of factors reflecting flood severity, flood vulnerability and the cost of the mitigation measures, which implies that the decision framework needs to combine both social-economic parameters and flood extent prediction analysis. A socio-economic vulnerability index (*SEVI*) is developed here to represent social-economic factors and its use demonstrated within a Multi-Criteria Decision Analysis (MCDA) for assessing flood levee options for a central basin of Jakarta, Indonesia. The variables defining the *SEVI* are selected based on available national social-economic data reported for Indonesia with overlapping information removed using Pearson's correlation analysis. Two different methods are used to further scale the *SEVI* which is developed along administrative boundaries into a *Net SEVI* which is dependent on the predicted flood hazard as resulting from the levee plan options while capturing uncertainty in the rainfall forecasting. The MCDA technique adopted uses criteria of *Net SEVI*, annual expected loss, graduality and levee construction cost for analyzing six different levee plans and with uncertainty in the rainfall incorporated. The *Net SEVI* thus specifically reflects the social-economic impact on the flood affected population and this approach thereby provides a higher degree of granularity in the flood mitigation decision process. The MCDA decision framework developed is general in that the *Net SEVI* can be applied for consideration of other flood mitigation strategies. Here it is shown that the inclusion of the *Net SEVI* criteria changes the best choice levee plan decision to a higher protection level for the basin considered.

Key words: *SEVI*, Rainfall uncertainty, Graduality, Annual expected loss, MCDA

1. Introduction

Flood disasters can cause massive losses of human life and damage to infrastructures, and severely impact on the economic activities of the affected areas. Population trend predictions from the Intergovernmental Panel on Climate Change (IPCC) indicate that by the 2080s, up to 20% of the world's population will live in river flood prone areas (IPCC 2007). In 2010 the global population exposure to a 100-year river flood was estimated at 805 million, almost twice the 1970 level, and further predicted to increase by 31% in 2050 (Jongman et al. 2012). Changes in rainfall, increases in socio-economic activities, and variations in basin parameters due to urbanization are the main reasons for this trend. Traditionally various mitigation measures are implemented to reduce the flood risk. Channelization, levees, diversion of flood water and mitigation reservoirs are the most common structural mitigation measures (Thampapillai and Musgrave 1985; Vojinović and Abbott 2012). Land use planning, flood zoning, flood proofing and post-flood rehabilitation measures are various non-structural measures (Faisal et al. 1999; Vojinović and Abbott 2012). The prediction of flood impact (e.g. extent, depth, duration) when deciding on a particular flood mitigation scheme become more complicated due to uncertainty in the parameters and response of a hydrosystem. For example, decision on detention tanks as flood mitigation measures are analyzed with multi objective optimization with associated uncertainties in rainfall intensity, catchment permeability, economic factors and capacity of existing storage incorporated (Duan et al. 2016; Li et al. 2015). Studies were reported on the effect of uncertainty in the rainfall magnitude and its patterns (e.g. (Maskey et al. 2004; Overeem et al. 2008) and further extended to include climate change (Chen et al. 2011; Prudhomme et al. 2003). Uncertainty in the forecasted rainfall is one of the biggest sources of uncertainty in streamflow forecasting (Apel et al. 2008; Ma et al. 2016).

The social and economic dimensions of vulnerability are also key factors that need to be considered in the flood risk management and mitigation decisions. These depend on the socio-economic condition of the basin/catchment. The social dimension of vulnerability typically uses measures of poverty, social exclusion, demography, education, health and well-being, while the economic dimension uses the gross domestic product, income-level and unemployment (Birkmann 2013). The social and economic measures of vulnerability cannot be clearly separated as above in all cases. The challenge is to quantify these as based on available data, and to include them in forecasts of flood risk. For example, a Prevalent Vulnerability Index (PVI) was developed by Cardona

(2006) which measures and compares the vulnerability across South and Central American countries at the country level. The PVI quantitatively ranks the vulnerability using three separated components of exposure in flood prone areas (i.e. the direct impact of the flood on population and infrastructures), socio-economic fragility (indirect or intangible impacts) and lack of resilience (indicated by lower levels of social and economic wealth which provide resistance). An earlier work by Connor and Hiroki (2005) formulated a Flood Vulnerability Index (FVI) by summarizing the main influencing factors under four components of meteorological, hydrological, socio-economics and countermeasures. The FVI was tested over different spatial extents of river basin, sub-catchment and urban areas (densely populated areas) with social, economic, environmental, and physical components being linked with the vulnerability factors of exposure, susceptibility and resilience (Balica et al. 2009). In both the PVI and FVI indices, variables used in each of their respective components are very extensive for which data may not be available. The variables and data needed for the FVI also depended on the spatial extent considered and have duplicating effects which Balica and Wright (2010) reduced by correlations analysis. Birkmann (2007) also noted that the country-scale PVI contains a large number of variables which needed a review for their applicability when applied to sub-national scales. Furthermore the social and economic dimensions of vulnerability are qualitative assessments with engineering aspects not reflected in the indices used. As such they are developed to compare across study areas, and not applicable for coupling with engineering decision frameworks in assessing flood mitigation schemes for a specific affected area.

