Decision making on flood mitigation incorporating uncertainty, socio-economic factors and a changing future

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**Decision Making on Flood Mitigation
incorporating Uncertainty, Socio-economic
Factors and a Changing Future**

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2018

**Decision Making on Flood Mitigation incorporating
Uncertainty, Socio-economic Factors and a Changing Future**

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Symbols and Abbreviations

The abbreviations used in this report are listed below. The standard mathematical symbols and units are not defined here which follows the standard practice.

AEL	Annual expected loss
AHP	The Analytical Hierarchy Process
ANP	Analytical Network Process
AR4	IPCC fourth assessment report
AR5	IPCC fifth assessment report
ArcGIS	Arc-geographic information system
ARF	Area Reduction Factor
C	Construction Cost
CanESM2	Canadian Earth System Model
CF	Temporal Change Factor
CMIP5	Coupled Model Intercomparison Project Phase 5
CN	Curve Number
D-D	Depth-Damage
DDF	Depth Duration Frequency
DEM	Digital Elevation Model
DKI	Daerah Khusus Ibukota or Special Capital Region
DPU	Dinas Pekerjaan Umum or Public Works Department
ELECTRE	Elimination and Choice Expressing Reality
EOL	Expected Opportunity Loss
FVI	Flood Vulnerability Index
G	Graduality

GEV	General Extreme Value distribution
GCM	Global Circulation Models
GHG	Green House Gas
HEC-HMS	Hydrologic Engineering Centre-Hydrologic Modelling System
HEC-RAS	Hydrologic Engineering Centre-River Analysis System
ICRM	Institute of Catastrophe Risk Management
IDR	Indonesian Rupiah
IPCC	Intergovernmental Panel on Climate Change
LAM	Limited Area Model
Landsat TM	Landsat Thematic Mapper
LARS-WG	Long Ashton Research Station Weather Generator
LP3	Log Pearson Type III
MCDA	Multi-Criteria Decision analysis
ML	Maximum likelihood
NEX-GDDP	NASA Earth Exchange Global Daily Downscaled Projections
PVI	Prevalent Vulnerability Index
PRC	Percentage Reduction in Correlation
PROMETHEE	Preference Ranking Organization Method of Enrichment Evaluation
PWA	Jakarta Public Works Agency
RCM	Regional Climate Models
RP	Return Period
RCF	Relative Change Factor
RCP	Representative Concentration Pathways
SCS	Soil Conservation Service

SD	Statistical Downscaling
SDSM	Statistical Downscaling Model
SRES	Special Report on Emissions Scenarios
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
US\$	United States Dollars

List of Publication

1. Daksiya V., Mandapaka P. and Lo E.Y.M. (2017) Assessment of Changes in Daily Rainfall Extremes in Jakarta using Climate Projections and Nonstationary Extreme Value Analysis. Paper presented at the Asia Oceania Geosciences Society, 14th Annual Meeting, Singapore, 6th-11th Aug
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5. Mandapaka P.V., Daksiya V., X. Qin and Lo E.Y.M. (2015) Assessing the effect of changing climate on daily rainfall extremes in Jakarta – A weather generator approach. World Engineer's Summit (WES) on Climate Change 2015. Singapore

Abstract

The decision-making process in flood mitigation typically involves many factors reflecting flood severity, flood vulnerability and the cost of the mitigation measures. In this PhD study, a Multi-Criteria Decision Analysis (MCDA) decision framework for optimal decision making in flood protection design, specifically levees are developed. This framework accounts for climate change, increasing urbanization, and evolving socio-economic features of the flood plain, and as well as for uncertainties in rainfall predictions. The changing climate and the growing urbanization alter the flood frequencies with large uncertainties that strongly influence future projections. These uncertainties make the flood mitigation decision more complex. Thus, uncertainties involved in both current and future conditions are quantified via computation of the expected values of change indices developed. The MCDA uses as its criteria the annual expected loss, graduality, a newly developed Socio-Economic Vulnerability Index (SEVI) and levee construction cost. It is further demonstrated for a central basin of Jakarta, Indonesia. The annual expected loss at current conditions is calculated with recorded rainfall data as fitted using the Log Pearson Type III distribution. The graduality represents the severity with change in discharge as reflected by the deviation from linearity between percentile discharge and percentile loss values. The SEVI reflects the social and economic impact on the flood affected population via scaling with the flood inundation area and depth while capturing uncertainty in the rainfall forecasting. Temporal change factors (CF) as calculated from a statistically downscaled global gridded rainfall projection, the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) are applied for future rainfall (specifically 2031-2070). The uncertainty across the 20 Global Climate Models (GCM's) is quantified via an expected CF scaled across the GCMs via an inverse distance method. Landsat data over year 1989-2009 is classified into various land use, including urban, and is used to develop urbanization trends and projected to year 2050. The impact of climate change and urbanization are incorporated in the MCDA flood decision framework through the criteria being recalculated under the future conditions.

The changing climate, growing urbanization and the socio-economic features, are shown to drive the best choice of levee protection plan towards higher protection levels under the future time period considered. Inclusion of socio-economic factors is also shown to change the best plan. The developed methodology and the results are expected to guide decision making in flood mitigation and can be extended to include decision-making on other flood mitigation measures as well as additional sources of uncertainties.

Chapter 1

Introduction

1.1 Background

Flooding is a natural hazard which causes massive damages and leads to loss of life, property and infrastructures. The latter includes power generation and transmission systems, communication systems, drinking water supply, sewer disposal facilities and transport facilities. This in turn not only impacts on the livelihood and productivity of the affected region, but also the cost of rehabilitation and reconstruction may also adversely impact on the region's economy. Furthermore, many flood events have led to waterborne diseases. Statistics show that in the last 10 years, 2,949 flood events have been recorded around the world with 2.2 billion people affected (EM-DAT, 2014). It has led to 530 billion US\$ of economic loss and 155,026 deaths. Even in today's technologically advanced world, floods affect people in some part of the world every day.

Various types of flood mitigation measures are implemented to reduce the flood risk. One common method is to predict future events and design protections against future such flood hazard. Channelization, levees, diversion of flood water and use of flood mitigation reservoirs are some of the most common structural mitigation measures

(Thampapillai and Musgrave, 1985). Flood proofing and zoning, land use planning and post-flood rehabilitation measures are various non-structural measures (Faisal et al., 1999; Vojinović and Abbott, 2012). While numerous mitigation measures are practiced to decrease the flood risk, there are still frequent failures due to poor designs or decisions, often leading to severe damages (VDEM and VTCGIT, 2013). Levee overtopping and structural failures of levees have been reported in past flood event (VDEM and VTCGIT, 2013; DEMA, 2003). Therefore, suitable mitigation measures need to be chosen and implemented. Furthermore to be well protected against future floods, it is also necessary to have a good flood forecast and decision making framework. Hydrologic and hydraulic models readily generate predictions of the flood hazard level, but flood risk also depends on the exposure and vulnerability towards the flood. Flood risk reduction can be achieved by either reducing the flood hazard or reducing the exposure and the vulnerability. The changing climate and the rapid urbanization further alter the flood frequency and the level of socio-economic development influences on the level of protection required and thus the corresponding exposure to the flood.

1.2 Challenges in flood mitigation decision process

Decision making on flood mitigation measures involves significant statistical parameterization and analysis. The future conditions are also predicted from the historical data and processes recorded and any variation in parameters is inferred from historical records. However current flood forecasting methodologies and parameters that represent such natural systems are not fully reflective of the actual natural systems with their uncertainties. Such uncertainties as involved in each component of flood forecasting will affect the final decision.