In the work reported here, we developed a vulnerability index termed as the Socio-Economic Vulnerability Index (*SEVI*) that characterizes the socio-economic aspects and vulnerability of a specific catchment, and demonstrate its application for a central basin in Jakarta, Indonesia. Two different methods are developed to further translate the *SEVI* which is developed along administrative boundaries using reported socio-economic data reported for Jakarta into a *Net SEVI* that is dependent on the predicted flood hazard. This is needed as the hazard is dependent on the differing engineering mitigation, specifically levee plan options considered. We show how the *Net SEVI* is further implemented within a flood mitigation decision framework that also incorporates the effect of rainfall uncertainty for differentiation across the different levee protection plans. In this the *SEVI* is coupled with the flood hazard level within a Multi-Criteria Decision Analysis (MCDA) framework to decide on the best levee

plan. In contrast to the earlier reported social and economic vulnerability indicators (e.g. PVI and FVI) which are developed to compare across different study areas and independent of hazard severity, the *Net SEVI* explicitly reflects the impact on the flood-affected area and population as dependent on the levee plan, thus providing a much higher degree of granularity in the flood mitigation decision making process.

The specific basin in Jakarta, Indonesia, is chosen for the development of the *SEVI* as Jakarta is a highly flood prone city with population of 10 million people as of 2015 (BPS 2005-2015(a)). The Jakarta flood model as developed by Lo and Chen (2013) is adopted here and summarized in Section 2. Section 3 describes the formulation of the *SEVI* while Section 4 describes the use of the *Net SEVI* as one of the criteria in the MCDA framework along with other criteria including levee construction costs, annual expected direct flood losses and graduality. Results and discussion and the effect of the *Net SEVI* on the MCDA decision process are presented in Section 5.

2. Jakarta flood model

Jakarta, the capital of Indonesia, is located on the Java Island (Fig 1) being its northern coast. The capital region, also known as the Jakarta DKI region, experiences frequent flooding due to overflow from its two main rivers, the Ciliwung and Cengkareng Rivers. As also shown in Fig 1(a) the study area termed as ‘central basin’ adopted here includes large commercial areas in Jakarta as bounded by the Ciliwung River with its lower reach of the West Banjir Canal (WBC) to the east and Cengkareng River to the west. This central basin covers an area of 190 km². The flood model was adapted from Daksiya et al. (2015) as developed in Lo and Chen (2013). For this study, rainfall data from the three closely located gauge stations Ciliduk, Halim and Priuk with locations shown in Fig 1(a)) over 1984-2006 (i.e. 23 years) were combined together using the station year method to produce a longer record with the implicit assumption of spatial homogeneity. The combined annual maximum rainfall data was fitted with the Log Pearson type III (LPIII) with the goodness of fit tested statistically with Kolmogorov–Smirnov and probability plot correlation coefficient tests. For the hydrological modelling, this point rainfall was uniformly distributed over the entire basin with an Area Reduction Factor (ARF) of 0.75 and temporally over 24-hours using Soil Conservation Service (SCS) Type 1A distribution. Here the ARF is calculated following prior studies done for Jakarta (Boerema 1925; Partner_For_Waters 2007). The hydrology and hydraulics calculations were performed

using the Hydrologic Engineering Centre (HEC) Hydrologic Modelling System (HMS) and River Analysis System (RAS) codes. The one dimensional HEC-RAS calculations procedure were further modified to first determine the overflow from the overtopped main rivers into the central plain using a weir formula applied along the river banks. The overflow together with flow from the local rainfall was then re-used in a subsequent HEC-RAS run for the flood plain analysis. Arc-GIS was finally used in inundation mapping and the loss calculated with a loss model developed by Lo and Chen (2013). This Jakarta flood model was earlier calibrated for Jakarta's Feb 2007 and Feb 2002 historical flood events and using recorded rainfall for those events. The comparison between the observed and the simulated stage levels at three different locations Katulampa, Depok and Manggarai (refer Fig 1(a)) along the river Ciliwung are shown in the Fig 2 for the Feb 2002 and Feb 2007 historical flood. It is noted that these calibrations used more extensive rainfall data over the catchment but the data was limited to the duration of the flood events. However the flood model once calibrated is applicable for calculating the annual expected loss together with the longer duration rainfall data as derived here. In addition the HEC-RAS modelled inundation extent is driven by the peak discharge values and thus is dependent on the accuracy in the peak discharge and stage predictions. The percentage differences between the calibrated and observed peak stage at Katulampa, Depok and Manggarai for the 2007 (2002) event are 0.6 (3.0), 5.4 (1.3) and 5.3 (7.1) % respectively. The corresponding percentage differences in peak discharges are 1.4 (7.5), 9.8 (2.4), 21.4 (16.4) %.

For the current study on the central plain, plots of the total overflow from the rivers, increase in inundation area arising from the overflow and resulting loss as a function of annual maximum daily rainfall are generated for six levee systems (Table 1) and shown in Fig 3. The range of annual maximum daily rainfall of 100-275mm/day corresponds to a rainfall return period range of 2-1000 years. The levee plans indicated, which represent alternative flood mitigation options, were set to safely convey discharge as driven by rainfall amount corresponding to various return periods.

Table 1 Levee Plans

Alternatives	Description
Plan 0	Current level (do nothing)
Plan 1	Protect up to 50yrs Return Period (RP) rainfall (Cengkareng and Ciliwung with WBC)
Plan 2	Protect Ciliwung with WBC up to 50yrs RP rainfall & Cengkareng up to 100yrs RP rainfall
Plan 3	Protect Ciliwung with WBC up to 100yrs rainfall & Cengkareng up to 50yrs RP rainfall
Plan 4	Protect up to 100yrs RP rainfall (Cengkareng and Ciliwung with WBC)
Plan 5	Protect up to 250yrs RP rainfall (Cengkareng and Ciliwung with WBC)

(a) River catchment and rain gauge locations

(b) Java Island, Indonesia

Figure 1 Studied central river-basin within the larger Jakarta catchment area

(a) Katulampa

(b) Depok

(c) Manggarai

Figure 2 Feb 2002 and Feb 2007 historical flood event calibration for Ciliwung: Comparison of simulated stage level with the observed stage level at three gauging stations. Here the simulated discharges from HEC-HMS are converted to stage level using stage-discharge formulas.

(a) Overflow vs daily rainfall

(b) Inundated area vs daily rainfall

(c) Loss vs daily rainfall

Figure 3 Flood model results of overflow, inundated area and loss plotted against annual maximum daily rainfall for the studied central basin of Jakarta

3. Development of Socio-economic Vulnerability Index (*SEVI*)

An index to represent the socio-economic factors of a hydrosystem necessarily requires local knowledge and data, e.g. social and economic data covering population parameters, gross regional domestic product and developmental status, and as well as the flood affected population, which depends on the flood extend. The data used to define the index are thus location dependent as well as dependent on the flood mitigation measure being considered.

Socio-economic data for Jakarta were available from the *Jakarta in Figures* annual reports for years 2005-2014 (BPS 2005-2015(a)) and the *Statistical Yearbook of Indonesia* 2015 (BPS 2015(b)). Fifteen data items representing population, development status and economic activities of Jakarta covering years 2005-2014, as relevant for assessing flood vulnerability were collected. Seven of the variables are at district level (North, South, East, West, Central Jakarta and Thousand Islands) and comprise the population density, population growth, % population young (< 5 years), poor population, number of beds per 1000 people, literacy rate and % unemployment. The remaining eight are available at provincial level (Jakarta province) and comprise imports and exports, gross regional domestic product, Gini Index, Human Development Index, child mortality, number of industries, % of monthly expenditure for insurance and taxes, and amount of investment. These data items are typically used in the literature to reflect the socio-economic dimension (e.g. Balica and Wright 2010; Cardona 2006). The central basin being studied here spanned parts of North, South, East, West and Central Jakarta.

The data items were analyzed to avoid duplication effects by consideration of the information content while under the constraint of data availability. The data were also separated into social and economic components in order to reflect each component independently. The selected social component has six variables and comprise the population density (P_D), population growth (P_G), % population young (< 5 years) (Y), poor population (P_P), number of beds per 1000 people (B) and literacy rate (L). The selected economic component has four variables and comprise the per capita GDRP (G_P), unemployment (U), local and foreign investment (I_v) and % of monthly expenditure for insurance and taxes (I_n). The social component includes population measures of density and growth rate as they represent the concentration of people under present and future conditions. It also includes the % of population young (< 5 years old) and the literacy rate as these reflect the ability to respond during an emergency situation. The number of beds represents the hospitalization capacity of the area which indirectly reflects the preparedness to recover. The vulnerability is directly proportional to the first four variables and is inversely proportional to the last two. As for the economic component, the first three variables represent the wealth of the area with vulnerability directly proportional to them, and the last reflects the preparedness with vulnerability being indirectly proportional.

The Pearson correlation test was further conducted to quantitatively assess the duplication effects amongst

the selected variables with results shown in Table 2. The correlation coefficient is calculated using Eq 1 with $|r|$ values closer to 1 reflecting strong linear dependence of the variables x and y being tested.

$$r = \frac{\sum_{n=1}^N (x_n - \bar{x})(y_n - \bar{y})}{(N-1)s_x s_y}, \quad (-1 \leq r \leq 1) \dots\dots\dots \text{Eq 1}$$

Table 2 Correlation between variables

Social Variables	P_D	P_G	Y	P_P	B	L	Economic Variables	G_P	U	I_v	I_n
P_D							G_P				
P_G	0.096						U	-0.461			
Y	0.877	-0.320					I_v	0.382	-0.649		
P_P	-0.157	-0.140	-0.009				I_n	-0.169	0.119	0.098	
B	0.815	-0.381	0.847	-0.090							
L	0.139	0.416	-0.190	-0.774	-0.013						