The major challenges involved in water resource decision making as also applicable to flood mitigation decision making. These are (i) identifying the influencing factors covering social, economic, environmental and technical components, (ii) quantifying the factors so to be readily used as criteria in the decision framework, (iii) accounting for uncertainties involved in the criteria, and (iv) the decision framework itself (Keeney and Wood, 1977; Su, 2013). The flood risk is further determined by three components, hazard (threat level with its probability of occurrence), exposure (e.g. population and assets in the flood zone) and vulnerability (coping capacity) (Jongman et al., 2012; Kron, 2005). The changing climate, growing urbanization and evolving socio-economic level are the main factors affecting the flood risk. Each of these components involves a number of quantitative and qualitative variables that further increases the associated uncertainties, thereby increasing the complexity of flood risk assessment. These uncertainties while currently large, are potentially reducible. Some uncertainties can be reduced through improved modelling and with quantification and propagation of uncertainty sources (Kay et al., 2009). In flood forecasting and decision making for mitigation measures, the propagation of uncertainty sources and its quantification is important because this leads to an overall quantification of the model uncertainty.

Decision makers typically define the decision making approach and associated criteria to reflect the major system variables as based on the purpose of the study and availability of data. Jun et al. (2013) reported on flood risk vulnerability under changing climate in South Korea using a multi-criteria approach. Vulnerability was assessed with three criteria comprising of exposure, sensitivity and adaptive capacity. Lim and Lee (2009) evaluated the flood damage reduction alternatives with a spatial Multi-Criteria Decision Analysis (MCDA) technique. Flood depth, flood damage, land use disruption, drainage capacity and flood risk zone were used as the primary criteria in the analysis. The first

four are the direct input of flood models and the raw data. The study area was divided into six different zones based on the flood Return Periods (RPs) and risk level was defined spatially to represent the criteria flood risk.

1.2.1 Rainfall and climate change

Flood risk assessment and design of flood mitigation measures are dependent on the hydrological responses to a design rainfall. Historically the use of a design rainfall is accepted and practiced, though this approach has a number of limitations particularly in handling uncertainties. Incorporating uncertainty in rainfall can provide improvements via uncertainty estimate as arising from the magnitude, temporal distribution, and spatial distribution of the rainfall (Beven and Hall, 2014; Maskey et al., 2004).

The on-going global warming as driven by increasing concentration of Green House Gases (GHGs) is expected to cause significant changes in the precipitation structure (e.g. amount, extremes, and spatial variability). Studies have provided evidence that climate change is leading to an increase in extreme rainfall events that drives catastrophic flood events (e.g. Hirabayashi et al. (2008); Milly et al. (2002); Westra et al. (2013)). Uncertainty in rainfall prediction under future conditions is made more complex due to climate change and significant uncertainties in the estimation of the changed rainfall (Arnell, 1999). This arise from the emission scenarios/ pathways assumed, the Global Circulation Models (GCMs) or Regional Climate Models (RCMs) used, and the downscaling techniques adopted. Though various research methodologies are reported to address such uncertainties, they basically analyse and quantify individual uncertainties separately as arising from GCMs (Prudhomme et al., 2003), emission scenarios (Kron, 2005), downscaling techniques (Khan et al., 2006), and uncertainty in model interdependency and non-stationary bias (Sunyer et al., 2014). Rainfall

forecasting and the impact of climate change in the flood forecasting have also been studied (Hirabayashi et al., 2013; Kay et al., 2006) but has not been extended to flood mitigation decision making.

1.2.2 Social and economic changes

Social and economic conditions of a basin/catchment can influence the flood vulnerability. Vulnerability is a multi-dimensional concept which involves quantitative and qualitative measures, each of which has with uncertainties. The social and economic dimensions of vulnerability are key factors that need to be considered in flood risk management and mitigation decisions. 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). These social and economic measures of vulnerability cannot be clearly separated as above in all cases.

Spatial variability of social and economic vulnerability have been analysed in several studies (Wood et al., 2010; Balica et al., 2009; Connor and Hiroki, 2005; Cardona, 2006). 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). Connor and Hiroki (2005) formulated a similar Flood Vulnerability Index (FVI) and which was further improved by Balica et al. (2009). These are developed to compare across countries or specific study areas. The variables used to calculate PVI and FVI are comprehensive and may have double counting effects. Furthermore, these indices are less concerned with engineering aspects and not readily incorporated into an engineering decision framework for assessing flood mitigation schemes.

1.2.3 Land-use changes

In the past few decades, the urban extent has rapidly increased world-wide due to dramatic population and economic growth. The urban population is projected to increase from 2.9 billion in 2000 to 5.1 billion in 2030 (UN, 2014) and urban land cover projected to increase 1.2 million km² by 2030, nearly tripling the 2000 global urban land area (Seto et al., 2012). Urbanization alter the hydro-metrological conditions and infrastructure concentrations. Urbanisation and industrialization contribute to the increment in rainfall amounts in downwind urban areas (Cinelli et al., 2014). Urbanization increases the artificial impervious surfaces which increase the flood run-off due to the reduced infiltration. This can be basically viewed as a variation in basin parameters due to urbanisation. Furthermore, increases in population and infrastructure development affect the exposure and vulnerability.

The future projections of urban extent and land-use patterns will add to the uncertainty in basin parameters such as basin roughness and imperviousness which will influence the flood risk analysis for future time periods. Studies that used urban growth models and urban cover projections to estimate the impact of urbanization in flood risk have been reported (Huong and Pathirana, 2013; Budiyo et al., 2016). The long-term flood mitigation decisions will be affected by the land-use/urbanization levels and which should be addressed.

To the author's knowledge, there is no reported work that systematically and fully analyse different uncertain features affecting a hydrosystem. While uncertainty in the rainfall forecasting and climate change are widely studied, uncertainty due to changing basin parameters and changing socio-economic factors are rarely incorporated in flood risk studies. Thus, there is a need to incorporate both uncertainty sources in flood

forecasting and decision making on flood mitigation measures which is the key goal of this PhD study.

1.3 Objectives and scope of the study

The main objective of this PhD research is to develop a decision frame-work for flood mitigation decision making and which accounts for climate change, growing urbanization, and evolving socio-economic features of the flood plain. The framework developed here will facilitate decision making to analyse different influencing factors and uncertainties involved. A specific basin in Jakarta, Indonesia, is chosen as demonstration for the framework as Jakarta is a highly flood prone city with a 2015 population of 10 million people (BPS, 2005-2015). The framework is specifically applied to a central basin of Jakarta to determine a best levee plan amongst several alternatives for flood protection in the future years. The below are the key objectives of the PhD work:

i. Identify and quantify major uncertainty sources present in hydrosystem

The factors influencing the behavior of a hydrosystem and uncertainties influencing the flood mitigation decision are identified and studied. This involves analysis of climate change, urbanization, social and economic features along with natural randomness of rainfall and associated uncertainties.

ii. Define a methodology to propagate the impact of uncertainties

The uncertainties in the rainfall (climate change), basin roughness (urbanization) and extreme value calculations (natural randomness) propagate into river discharges and then to flood loss where the exposure and socio-economic features comes to play. A methodology is developed to propagate these uncertainties to the loss.

iii. Develop a decision frame-work on alternative flood mitigation measures for future.

To obtain better decisions on flood mitigation measure selection, a MCDA decision making technique using the Preference Ranking Organization Method of Enrichment Evaluation (PROMETHEE) is used. The influencing factors and effect of associated uncertainties are folded into the decision making process with the various criteria adapted. This framework is lastly applied to the central basin in Jakarta, Indonesia to assess alternative levee plans.

1.4 Outline of the Thesis

Chapter 1 introduces the research topic and gives a general background to the research problem along with the objectives of this thesis work. A detailed literature review is given in the Chapter 2 while Chapter 3 discuss the extension of Jakarta flood model which includes hydrologic and hydraulic simulation for flood plain mapping.

The MCDA methodology used in development of flood decision framework is described in Chapters 4 along with the criteria development procedures. Chapter 5 details a comparative analysis of statistical downscaling tools for future rainfall projection. The results from flood decision framework is discussed in detail in Chapter 6 and Chapter 7 concludes this PhD work with recommendations.

Chapter 2

Literature review

2.1 Introduction

Researchers have shown that damages due to flood are rising alarmingly because of the rapid increase of anthropogenic disturbances to nature (Arnell, 1999; Kay et al., 2009; Luino et al., 2012). Decision making on flood mitigation is influenced by a number of external factors such as climate change, socio-economic variability, urbanization trends, land subsidence issues, mitigation measures currently implemented and planned, with many of the factors being further complicated by the associated, potentially large uncertainties. In particular, the impact of climate change, socio-economics factors and urbanization trends on flooding are rarely analysed together. The climate change uncertainty is extensively studied in the literature but seldom analysed together with socio-economics and urbanization for a more comprehensive flood mitigation decision making.

In this literature review chapter, the reported methods and procedures to analyse climate change impact on rainfall with its associated uncertainties, flood vulnerability measures indices and urbanization are discussed and reviewed in detail, Furthermore the classical

MCDA decision-making technique as used in this thesis for flood mitigation decision making framework incorporating uncertainties are reviewed.

2.2 Multi criteria decision analysis (MCDA)

MCDA is one of the most common and straight forward techniques which addresses complex decision making problems. MCDA is a methodology used to arrive at a decision by considering different influencing criteria that are typically measured using different scales e.g. units. MCDA techniques are directly applicable in selecting the best solution for problems with more than one conflicting criteria with multiple solutions (or alternatives) being possible (Ishizaka and Nemery, 2013). As the importance of each criterion is defined by their respective weightage assigned, MCDA could further provide transparency and accountability to the decision procedure (Brown et al., 2001; Joubert et al., 1997) through the explicit weightage assigned. The essential attributes of MCDA in wide application fields are (i) takes into explicit account multiple, conflicting criteria, (ii) ability to structure the management problem, (iii) provides a model that can serve as a focus for discussion and (iv) offers a process that leads to rational, justifiable, and explainable decisions (Belton and Stewart, 2002). The MCDA process of decision making contains the following stages (Hajkowicz and Collins, 2007):

- i. Choose the criteria and the finite set of decision options (alternatives)
- ii. Obtain performance measures and interpret these measures with preference functions developed from expert judgements, or calculated from environmental and/or economic models
- iii. Rank or score the options – apply weights to criteria and obtain the overall performance rank or score with the MCDA technique

There are number of MCDA techniques available, but none are considered optimal as each have their own strength and limitations. Some of the widely used MCDA techniques are described below (Hajkowicz and Collins, 2007; Cegan et al., 2017; Pohekar and Ramachandran, 2004; Mateo, 2012b):

Multi-criteria value function: Here the weighted sum method and weighted product method are commonly used. Weighted sum method is applicable only when all the data are expressed in the same units. The weighted product method is expressed using a preference value of alternative.

Outranking approaches: This is basically a pairwise comparison method where each of the alternatives are compared with all others with respect to each of the decision making criteria individually. It further uses utility functions which represents the preference of each criteria along with the criteria weights. The PROMETHEE and the Elimination and Choice Expressing Reality (ELECTRE) are the well-known outranking techniques.

Distance to ideal point method: Here geometric distances from ideal solution for each of the alternatives are calculated after applying the weight to the criteria. The alternative which is the closest to the positive ideal solution and furthest from the negative ideal solution is chosen as the best solution. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is one of such approaches.

Pairwise comparison: This approach compares criteria and alternatives over every unique pair. The comparisons are used to attain a decision by comparing performance scores across options and various scaling systems can be used. The Analytical Hierarchy

Process (AHP) and Analytical Network Process (ANP) are two such widely used pairwise comparison methods.

Fuzzy set analysis: This is based on a gradual transition from one class to another. Items can have partial membership in multiple sets. It can handle uncertainty in class boundaries in MCDA problems.

Tailored methods: Various new MCDA methods are reported by adaptation of existing techniques, or with new algorithms. For example, Hyde et al. (2003) adapted the weighted summation to create a ‘reliability based approach’ to MCDA involving the use of rank correlation coefficients.

There is no globally accepted technique for the selection of a MCDA technique for a specified application. Decision makers after identifying their problems, choose a suitable MCDA technique based on availability of input data, computational expense and effort. Table 2.1 shows the classification of widely used MCDA techniques based on four different application categorises by Ishizaka and Nemery (2013). More than one approach is applicable for one particular type of problem and an approach is able to solve more than one type of problem.

MCDA is widely used across disciplines covering mathematics, management, engineering, psychology, social science and economics. Hajkowicz and Collins (2007) provided a review of MCDA applications in the field of water resources planning and management covering water policy evaluation, strategic planning, and infrastructure selection. Fuzzy analysis, paired comparison and outranking approach are the MCDA techniques commonly used. Examples are Compromise Programming technique as applied to urban water supply alternative options (Abrishamchi et al., 2005); Multi attribute utility theory for irrigation system evaluation (Raju and Vasan, 2007) and AHP

for storm water management practices (Young et al., 2010). Porthin et al. (2013) further analysed and ranked alternative solutions aimed at climate change enhanced flood risks adaption using MCDA.

Table 2.1 Problems and applicable MCDA techniques

Choice problem	Ranking problem	Sorting problem	Description problem
AHP	AHP	AHP Sort	
ANP	ANP		
MAUT/UTA	MAUT/UTA	UTADIS	
MACBETH	MACBETH		
PROMETHEE	PROMETHEE	FLOW SORT	GAIA, FS-Gaia
ELECTRE I	ELECTRE III	ELECTRE-TRI	
TOPSIS	TOPSIS		
Global programming			
DEA	DEA		

2.3 Rainfall forecasting and climate change

Flooding is usually a direct response to rainfall experienced over a certain duration (Chandler et al., 2014). Uncertainty in the forecasted rainfall is one of the biggest sources of uncertainty in streamflow forecasting (Apel et al., 2008; Yu et al., 2016) with corresponding implications on flood. The uncertainty mainly arises from the rainfall magnitude, and the temporal and spatial distribution, all of which are further amplified with climate change.

Conventionally, a design rainfall obtained from frequency analysis as based on historical recorded data is typically used for hydraulic structure design and for flood risk management decisions. Frequency analysis is an estimation procedure to relate the

magnitude of the event with its probability of occurrence through standard probability distributions. The hydrologic data are assumed to be independent and identically distributed, and the hydrologic system is assumed to be stochastic (Chow et al., 1988). Usually a RP is used to represent an exceedance probability in hydrologic analyses; which is simply defined as the inverse of exceedance probability. Normal distribution, General Extreme Value distribution (GEV), Log Pearson Type III (LP 3) are the standard probability distributions widely used in hydrosystem analysis. It is noted that in such frequency analysis, predictions are uncertain because of inherent variability in the data and in the assumed distributions. The degree of uncertainty in the predicted rainfall depends on the sample size, the extent of extrapolation, and the underlying probability distribution used (Tung et al., 2006). Rainfall forecasting, and its related uncertainties applied for this PhD work are further described discussed in Section 4.3.

2.3.1 Climate change

Climate change is defined as a ‘change in the state of the climate that can be identified (e.g. via statistical tests) by changes in the mean and/or the variability of its properties, and that which persists for an extended period, typically decades or longer’ (IPCC, 2014). For the last two decades, climate change has been a priority topic of research worldwide. The Intergovernmental Panel on Climate Change (IPCC) Climate Change 2007-Synthesis Report (IPCC, 2007) mentioned that ‘changes in atmospheric concentrations of GHGs and aerosols, land cover and solar radiation are the main three causes that alter the energy balance of the climate system’. The effect will be reflected via changes in precipitation intensity and frequency, atmospheric temperature and in sea-level rise.

Climate change adds to the variability in flood frequency analysis (Arnell, 1999; Hirabayashi et al., 2013; Kay et al., 2006), which then alter the design frequency of

hydraulic structures and the mitigation decisions. Figure 2.1 shows the forecast results of flood RP in the 21st century corresponding to the 100-year flood of the 20th century. For example, in South East Asia, a 100-year 20th century flood is forecasted to occur with 5-25 years RP in the 21st century.

Figure 2.1 Variation in flood frequency under climate change (Source: Hirabayashi et al. (2013))

Climate change models are the only current tool that accounts for the complex set of processes and enable predictions of future climate. These 3-D mathematical models are built on the physical principles of fluid mechanics, thermodynamics and relative heat transfer. GCMs used to predict the future climate globally further have two main coupled models namely the atmospheric and the ocean in order to account for moisture in the atmosphere.