A cut-off value of 0.7 (following Balica and Wright 2010) was used to remove correlated variables. Amongst the social variables, the number of beds per 1000 people B , % population young (age < 5 years) Y and population density P_D were significantly correlated with each other, since the planning of hospitals are strongly driven by population measures such as density P_D and the % population young (< 5 years) Y . The literacy rate L is, as expected correlated with poor population P_P since low educational levels are associated with low economic status. The final list of social variables is thus reduced from six to three by keeping only the population density P_D , population growth P_G and literacy rate L . The number of economic variables remains unchanged at four. The data are summarized in Table 3 for year 2014 at district level (if available) and otherwise at Jakarta provincial level where the values are further normalized spatially by the number of districts (as available) and temporally over 2005-2014 using Eq 2. In the equation variables with vulnerability being directly proportional [D] and indirectly proportional [ID] are normalized separately in order to get positive normalized values.

$$I_{m,n[D]}^t = \frac{x_{m,n}^t - x_{nmin}}{x_{nrank}} \text{ and } I_{m,n[ID]}^t = \frac{x_{nmax} - x_{m,n}^t}{x_{nrank}} \dots\dots\dots \text{Eq 2}$$

where:

$x_{m,n}^t$ – raw data for variable n and district m in year t

$I_{m,n}^t$ – normalized values of variable n and district m in year t

$x_{n_{rank}} = x_{n_{max}} - x_{n_{min}}$

$x_{n_{max}} = \max(x_{m,n}^t)$; $x_{n_{min}} = \min(x_{m,n}^t)$ – Maximum / minimum over districts and years (m number of districts and t number of years) for variable n

Table 3 Normalized socio-economic variables and resulting *SEVI* for the year of 2014

District/ Province	Social variables			Economic variables				$SEVI_m$
	P_D	P_G	L	G_P	U	I_v	I_n	
North	0.213	0.402	0.341	1.000	0.132	0.351	0.660	0.854
South	0.603	0.400	0.320	1.000	0.000	0.351	0.660	0.944
East	0.566	0.397	0.346	1.000	0.091	0.351	0.660	0.962
West	0.983	0.416	0.333	1.000	0.163	0.351	0.660	1.121
Central	1.000	0.373	0.317	1.000	0.038	0.351	0.660	1.075
Jakarta	1.000	0.384	0.393	1.000	0.534	0.351	0.660	1.228

The social economic dimensions of vulnerability are combined as one criterion for the later MCDA analysis. For this, a *SEVI* was first calculated as the weighted sum of normalized social (S) and economic (E) variables from Table 3 separately using Eq 3 for each of districts contributing to the central basin of Jakarta as well as for the Jakarta as a whole, and then added via Eq 4. The values for $SEVI_m$ shown in Table 3 assumed equal weighting. Values from Year 2014 are used as they are most representative of the current status.

$$SEVI_{m(S,E)} = \frac{\sum_{n=1}^N I_{m,n} \times w_n}{\sum_{n=1}^N w_n} \dots\dots\dots \text{Eq 3}$$

$$SEVI_m = SEVI_{m(S)} + SEVI_{m(E)} \dots\dots\dots \text{Eq 4}$$

where

$SEVI_m$ – Socio-Economic Vulnerability Index for m^{th} district

$I_{m,n}$ – normalized value of n^{th} variable and m^{th} district

w_n – weightage for n^{th} variable

The effect of unequal weightage is also assessed. The magnitude gradient provides a ready indication of the significance of each variable and is, therefore used as an indication of its weight as applied by Balica and Wright (2010) when minimizing the number of variables in their FVI. The social dimension of vulnerability (V_S) being proportional to P_D and P_G and inversely proportional to L is expressed in Eq 5 with vulnerability increasing with P_D and P_G while decreasing with literacy L . Similarly the economic dimension of vulnerability (V_E) is proportional to G_P , U and I_v and inversely proportional to I_n . The gradient ∇V shown in Eq 6 is the derivative of the vulnerability functions. This was calculated, then normalized and averaged over years 2005 – 2014 with results shown in Table 4. As shown the resulting values have almost equal magnitudes indicating that each of the 7 social economic variables has approximate equal importance in defining the *SEVI*. Thus equal weights are mainly used for the subsequent analysis.

$$V_S = \left[\frac{P_D \times P_G}{L} \right] \text{ and } V_E = \left[\frac{G_P \times U \times I_v}{I_n} \right] \dots\dots\dots \text{Eq 5}$$

$$\nabla V_S = \begin{bmatrix} \frac{P_G}{L} \\ \frac{P_D}{L} \\ -\frac{P_D \times P_G}{L^2} \end{bmatrix} \text{ and } \nabla V_E = \begin{bmatrix} \frac{U \times I_v}{I_n} \\ \frac{G_P \times I_v}{I_n} \\ \frac{G_P \times U}{I_n} \\ -\frac{G_P \times U \times I_v}{I_n^2} \end{bmatrix} \dots\dots\dots \text{Eq 6}$$