The IPCC has developed a number of emission scenarios that explored different development pathways covering a wide range of demographic, economic and technological driving forces to arrive at various GHG emission scenarios for the future. As described in Prudhomme et al. (2003), these scenarios are built on assumptions made on the future trend of population growth, energy demand, GHG emissions and land use.

Scenarios are divided into families which cover a wide range of key future characteristics (IPCC, 2000). The climate projections of IPCC fourth assessment report (AR4) is based on the Special Report on Emissions Scenarios (SRES) (IPCC, 2007) and the IPCC fifth assessment report (AR5) is based on Representative Concentration Pathways (RCP) (IPCC, 2014). RCP 8.5 is the extreme scenario that follows a ‘business as usual’ trend in fossil fuel use. It is comparable with SRES extreme scenario A2 scenario (see Figure 2.2). Figure 2.2 shows the relative precipitation change for two seasons (December–February (DJF), and June–August (JJA)) from the time 1986-2005 to 2081-2100. Stippling marks, hatching marks and white areas represent high robustness, no significant change and inconsistent model responses respectively. For example, Australia shows an 10-20% decrease in the relative precipitation. RCP 4.5 and 6.0 are intermediate scenarios which can be compared with SRES B1 and B2 respectively. Lately the RCP 2.6 requires strong GHG emission mitigation (Knutti and Sedlacek, 2013; Rogelj et al., 2012; van Vuuren and Carter, 2014).

Figure 2.2 Comparison between RCP and SRES extreme scenarios (Source: Knutti and Sedlacek (2013))

2.3.2 Downscaling

Downscaling is a method used to scale down the GCM results for studies at smaller regional or catchment levels. Results from GCMs are coarse (typically 1°–2.5°) in spatial resolution and need to be downscaled to be applicable for local hydrology and climate change impact studies. This is because the resolution of GCMs would not capture regional sub-grid features (topography, land surface processes and cloud physics) that influence rainfall (Kannan et al., 2014). Downscaling is an essential tool to bridge between GCM scales and regional/local scales. Statistical and dynamic downscaling are the two approaches to scale down to finer resolution and even to a station scale.

Dynamical downscaling:

Here time varying outputs from GCMs are used as boundary conditions to drive a numerical model RCM at higher spatial resolution (typically 50km) with the use of complex algorithms to analyse atmospheric physics. Dynamical downscaling is also used to increase temporal resolution which gives (sub-) daily rainfall from GCM outputs.

The main advantage of dynamic downscaling is that the downscaled atmospheric variables in finer spatial and temporal resolution can be directly used in hydrologic models. The main drawback is its computational cost (Mujumdar and Nagesh Kumar, 2012). Thus its only available for limited areas and even then RCM outputs may still too coarse for some practical applications, e.g. small scale hydrology application (Chen et al., 2011).

Statistical downscaling (SD):

In SD, a quantitative relationship is established between large scale atmospheric variables (predictors) and observed local variables (predictands) at a local site. Wilby et al. (2004) categorized the types of relationship between predictors and predictands as

frequencies of extremes, statistical distribution parameters and the function of predictands. SD is built on the following assumptions (Wilby and Wigley, 2000):

- Physical relationships exist between large-scale predictors and local predictands.
- Relationships developed for past climate are valid under future climate conditions.
- Predictor variables and their properties are simulated well in GCMs.

SD is preferred in hydrological impact assessments because they provide good fits to observed local data while requiring comparatively less computational costs and thus provide quick results (Mujumdar and Nagesh Kumar, 2012). Their domain of application can also be easily transformed from one to another. SD techniques can be categorized into three (Hessami et al., 2008; Chen et al., 2011; Raje et al., 2013; Wilby et al., 2004) as follows:

- a) Transfer function: A linear or nonlinear relationship is developed between the predictors and predictands. Regression models, artificial neural network, canonical correlation, principal component analysis and independent component analysis are the widely used methods (Raje et al., 2013). This employs a full range of available predictors but representation of observed variance and extreme events is poor (Wilby et al., 2004).
- b) Weather typing/classification: Local meteorological variables are grouped into a finite number of weather types or states based on their synoptic similarities (Wilby et al., 2004). The local and large-scale variables are then closely linked, but the reliability of the model depends on stationary relations between predictors and predictands (Chen et al., 2011). The advantage of weather typing is that it develops a physically interpretable linkage between weather patterns and surface climatic conditions (Robert L. Wilby, 2017). However the drawback

are intra-type variations in surface climate may not be modelled and circulation schemes may be insensitive to future climate (Wilby et al., 2004).

- c) Weather generator: This generates time-series of synthetic weather statistically 'identical' to observations (Semenov and Barrow, 2002). Markov chain is used to model precipitation occurrence in most of the weather generator models and the precipitation amount follows a given distribution. Markov chain determines the day as wet or dry in a random process as conditioned on state of the previous day (Anandhi et al., 2013). The secondary variables of precipitation amount, temperature and solar radiation are conditioned with precipitation occurrence. Weather generators can generate sub-daily temporal outputs, spatial interpolation of model parameters and produce large scale ensembles. The disadvantage is in the use of arbitrary adjustment factors for future projections and unanticipated effects on secondary variables (Wilby et al., 2004).

SD is generally suitable for small areas and complex environment but not suitable for regions with poor data availability (Goyal Manish et al., 2013). Two popular models/packages LARS-WG and SDSM as freely available to statistically downscale the climate variables for hydrological impact study are discussed in the following sections. The performance of these two SD techniques for their use in the PhD for Jakarta future rainfall are compared in the later Section 4.3.1.

2.3.3 LARS-WG

The Long Ashton Research Station Weather Generator (LARS-WG) is a stochastic weather generator which simulates synthetic weather data for current and future climate conditions. Daily synthetic data can be generated for climate variables such as precipitation (mm/d), maximum and minimum temperature (°C) and solar radiation ($\text{MJm}^{-2}\text{day}^{-1}$) for specified single location (or station). The generated synthetic data can

be used to fill the missing climate data series. LARS-WG can also be used to generate data for ungauged sites using observed data properties from neighbouring stations (Hashmi et al., 2011).

The LARS-WG model involves three major steps: (i) determining statistical characteristics of observed data, (ii) comparing statistical characteristics of observed data and the generated data, and (iii) generating synthetic data based on statistical characteristics of the observed data (Semenov and Barrow, 2002). For future time period, the model generates synthetic time series based on a relative change factor approach. The relative change factor is driven by wet/dry spells average length and precipitation statistics, comparing future with baseline time period.

Table 2.2 Available GCMs and emission scenarios in LARS-WG 5.5

GCM Models	Model Acronym	Emissions scenarios
BCM2.0 (Norway)	BCM2	SRA1B, SRB1
CGCM33.1 (T47) (Canada)	CGMR	SRA1B
CNRM-CM3 (France)	CNCM3	SRA1B, SRA2
CSIRO-MK3.0 (Australia)	CSMK3	SRA1B, SRB1
FGOALS-g1.0 (China)	FGOALS	SRA1B, SRB1
GFDL-CM2.1 (USA)	GFCM21	SRA1B, SRA2, SRB1
GISS-AOM (USA)	GIAOM	SRA1B, SRB1
HadCM3 (UK)	HadCM3	SRA1B, SRA2, SRB1
HadGEM1 (UK)	HADGEM	SRA1B, SRA2
INM-CM3.0 (Russia)	INCM3	SRA1B, SRA2, SRB1
IPCM4 (France)	IPCM4	SRA1B, SRA2, SRB1
MIHR (Japan)	MIHR	SRA1B, SRB1
ECHAM5-OM (Germany)	MPEH5	SRA1B, SRA2, SRB1
CCSM3 (USA)	NCCCSM	SRA1B, SRA2, SRB1
PCM (USA)	NCPCM	SRA1B, SRB1

The latest version LARS-WG 5.5 is capable of generating future precipitation time series using 15 GCMs under AR4 emission scenarios (Table 2.2) for three future time periods of 2011–2030, 2046–2065, and 2081–2099. An advantage of using LARS-WG is that it allows for an assessment of GCM model uncertainty due to 15 GCMs used. However, one drawback is that the latest version of LARS-WG (version 5.5) follows the IPCC AR4 for future climate scenarios and not the most recent AR5 RCP scenarios. More specifically, synthetic rainfall series can only be obtained for AR4 scenarios A1B, B1, and A2. It is noted that there are a few recent studies where LARS-WG is employed with RCP (Ma et al., 2016; Semenov and Stratonovitch, 2015). However, this LARS-WG 6.0 version is still undergoing final tests (personal communication, Michael Semenov) and not yet released.