Table 4 Weights (w_n) derived from gradient vector

Variables	Social variables			Economic variables			
	P_D	P_G	L	G_P	U	I_v	I_n
Weights	0.334	0.333	0.333	0.228	0.258	0.255	0.259

4. Compiling *SEVI* with engineering framework within MCDA

Multi criteria decision analysis (MCDA) is one of the most common and widely applied techniques in complex decision making problems. It is applicable when there is more than one conflicting criteria and multiple solutions. The Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE) is a straightforward outranking MCDA approach which adopts a transparent computational procedure to analyze a finite set of alternatives among conflicting criteria (Georgopoulou et al. 1998). It further allows the best alternative solution to

be chosen based on a net outrank value.

This framework developed by Daksiya et al. (2015) for the central basin of Jakarta (Fig 1) with six alternative levee plans (Table 1) is used here. The criteria there were the annual expected loss, graduality, and cost of construction with the first two reflecting the flood severity with the uncertainty in the rainfall estimate incorporated, and the latter reflecting the construction cost of the levee plans. The rainfall uncertainty was set as the confidence interval in the rainfall frequency analysis as fitted using the LPIII probability distribution of annual maximum daily rainfall. This uncertainty was further assumed to be normally distributed as shown in Fig 4 and set using the 99.7% confidence interval (average of upper and lower confidence limit) which corresponded to three times the standard deviation. This uncertainty of forecasted rainfall is propagated into uncertainty in the river discharge, overflow from the levees and the economic loss in the central basin using the curve fits shown in Fig 3.

Figure 4 The Log Pearson type III probability distribution fit and its 99.7% confidence interval for annual maximum daily rainfall for the combined station data (Ciliduk, Halim and Priuk) over years 1984-2006.

Uncertainty in the daily rainfall is assumed to be normally distributed.

The annual expected loss E_L is defined as the loss value expected in each year and is obtained by integration of the loss at each return period rainfall (E_{L_T}) multiplied by the probability of the return period rainfall as given by the LPIII pdf distribution. However the loss at each return period rainfall E_{L_T} has uncertainty as arising from uncertainty in the rainfall estimate/forecasting. E_{L_T} is thus expressed as the integration of the product of the random loss L_{i_T} and its probability density $f_T(L_{i_T})$. The latter which while unknown can be replaced by the known

probability of occurrence $f_T(R_{i_T})$ of an uncertain rainfall value R_{i_T} via the normal distribution (Fig. 4) and its loss L_{i_T} . The annual expected loss E_L is then computed with summation replacing integration as.

$$E_L = \sum_{j=0}^m \left(\sum_{i=0}^n L_{i_T} \cdot f_T(R_{i_T}) \cdot \Delta R_T \right) f(R_j) \cdot \Delta R \quad \text{Eq 7}$$

$$i = 1, 2, 3 \dots n, j = 1, 2, 3 \dots m$$

where

E_L – annual expected loss

L_{i_T} – i^{th} loss value with a pdf $f_T(L_{i_T})$ at return period T

$f_T(R_{i_T})$ – pdf (normal distribution) of the uncertain return period rainfall R_{i_T} at each return period T

$f(R_j)$ – pdf of return period rainfall representing natural randomness modelled by LPIII distribution

The graduality G indicates the progressiveness of flood loss as defined in De Bruijn (2005). Graduality uses the progressiveness or the increase in loss with increasing discharge and large increases in loss which correspond to small G values are not preferred. Here G is computed following De Bruijn (2005) by using the difference between the relative increase in discharge (expressed in percentile terms) and the resulting relative increase in the loss (similarly expressed in percentile), and with the values summed (see Eq 8). As defined the graduality physically represents the deviation from a linear relation between percentile discharge and percentile loss value with $G \approx 1$ for small deviation from linear and which is preferred. The maximum difference between the percentile discharge and percentile loss value is around 200 for the case here. Thus the summation is divided by 200 for normalization to have G values between 0 – 1. The loss values are also replaced with the expected loss to account the rainfall uncertainty and the graduality was calculated for all six levee plans for use as a criteria in the MCDA framework. The maximum and minimum loss and discharge are kept to be consistent with the 2 and 1000 years return period rainfall respectively. The difference between the loss percentiles $E_L'_{j-1}$ are calculated using Eq 8 and with a similar procedure for the discharge.

$$G = 1 - \frac{\sum_{j=0}^m \left| \Delta Q'_j - \Delta E_{Loss}'_j \right|}{200} \quad j = 1, 2, 3 \dots m.$$

$$\Delta E_L'_{j-1} = E_L'_{j-1} - E_L'_{j-2}$$

$$= \left[\frac{100(E_{Lj} - E_{Lmin})}{(E_{Lmax} - E_{Lmin})} \right] - \left[\frac{100(E_{Lj-1} - E_{Lmin})}{(E_{Lmax} - E_{Lmin})} \right] \quad \text{Eq 8}$$

where $E_{L_{min}}$, $E_{L_{max}}$ are the loss at 2 and 1000 years of rainfall return period