2.3.4 SDSM

The Statistical Downscaling Model (SDSM) is a combination of multiple linear regression and stochastic hybrid weather generator developed by Wilby et. al (2002; 1999) and which has undergone a number of improvements since. In this model, large scaled atmospheric variables are linearly conditioned with local scale precipitation occurrence and intensity. SDSM needs two types of input daily data: the local predictands of interest (daily rainfall in our case) and the large-scale regional predictors from the GCM grid that covers the study area. SDSM operates with five steps, (i) predictor variable screening (ii) calibration (iii) synthesis of observed data (iv) future projections (v) statistical analysis and testing (Wilby et al., 2002).

Predictor variables screening is the most important step in SDSM as the selected predictors determine the future predictands. Correlations between the predictors and the predictand is analysed and the variance with a specific confidence interval is calculated monthly. Wilby et al. (2002) suggested to use partial correlation or stepwise regression

to choose the appropriate predictor set while Mahmood and Babel (2013) have developed a framework for predictor screening in SDSM using a correlation matrix.

There are three sub-models available in the calibration phase: annual, seasonal and monthly. The monthly sub-model derives 12 different regression calibrated parameters for each month, while the annual sub-model derives similar regression parameters for all 12 months. A direct relation is assumed between large scale predictors and local scale predictands in unconditional models (e.g. temperature). The predictand precipitation amount is modelled as conditional where it depends on an intermediate variable, the probability of wet and dry day occurrence. User can specify the number of ensembles during the generation process. The future time series are generated using predictor variables given by GCMs. It has been reported that SDSM has superior capability of analysing local climate (Liu et al., 2016; Khan et al., 2006; Wilby et al., 2002).

2.3.5 Rainfall uncertainty with climate change

Rainfall frequency analysis is done by fitting the observed rainfall data to standard probability distribution curves (e.g. LP3, GEV). In this, all predictions have uncertainty because of inherent variability in the data and in the assumed distributions. Overeem et al. (2008) analysed such uncertainty in rainfall depth-duration-frequency (DDF) curves developed using standard probability distribution functions. Confidence interval of these fitted DDF curves was used to analyse the uncertainties.

Maskey et al. (2004) analysed temporal rainfall uncertainty and its propagation into flood forecasting. This was achieved by disaggregation of rainfall into sub-periods and fuzzy set theory applied. The result showed that the output uncertainty due to the uncertain temporal distribution of rainfall could significantly dominate over the uncertain quantity of rainfall.

Uncertainty in rainfall prediction under future conditions is made more complex due to climate change and the significant uncertainties in the estimation of climate change on rainfall (Arnell, 1999). This arise from:

- a) Uncertainty in the future emission of GHG and in GHG forcing for GCMs.
- b) Uncertainty in the simulation of regional climate changes, with greatest uncertainty in the simulation of changes in regional precipitation.
- c) Uncertainty in translation of regional climate changes to changes at the scale of the catchment.
- d) Uncertainties in the translation of changes in climate into change in hydrological response.
- e) Uncertainty in stationarity assumptions and the analysis techniques

The first three sources reflect the uncertainties in the emission scenarios/pathway and the use of different climate sensitivities. The fourth reflects the ability of GCMs, the fifth arises from the downscaling techniques, and the sixth comes from the uncertainty in hydrological models.

Uncertainty in daily precipitation from different SD methods comparing SDSM, LARS-WG and artificial neural network were analysed by Khan et al. (2006). It was concluded that SDSM and LARS-WG could downscale daily rainfall with 95% confidence interval. Uncertainty from GCMs is dominant compared to related uncertainties from e.g. in emission scenarios, climate sensitivity, downscaling techniques, hydrological modelling (Shahabul Alam and Elshorbagy, 2015; Prudhomme and Davies, 2009; Prudhomme et al., 2003; Kay et al., 2009). In this PhD study, SDSM and LARS-WG models are compared and the uncertainty from GCMs analysed and quantified via a change factor technique being applied on the rainfall (see Section 4.3).

2.4 Socio-economic conditions

The social and economic features of a flood plain largely determine the exposure level to a flood hazard. In turn, the economic status influences the implementation of a mitigation measure. It is necessary to account for both exposure and vulnerability in the flood mitigation decision process.

The concept of vulnerability differs over the fields of study and more importantly changes over time. Balica et al. (2009) defined vulnerability as ‘the measure of expected harm under certain conditions of exposure, susceptibility to flood and resilience’. Vulnerability is often measured with indices which facilitates the decision-making processes. A number of vulnerability indices are developed in the literature (Balica et al., 2009; Connor and Hiroki, 2005; Balica, 2012). Environmental Vulnerability Index, Economic Vulnerability Index, Social Vulnerability Index, Water Poverty Index and Disaster Risk Index are some of the examples. There are also indices developed specifically for a particular hazard event e.g. FVI, Coastal Vulnerability index and Drought Vulnerability index. The variables for such indices are usually selected based on two standard approaches (i) deductive - theoretical explanation of relationships between influencing factors and (ii) inductive-statistical analysis (Balica, 2012). The indices involve uncertainties from both the subjective nature of variable selection and in the vulnerability concept itself (Balica, 2012). The key challenges in index developments are (Balica, 2012; de Ruiter et al., 2017):

- a) Selection of variables and corresponding weights
- b) Lack of data for calculation especially in developing countries
- c) Extremely difficult to verify the index where exposure is continuously increasing
- d) Vulnerability is always a subjective concept
- e) Influenced by real complex life reflections (communities, societies)

2.4.1 Prevalent Vulnerability Index (PVI)

Cardona (2006) developed a system of indicators to quantify progress in managing flood risk and to compare vulnerability in different south American countries. The vulnerability is defined as inherent to the system and independent of the flood. The vulnerability conditions are depicted by measuring the exposure and susceptibility-ES (i.e. the physical impact), socio-economic fragility-SF and lack of social resilience-LR (intangible/indirect impact) (Cardona, 2006). The socio-economic variables were divided into above three categories as shown in Table 2.3 and the final PVI is a combination of ES, SF and LR. Birkmann (2007) reviewed risk and vulnerability indicators and concluded that the PVI variables are more comprehensive in terms of variable selection.

Table 2.3 Variables for PVI estimation

Exposure & susceptibility (ES)	Socio-economic fragility (SF)	Lack of resilience (LR)
Population growth	Human poverty index	Human Development Index
Urban growth	Dependents as proportion of working age population	Gender-related Development Index
Population density	Gini index	Social expenditure; on pensions, health, and education
Poverty population	Unemployment	Governance Index
Capital stock	Inflation, food prices	Insurance of infrastructure and housing,
Import and export of goods and services	Dependency of Gross domestic product DP growth of agriculture	Television sets per 1000 people
Gross domestic fixed investment	Debt servicing	Hospital beds per 1000 people
Arable land and permanent crops	Human-induced Soil Degradation (GLASOD)	Environmental Sustainability Index

2.4.2 Flood Vulnerability Index (FVI)

Connor and Hiroki (2005) formulated a FVI by categorizing the influencing factors under four components of meteorological (MC-amount of water entering the basin), hydrological (HC-difficulties in leaving the basin for the entered water), socio-economics (SC-vulnerability of the basin in terms of population and economics) and countermeasures (CC-extent of resilience or resistance). It measures the flood vulnerability at the basin level due to climate change and aim to assist in flood preparation policy and decision making. Possible variables for the index are identified via a group of 50 participants at the Asian Development Bank's Water Week 2004 and more details are found in Connor and Hiroki (2005).