In the above the severity of the flood and the uncertainty in the forecasted rainfall are reflected in the calculated annual expected loss and graduality values which represents two criteria for MCDA analysis. The levee construction cost of each of the alternative levee plans is used as the 3rd criteria and calculated using the cost estimate for levee construction from Cho et al. (2007) based on their study for Orleans, France (see Fig 5). The *SEVI* from Section 3 is added as the fourth criteria to incorporate the socio-economic aspects in the decision framework.

Figure 5 Construction cost of levee per foot from Orleans, France, source: Cho et al. (2007)

It is noted that the *SEVI* as developed in Section 3 is independent of alternative levee plans since the socio-economic factors are related to non-structural features. Hence a further *Net SEVI* as based on the flood affected population and thus the levee plans are developed, and in which uncertainty in forecasted rainfall is included. Two different methods were studied for the development of *Net SEVI*.

Method 1

The first method uses the ratio of population in the inundated area to the total study area, i.e. an inundated area ratio to weigh the six levee plans to arrive at a *Net SEVI*. However it was found that for this central basin, the downstream part of the flood plain close to the sea was fully inundated for almost all rainfall events. As such the severity of flood thus could not be represented by the inundated area alone and the inundation depth should also

be considered. This depth effect is incorporated as the ratio of expected overflow rate from the rivers to the central basin (Fig 3b) to the expected discharge at the river mouth. Here the expected values of overflow and discharge are used to reflect the uncertainty in rainfall forecasting.

The approach of using the inundation area ratio alone is shown in Eq 9 where the summation of $SEVI_m$ over the district level is performed as weighted with the inundation area ratio for the six different levee plans to arrive at the $Net SEVI_{A_i}$ for levee plan i . The approach incorporating the depth effect for all levee plans is reflected by Eq 10. Here it is noted that the expected overflow and the expected discharge are not district distinct therefore the $SEVI$ for whole Jakarta ($SEVI_J$) is used. Both were thus used together as independent criteria in the MCDA analysis to assess the effect on the outcome.

$$Net SEVI_{A_i} = \sum_{m=1}^5 \frac{Population\ in\ expected\ inundated\ area_{i,m}}{Total\ Population_m} \times SEVI_m \dots\dots\dots Eq\ 9$$

$$Net SEVI_{D_i} = \frac{Expected\ over\ flow\ to\ the\ central\ basin_i}{Expected\ discharge\ at\ the\ mouth} \times SEVI_J \dots\dots\dots Eq\ 10$$

$SEVI_m$ – $SEVI$ for district m

$SEVI_J$ – $SEVI$ for whole Jakarta

$Net SEVI_{A_i}$ – $net SEVI$ based on area ratio for plan i

$Net SEVI_{D_i}$ – $net SEVI$ based incorporating depth for plan i

Method 2

The uncertainty in the forecasted rainfall does not directly impact on all the variables used to define the $SEVI$. Therefore in Method 2, only the social and economic variables directly impacted were modified. Specifically variables P_D , L and U were replaced by actual population, literate population and unemployed population values by multiplication with the expected inundation area as was done for the expected loss shown in Eq 7. The remaining variables which were not directly affected by flood inundation as per their definition were kept unchanged. All these variables were then normalized temporally and spatially as before (refer to Eq 2) and over all alternative plans. The $SEVI_m$ shown in Table 3 was re-calculated with Eq 3 and 4 for all the districts m and plans i as $SEVI_{m_i}$, and the $Net SEVI_i$ was obtained from Eq 11 as the summation of $SEVI_{m_i}$ over the districts for each plan i separately.

$$Net SEVI_i = \sum_{m=1}^5 SEVI_{m,i} \dots\dots\dots Eq 11$$

Methods 1 and 2 above were used as alternate forms of the socio-economic criterion along with the criteria of expected loss, graduality and construction cost. The performance values of criteria are given in the Table 5. In the Table, the standard deviations of the performance values are also listed and are later used in the MCDA analysis, specifically in the preference function.