The FVI was further improved to quantify vulnerability at different spatial scales; river basin, sub-basin and urban area by Balica et al. (2009), and to explain the vulnerability characteristics at different spatial scales. The flood vulnerability is defined by compiling the factors of exposure (proneness to flood due to the location), susceptibility (chance of being harmed during the flood) and resilience (capability of maintaining sufficient level of efficiency and recovery capacity). The dimensionless FVI was calculated for four different components of social, economic, environmental and physical using 28 variables in total. Mathematical models (derivative and correlation) and expert survey were used to reduce the number of variables from 71 to 28 (Balica and Wright, 2010). A gradient of FVI with respect to variables ($x_1, x_2 \dots x_n$) for the four components and three spatial scale were further calculated (Equation (2.1)). The ∇FVI could then indicate the significance of the variables.

$$\nabla FVI = \left(\frac{\partial FVI}{\partial x_1}, \frac{\partial FVI}{\partial x_2} \dots \dots \dots \frac{\partial FVI}{\partial x_n} \right) \quad (2.1)$$

Balica and Wright (2010) for example, developed a set of finalized variables for urban area scale as summarized in Table 2.4. The total FVI is calculated by summation over the components.

Table 2.4 FVI components and variables

Component	Variable
Social	Population density, Cultural heritage, Population growth, Disable people, Child mortality, Past experience, Awareness and preparedness, Shelter, Warning system, Evacuation road, Emergency service
Economic	Industries, Contact with river, Unemployment, Urban growth, Human development index, River discharge, Flood insurance, Amount of investment, Dam-storage capacity, Drainage system
Environmental	Urban growth, Rainfall, Evaporation rate, Land use
Physical	Topography, Contact with river, Evaporation rate/Rainfall, Storage/Yearly runoff, Dikes and levees

2.5 Urbanization

Urbanisation is taking place in many locations worldwide and especially in developing countries as driven by economic and technological developments. It also has a strong impact on hydrologic cycle. Variation in the catchment parameters will be reflected in the runoff (Leopold, 2006; Miller et al., 2014). In terms of effects on flood forecasting, the runoff quantity will be increased, and lag time of the catchment will be reduced. The increase in flood damage recorded in recent decades has mostly resulted from increased human activity (urbanization) in floodplains (Luino et al., 2012), which altered the basin parameters and the exposure level, and which would also lead to expensive flood mitigation efforts. To have effective flood protection it is thus necessary to project urban

pattern for future years. It is expected to have increased flood risk from climate change and to introduce more uncertainty in the flood forecasting.

Remote sensing technology and Arc-geographic information system (ArcGIS) tool are key tools for flood studies, especially for land use monitoring and for runoff response analysis (Suriya and Mudgal, 2012). Land use classification is a widely used technique to categorize and extract the land use patterns from remotely sensed data. Li et al. (2015) mapped the annual urban area pattern for Beijing covering 30 years using a classification method. Supervised classification techniques is widely used, which is reported to be more accurate than unsupervised classification (Kim, 2016; Rawat and Kumar, 2015; Suriya and Mudgal, 2012). Here it is adapted for use in this PhD study (see later Section 4.4.1) to characterize land use change in Jakarta.

Increased severity of flood due to land use changes and rapid urbanization are reported in the literature (Suriya and Mudgal, 2012; Xu and Zhao, 2016; Rafiei Emam et al., 2016; Huong and Pathirana, 2013). Land use projection models (e.g. cellular automata models) have been used to project future the land use patterns (Farjad et al., 2017; Yang, 2003) and though the predictions are uncertain, urban growth showed a general trend of the future. Thus it is important to include urbanization projections in flood mitigation decisions (Suriya and Mudgal, 2012).

Chapter 3

Jakarta flood modelling and loss estimation

A Jakarta flood model combined with a financial loss model has been developed at the Institute of Catastrophe Risk Management (ICRM), NTU (Lo and Chen, 2013). This PhD study used this existing model with modifications to use within the MCDA framework. This chapter briefly describes the flood model process which starts from rainfall to the flood damage.

Jakarta, the capital of Indonesia, is located on Java Island (Figure 3.1) at 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. Both rivers flow from south to north and drain into the Java Sea. Ciliwung is the longest river in Jakarta and flows through the Jakarta city centre. As shown in Figure 3.1, the study area adopted a 'central basin' which included 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 covered an area of 190 km². The hydrology and hydraulics calculations were performed using the Hydrologic Engineering Centre (HEC) Hydrologic Modelling System (HMS) and River Analysis System (RAS) codes for the Ciliwung and Cengkareng river basins and ArcGIS was

used to map the inundation area. Short description of the HEC-HMS and HEC-RAS are provided in Appendix A.

Figure 3.1 Studied central river basin within the larger Jakarta catchment area. (a)

River catchment and rain gauge locations. (b) Java Island, Indonesia

3.1 Rainfall Data

Annual maximum daily rainfall for the period 1916 to 2003 (Jakarta and Bogor) and daily rainfall for the period 1984 to 2006 (Ciliduk, Halim, Priuk and Depok) data were available from the Institute of Water Resources, Bandung. The annual maximum daily rainfall from the observed data was fitted with the LP3 probability distribution. Figure 3.2 shows the probability of exceedance of annual maxima along with the fitted LP3 distribution for the four stations using the more recent data of 1984-2006. The 95% confidence intervals were obtained using the Monte Carlo approach from Kottegoda and Rosso (1997). The empirical exceedance probabilities at all four stations were within the 95% confidence interval illustrating that LP3 distribution is a good fit to the observed

record. However, it is noted that the confidence interval is slightly larger for Depok compared to other stations.

Figure 3.2 Annual maximum of daily rainfall fitted with LP3. The shaded region shows 95% confidence interval.

Figure 3.3 LP3 fit of combined annual maximum rainfall from Jakarta and Bogor for the period of 1916-2003

Flood modelling including hydrology and hydraulics modelling were simulated by using rainfall data from Jakarta and Bogor. This is because these stations have longer period of record of 85 years (1916-2003, where 1940, 1946, and 1975 are missing) and 40 years (1916-2003, where 1940, 1942-1944, 1946-1972 and 1986 are missing) respectively. The rainfall stations Jakarta and Bogor which are 100 km apart were further combined through the station year method (Buishand, 1991; Raghunath, 2006) to produce a longer record with the implicit assumption of spatial homogeneity. The observed annual maximum rainfall data from the combined stations were fitted with the LP3 as shown in Figure 3.3. The daily rainfall with 50, 100, and 250 years of RP are estimated as 204.1, 224.8 and 253.0 mm/day respectively. 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 24h using soil conservation service (SCS) type 1A distribution. *It is noted that the standard Type 1A distribution is used here as no standard distribution is reported in the open literature for Jakarta, Indonesia.* Also, the ARF is calculated using Equation (3.1) by following prior studies done for Jakarta (Partner_For_Waters, 2007; Boerema, 1925).

$$ARF = 1 - 0.006A^{0.6} \quad (3.1)$$

where A = catchment area (km^2)

The climate change analyses of Section 4.3 further require daily rainfall time series. Thus, the daily records of Ciliduk, Halim and Priuk were used. As shown later the loss curves of Section 3.4 developed using a daily maximum rainfall amount as input, and thus independent of the particular rainfall data set used in its development. Rainfall data from Ciliduk, Halim, and Priuk thus were fitted with LP3 and used for the climate change analysis in Section 4.3. Depok was not used except for SD model comparison (later Section 4.3.1) due to its poorer LP3 fit (ref Figure 3.2).