Table 5 Performance values of alternative levee systems

Alternative solutions	Annual expected Loss (Mill US \$)	Graduality	Construction cost (Mill US \$)	Method 1		Method 2
				$Net SEVI_A$	$Net SEVI_D$	$Net SEVI$
Plan 0	14.5678	0.9383	0.0000	0.0071	0.0561	5.7384
Plan 1	3.2973	0.7268	9.5091	0.0023	0.0133	4.5251
Plan 2	2.9560	0.7175	13.4272	0.0021	0.0103	4.4730
Plan 3	2.6471	0.7061	42.5927	0.0014	0.0093	4.3317
Plan 4	1.4945	0.6167	46.5108	0.0012	0.0066	4.2758
Plan 5	0.5183	0.5098	92.4034	0.0003	0.0018	4.0770
Standard deviation	5.1600	0.1421	34.1184	0.0024	0.0199	0.5938

The PROMETHEE MCDA technique is applied here to analyze and rank the six different levee plans. The difference d_k between the performance value $x_{i,k}$ and $x_{j,k}$ (Eq 12) with performance values in Table 5 is used in the preference function $F_{k(P_i, P_j)}$ between alternatives P_i and P_j for criteria k (Eq 13). A common preference function of the Gaussian is adopted for all the criteria (Su and Tung 2014) with inflection points defined by the standard deviation of performance values as given in the Table 5. In this case the annual expected loss, construction cost and socio-economic indicator $Net SEVI$ were minimized while the graduality was maximized.

$$d_{k(P_i, P_j)} = x_{i,k} - x_{j,k} \dots\dots\dots Eq 12$$

$$F_{k(P_i, P_j)} = f(d_{k(P_i, P_j)}) \dots\dots\dots Eq 13$$

The preference index $\pi [P_i, P_j]$ (Eq 14) is the weighted average of preference functions over all criteria k .

Here equal weights are used. The positive outranking flows $\pi^+[P_i]$ as defined indicates how much plan P_i is preferred over others while the negative outranking flows $\pi^-[P_i]$ indicates how much all other plans are preferred P_i . A final outranking index $\pi [P_i]$ which is the summation of positive and negative outranking values (Eq 15) is used to rank the levee plans for a final decision.

$$\pi [P_i, P_j] = \frac{\sum_{k=1}^K w_k F_k(P_i, P_j)}{\sum_{k=1}^K w_k} \dots\dots\dots \text{Eq 14}$$

$$\pi^+[P_i] = \frac{\sum_{j=1}^N \pi [P_i, P_j]}{N-1} ; \quad \pi^-[P_i] = \frac{\sum_{j=1}^N \pi [P_j, P_i]}{N-1}$$

$$\pi [P_i] = \pi^+[P_i] - \pi^-[P_i] \dots\dots\dots \text{Eq 15}$$

where N represents the number of alternatives.

5. Results and discussion

The six alternative levee plans for flood mitigation in the central basin are ranked with the net outranking value in the PROMETHEE MCDA technique described above with results shown in Table 6. The criteria comprising annual expected loss, graduality and construction cost of levee systems were tested with the *Net SEVI* criterion/ criteria from Methods 1 and 2 separately. Plan 2 (i.e. protect Ciliwung/WBC up to 50years and Cengkareng up to 100years RP rainfall discharges) is the best option with Method 1 where the socio-economic criteria has inundation area effects ($Net SEVI_A$) and depth effects ($Net SEVI_D$). Plan 1 is the second best while Plans 0 and 5 were the worst two among the alternatives. Method 2 where *Net SEVI* was used resulted in Plan 1 switching with Plan 2 among the best two Plans, and Plans 0 and 5 remaining as the worst two.

This ranking of the plans is qualitatively explained as follows. The construction cost criterion, and severity and exposure criteria (annual expected loss, graduality, *Net SEVIs*) are comparatively higher compared with rest for Plans 5 and 0 respectively. This resulted in Plans 5 and 0 being the worst two plans in both Methods. The construction cost for a given protection level in Ciliwung is higher than in Cengkareng due to its longer reach. Moving from Plan 1 (50yrs RP rainfall protection for both Ciliwung and Cengkareng) to Plan 3 (100yrs RP rainfall protection for Ciliwung and 50yrs for Cengkareng) has a higher construction cost than moving to Plan 2 (50yrs RP rainfall protection for Ciliwung and 100yrs for Cengkareng). Conversely the reduction in severity and exposure

criteria (annual expected loss, graduality, *Net SEVIs*) for Ciliwung are more significant than Cengkareng for a specific protection level, e.g. larger loss reduction results when moving from Plan 1 to Plan 3 than to Plan 2 (Refer Table 5). Overall River Ciliwung thus has more significant impact on the ranking than Cengkareng. For Ciliwung, the construction cost increment is larger than reduction in severity and exposure criteria (annual expected loss, graduality, *Net SEVIs*). This resulted in Plans 1 and 2 (Ciliwung with 50yrs RP rainfall protection level) to be ranked in the top and Plans 3 and 4 (Ciliwung with 100yrs RP rainfall protection level) to be the middle ranked plans.

Method 2 has uncertainty in rainfall reflected directly in the social variables P_D , L and U but expressed in actual population values via multiplication with the inundated area with uncertainty in rainfall incorporated. The PROMETHEE results are hence expected to be similar with Method 1 but where only *Net SEVI_A* (area effect) is used as socio-economic criteria; this being indicated as Method 1a in Table 6. Note Method 1a has the uncertainty in the rainfall incorporated in all the socio-economic parameters via the inundated area ratio in contrast to Method 2. The best four plans are unchanged between Methods 2 and 1a where the area effect is captured via both methods and only the worst plans are interchanged in ranking. A further comparison between Methods 1 and 1a (Table 6) has only the best two plans switched in ranking. Compared to Method 1a, the higher protection level Plan 2 was ranked first in Method 1 where the socio-economic criteria are captured with both inundation area and depth effect. Thus the inundation depth effect plays an equal role as the inundation area in deciding on the best plan.