3.2 Hydrologic and hydraulic model for Ciliwung and Cengkareng

The Ciliwung and Cengkareng catchments were divided into 63 and 33 sub-catchments respectively. The basin area, basin slope, channel slope and channel length were defined using ArcGIS tools and using a commercially procured Digital Elevation Model (DEM) with vertical accuracy (root mean square error) of 2.3m from Intermap Technologies Inc. The DEM for the lower lying coastal areas were further augmented with a higher resolution DEM (vertical accuracy of 1m) that was provided by the Dinas Pekerjaan Umum Jakarta (DPU, Public Works Agency). The interior models used in the HEC-HMS hydrologic simulation process are:

- a) Loss model: SCS curve number (CN) method
- b) Basin routing: Kinematic Wave
- c) Base flow: Recession method
- d) Channel routing: Kinematic Wave

Information on the values of imperviousness and CN were extracted from a DPU (2009) report. The land use pattern is used to define the percentage impervious and pervious area for each of the sub basin. Here, landcover details from year 2009 was used. The impervious area was defined as urban cover and the pervious area was defined as grass land. Figure 3.4 shows the calculated percentage impervious area in each of the sub basin in Ciliwung and Cengkareng river basin. The upstream is covered with maximum of 40% impervious area and downstream with maximum of ~85%. The CN values used are 98 and 39 for urban cover and grassland respectively. The base flow model parameters and routing models were derived through calibration.

Figure 3.4 Percentage impervious area in Ciliwung and Cengkareng river basin

The HEC-RAS model was developed only within the region of Jakarta DKI. In the HEC-RAS modelling, the river flow was assumed as steady and the mean sea was used as the boundary condition for design rainfall conditions. The HEC-RAS calculation procedure was 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. The flood extent was exported from HEC-RAS and inundation mapping was done with ArcGIS for the flood extent and depth results.

The models were calibrated with February 2002 and February 2007 historical flood event flow records as available from DPU. Simulated river flow were transformed into stage levels via the use of rating curves at Kebor Jeruk, Katulampa, Depok and Manggarai (ref Figure 3.1 for these four location) and compared with observed stage

level (Figure 3.5). The rating curves for the first three stations were from the Partner_For_Waters (2007) report while the last gauging station rating curve was developed at ICRM using gauge HEC-RAS simulations. It is noted that these calibrations used more extensive gauge rainfall data over the catchment, but the rainfall data were limited to the duration of the flood events. However, the flood model once calibrated would be applicable for calculating the flood maps at various RP rainfall as derived here. In addition, the HEC-RAS modelled inundation extent was driven by the peak discharge values and thus was 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 from Figure 3.5 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) and 21.4 (16.4) %.

Figure 3.5 February 2002 and February 2007 historical flood events calibration for river Ciliwung

3.3 Financial Loss Calculations

Flood financial loss is defined as the direct loss to residential, commercial and industrial buildings and calculated using depth-damage (D-D) loss curves shown in Figure 3.6.

The residential D-D curves were derived at ICRM (Lo and Chen, 2016) from actual insurance flood loss data in Jakarta and the commercial D-D curves were derived by adapting UK, USA, Japan and Germany commercial loss functions. The residential loss values were expressed as a ratio of loss to the Total Sum Insured and the commercial losses are expressed directly in Indonesian Rupiah (IDR) per area (m^2).

Figure 3.6 Depth-Damage curve for Jakarta (a) Residential (b) Commercial

As an overall bench marking, a test area of 2km^2 from the flooded Cengkareng district during the February 2007 flood event was selected as shown in Figure 3.7 and damages on residential, commercial and industrial buildings calculated with the predicted flood extent/depth and loss curves. The flood depth for all buildings was extracted using ArcGIS from the flood extent/depth generated in HEC-RAS. The residential and commercial loss curves were applied for separately to calculate the loss in the test area. The loss values were then extrapolated with population density and flooded area in each sub-district of Jakarta over the whole flooded area. In this the entire flood plain is assumed to be homogeneous and flood plain well represented by the 2km^2 test area scaled simply by population density. The resulting total loss calculated for Jakarta DKI during the February 2007 flood event was 814 Million US\$. This was reasonably close to that reported as 900 Million US\$ by Indonesia's National Development Planning Agency BAPPENAS (BPS, 2010).

Figure 3.7 Test area for loss calculations – Jakarta

3.4 Extension of Jakarta Flood Model to present work

Relationships between annual maximum daily rainfall to loss values are developed via usage of ICRM Jakarta flood model developed earlier. The design rainfall was determined from the LP3 fit for different RP (see Figure 3.3) and the hydrology model HEC-HMS was simulated for 5 days with a 2 days rainfall event where a 15mm/day antecedent rainfall was used for the first day. The design rainfall was distributed with SCS type 1A while the antecedent rainfall was uniformly distributed within the day.

Plots for the discharge at the Ciliwung and Cengkareng mouths, the total overflow from the banks of both rivers, increase in inundation area as arising from the overflow and resulting loss as a function of annual maximum daily rainfall were generated for different level of flood levee protections (see Figure 3.8). Here six different levee protection systems (Plan 0 to 5) were first simulated and one more added (Plan 6) in the latter part of this PhD study where future conditions are considered (see Table 3.1). The levee plans indicated in Table 3.1, which represent the alternative flood mitigation options to be considered, were set to safely convey discharge as driven by the rainfall amount corresponding to these RPs. The current levee system was defined as Plan 0 (do nothing option). Different combination of levee protection levels was used in Plan 2 and 3 to study the severity of the rivers and their overflow. The rainfall RP range of 10-400

years implied a daily rainfall of 150-270 mm/day as seen Figure 3.3. The frequency analysis using combined station (Jakarta and Bogor) is used to develop the curves shown in Figure 3.3. The loss values could be read from the curves under various combination of overtopping conditions and readily used in the MCDA analysis.

However, it is noted that the combined station data (Jakarta and Bogor) which has the longer yearly maximum record spanning 125 years was first used to develop the loss curves described in Section 3.1. Furthermore, these curves once developed are independent of input rainfall data set. In contrast the daily rainfall records as available for the stations Ciliduk, Halim and Priuk, and which is needed for defining the climate changed rainfall (see later Section 4.3) is used to define the loss arising from the various levee plans as plotted in Figure 3.8. This is for consistency when further applying the climate change factors on the rainfall under future conditions in the assessment of the levee plans. Thus, hereafter the combined station data from applying the station-year method on Ciliduk, Halim and Priuk rainfall data is used to generate the loss values arising from the various levee plans implemented.

Table 3.1 Levee protection Plans

Alternative	Description
Plan 0	Current level (do nothing)
Plan 1	Protect up to 50yrs 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)
Plan 6	Protect up to 400yrs RP rainfall (Cengkareng and Ciliwung with WBC)

Figure 3.8 Flood model results of discharge, overflow, inundated area and loss plotted against daily rainfall for the studied central basin of Jakarta.

Chapter 4

Methodology

A flood mitigation decision framework was developed and with the impact of rainfall and climate uncertainty, socio-economic features and urbanization on flood mitigation performance quantified via the criteria developed. The developed framework is thus able to rank the alternative levee plans and choose the best for the central basin of Jakarta.

The MCDA outranking technique, PROMETHEE developed and extended by Brans (1982) and Brans et al. (1986) is used here in the decision framework. This technique analyses a finite set of alternatives among conflicting criteria through a transparent computational procedure that is further readily understood by decision makers (Mateo, 2012a). Generally the process follows the sequence below (Hyde et al., 2003):

- a) Selecting appropriate criteria
- b) Formulating alternatives levee plans
- c) Weighting the criteria
- d) Assessing the performance of plans against each criterion
- e) Selecting a preference function for each criterion
- f) Applying PROMETHEE
- g) Making the final decision

The MCDA PROMETHEE decision making procedure is shown in Figure 4.1 indicating the respecting sections, tables and equations where the descriptions are given. The grey box summarizes the PROMETHEE outranking procedure.

Figure 4.1 Flowchart of MCDA PROMETHEE decision making procedure

As seen in Figure 4.1 PROMETHEE allows propagation of information within each criterion as formulated through performance values and preference functions of the alternatives. PROMETHEE requires the following information from the decision maker,

(i) relative importance of criteria (i.e. criteria weights) and (ii) the preference function. However, no specific guidelines are available for determining the criteria weights and this is a key limitation of PROMETHEE. Often equal weight is assumed as done here.