Table 6 Net outranking index and rank values

Alternative Levee Plans	Method 1		Method 2		Method 1a	
	Net Outranking Index	Rank value	Net Outranking Index	Rank value	Net Outranking Index	Rank value
Plan 0	-0.310	6	-0.154	5	-0.166	6
Plan 1	0.152	2	0.161	1	0.158	1
Plan 2	0.154	1	0.155	2	0.154	2
Plan 3	0.085	3	0.062	3	0.074	3
Plan 4	0.039	4	-0.003	4	0.001	4
Plan 5	-0.120	5	-0.221	6	-0.221	5

The weights calculated in Table 4 were next applied in calculating *SEVI* variables (see Eq 3) to assess the

effect of unequal weighting. Method 1 was used for the *Net SEVI* in re-computing the performance values in the PROMETHEE outranking analysis. While the performance values from using equal and unequal weights as expected differ, the difference in the criteria performance values (see Eq. 13) between plans are comparable resulting in the final ranking being unchanged across the plans.

The developed PRMETHEE, MCDA framework is further used to assess the importance of the socio-economic criteria relative to the other criteria by adjustments of the criteria weights (w_k in Eq 15). Three different cases were compared in Table 7, where the socio-economic criteria were assigned weights of 0 (no consideration), 1 (equal weightage) and 2 (socio-economic criteria having double weight), denoted as Cases 0, 1, 2 respectively. Method 1 was used in this assessment. Case 1 results are those shown in Table 7 where equal weights amongst the criteria were used. Comparison between Cases 0 and 1 shows that best plan moves to higher protection level (Plan 2) where the socio-economic criteria are included. Further Plan 0, the current protection level is ranked third in Case 0 but ranked as the worst in Case 1. The rank values of plans are changed especially the best two plans' ranks are switched by introducing the socio-economic criteria into the MCDA. The ranking in Cases 1 and 2 are exactly the same, i.e. ranking unchanged with doubling the weightage assigned to the *Net SEVI*. The socio-economic variables used here are from data for Year 2014. The robustness of the ranking to the year of the data used was tested via using the next most recent year's data of 2013. No changes in the ranking resulted.

Table 7 Net outranking index and rank values with weighted criteria in PROMETHEE

Alternative Levee Plans	Case 0		Case 1		Case 2	
	Net Outranking Index	Rank value	Net Outranking Index	Rank value	Net Outranking Index	Rank value
Plan 0	0.104	3	-0.310	6	-0.488	6
Plan 1	0.182	1	0.152	2	0.139	2
Plan 2	0.166	2	0.154	1	0.149	1
Plan 3	0.021	4	0.085	3	0.113	3
Plan 4	-0.074	5	0.039	4	0.087	4
Plan 5	-0.399	6	-0.120	5	0.000	5

6. Conclusion

The methodology presented here demonstrates how social-economic criteria can be incorporated into decision making on flood levee protection level and with uncertainty in the rainfall incorporated. A *SEVI* is developed to represent the social-economic factors as based on available reported social-economic data and the *SEVI* is further scaled into a *Net SEVI* that accounts for the social-economic impact over the specific flood affected area (extent and/or depth) as this will be dependent on the mitigation plan adopted. This is in contrast to previous measures of flood vulnerability (e.g. PVI and FVI) that provides only a general assessment without accounting for the specific mitigation measure being evaluated.

The practical utility of this work lies in the incorporation of socio-economic effects into a flood mitigation decision framework with the use of the *SEVI* demonstrated within a PROMETHEE MCDA framework for assessing flood levee options for a central basin in Jakarta, Indonesia. The final ranking process is shown to be robust to equal or unequal weights assigned to the variables in defining the *SEVI*, and to the scaling process of *SEVI* into a *Net SEVI* that reflects the direct inundation area and/or depth as dependent on each of the levee plans being assessed. Specifically of the 6 levee plans considered, it is shown that the best 2 plans remains the same best 2, though their order maybe interchanged. The latter is because the inundation depth has equal importance as the inundation area when deciding on the best plan. The effect on the decision due to the weight assigned to the social-economic criteria *Net SEVI* relative to other criteria is also assessed. This allows the decision maker the flexibility to set criteria weights to reflect local priorities. The decision framework developed here in general in that it accounts for socio-economic factors and can be readily extended to account for basin uncertainties beyond rainfall predictions and thus will find use in guiding such flood mitigation decision making.

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(a)

Figure 1

(b)

Figure 2

(a)

(b)

(c)

Figure 3

Figure 4

Figure 5