The decision making using PROMETHEE undergoes three phases: (i) construction of preference function, (ii) determination of outranking of each alternative relative to each other, and (iii) evaluation of a net outranking to yield a final decision (Su and Tung, 2014).

Construction of preference function: Alternatives (i.e. the levee plans) considered in decision making process are reflected via its own performance values and compared across through a preference function. It is noted that ‘the preference function is used to specify the degree of preference within the criteria’ (Su and Tung, 2014). The preference function for criteria k between alternatives P_i and P_j denoted by $F_{k(P_i, P_j)}$ is constructed as a function of the difference d_k between the respective performance values denoted as $x_{i,k}$ and $x_{j,k}$ as defined in Equations (4.1) and (4.2). For a criterion to be minimized, the preference function should be the mirror image of the maximizing preference function as shown in Figure 4.2.

$$d_{k(P_i, P_j)} = x_{i,k} - x_{j,k} \quad (4.1)$$

$$F_{k(P_i, P_j)} = f(d_{k(P_i, P_j)}) \quad (4.2)$$

Figure 4.2 Gaussian preference function for (a) maximizing and (b) minimizing criteria k

The shape of preference function for each criterion is defined to quantify the degree of performance for the alternatives. The standard preference function value should vary from zero to one. The Gaussian function (Equation (4.3)) is adopted here because it is continuous in its shape and derivative and Brans et al. (1986) also found that the stability of the results is much weaker if discontinuous (slope continuity) preference functions are used. The inflection point (s) in the Gaussian function is defined via the standard deviation of performance values of criteria. The Figure 4.2 shows the shape of the Gaussian preference function for maximizing and minimizing criteria.

$$F(d) = \begin{cases} 0 & d_{k(P_i, P_j)} \leq 0 \\ 1 - e^{-\frac{d_{k(P_i, P_j)}^2}{2s^2}} & d_{k(P_i, P_j)} > 0 \end{cases} \quad (4.3)$$

Determination of outranking values: In PROMETHEE a multi-criteria preference index (π) is defined as the weighted average of preference function, over all the criteria in the decision process.

$$\pi[P_i, P_j] = \frac{\sum_{k=1}^K w_k F_k(P_i, P_j)}{\sum_{k=1}^K w_k} \quad (4.4)$$

where w_k is the weight assigned to criteria k .

$\pi[P_i, P_j]$ then represents how much alternative P_i is preferred over P_j with respect to all the criteria considered. Outrank flows π^+ and π^- are calculated over all the alternatives as follows, where N represents the number of alternatives.

Positive outranking flow:

$$\pi^+[P_i] = \frac{\sum_{j=1}^N \pi[P_i, P_j]}{N-1} \quad (4.5)$$

Negative outranking flow:

$$\pi^-[P_i] = \frac{\sum_{j=1}^N \pi[P_j, P_i]}{N-1} \quad (4.6)$$

The positive out ranking flow $\pi^+[P_i]$ (Figure 4.3 (a)) indicates how much alternative P_i is preferred over others and this reflects the power of alternative P_i . Similarly, $\pi^-[P_i]$ (Figure 4.3 (b)) indicates how much other alternatives are preferred over P_i , i.e., the weakness of the alternative P_i .

Figure 4.3 PROMETHEE outranking flows

Evaluation of outranking relation: The PROMETHEE ranking method evaluates the preferences, indifferences and incomparability of alternative levee plans. It depends purely on the positive and negative outranking flow. The alternative with higher positive outrank flow along with lower negative rank flow forms the better choice (see Equation (4.7)). The complete ranking is based on the net ranking index $\pi[P_i]$ as calculated over all the alternatives. Alternative levee plans with higher $\pi[P_i]$ then become the better alternative.

$$\pi[P_i] = \pi^+[P_i] - \pi^-[P_i] \quad (4.7)$$

In the literature, there are examples of inclusion of uncertainties in the criteria for decision making techniques. Su and Tung (2014) proposed a quantitative risk measure based on the concept of an expected opportunity loss (EOL). EOL was then used to assess the relative performance of multiple decision alternatives and further extended to decision making problems involving multi criteria. The impact on the design alternatives from external uncertainty from lack of perfect understanding of decision environment, or from randomness inherent in a hydrosystem was studied. PROMETHEE was applied for two reasons: (i) PROMETHEE is amenable to probabilistic treatment for dealing with a MCDA problem under uncertainty and (ii) the logic of an EOL can be directly incorporated into it. The performance values were treated as random variables and Gaussian preference function was used. Here we followed this approach of using PROMETHEE in incorporating uncertainty as arising from rainfall which is then propagates particularly into the criteria and performance values.

Criteria that can accommodate the uncertain features of a hydrosystem are getting increased research focus. Tung et al. (2006) defined the annual expected damage with a computation approach for its calculation while De Bruijn (2004) worked on the

indicators of flood resilience. The criteria adapted in this PhD study are discussed in detail in following sub-sections.

The methodology followed is to analyse flood levee plans based on criteria representing climate change, urbanization and socio-economic aspects as shown schematically in the flowchart of Figure 4.4. Number in the boxes indicates the section where the descriptions are given. Blue, red and grey boxes represent current, future conditions and processing elements respectively. The climate change and rainfall projections, socio-economics and urbanization which influences the hydrosystem and the flood mitigation decisions; and related uncertainties are represented as input into the PROMETHEE via various criteria. The current condition considers four indicators of AEL, G, C and Net SEVIs as criteria. The difference between current and future is used for future condition (e.g. Δ Annual Expected Loss).

Lastly two current condition cases and three future condition cases are analysed. The current condition cases comprise a baseline case which considers uncertainty from rainfall frequency analysis and the addition of the socio-economic factors via the Net SEVIs. The future cases comprise the future rainfall and urban conditions as analysed individually and then together (see Figure 4.4).

Figure 4.4 Methodology Flowchart

4.1 Rainfall frequency analysis and criteria development

A design rainfall is the calculated rainfall amount as used in design of hydraulic structures and for risk assessment, and which is typically derived from a frequency analysis. Here the confidence interval from the frequency analysis is further used to represent the uncertainty in the rainfall prediction, i.e. based on the statistics of the observed data.

The frequency analysis uses annual maximum daily rainfall from the combined station (Ciliduk, Halim and Priuk) using the station-year method and fitted with the standard LP3 probability distribution. The rainfall uncertainty is set as the 99.7% confidence interval (average of upper and lower confidence limits) which corresponded to three times the standard deviation (see Figure 4.5(a)). This uncertainty is further assumed to be normally distributed (Gaussian distribution). The fitting uncertainty in Figure 4.5 (a) is from the observed daily rainfall data while the propagated uncertainties are from simulations using the Jakarta flood model described in Chapter 3, and particularly the results shown in Figure 3.8. In particular discharge at the Ciliwung mouth and Plan 0 is extracted from Figure 3.8 and shown in Figure 4.5 (b, c, d and e) for demonstrative purpose. Here the curves from Figure 3.8 is used obtain loss values for the combined station (Ciliduk, Halim and Priuk) rainfall (ref Section 3.4). The loss values from at any given rainfall value is thus read from the curves developed in Section 3.4 (ref Figure 3.8). Therefore, uncertainty in rainfall values as distributed following the Gaussian distribution is readily transformed into an uncertainty loss distribution.

Figure 4.5 Propagation of uncertainty from rainfall data to annual loss

4.1.1 Annual expected loss (AEL)

A prediction of the damage which is expected to occur annually through statistical analysis is termed the Annual expected loss (AEL). Tung et al. (2006) developed an AEL for hydraulic structures and quantified the uncertainty arising from flood frequency analysis via integrating the probability function of flood magnitude at different T year of RP. The AEL then follows from natural randomness.

The AEL was adapted here and improved to quantify uncertainty in the loss. The corresponding loss values were obtained from the loss curves shown in Figure 3.8 for the rainfall values resulting from frequency analysis. The AEL, denoted as E_L , defined as the loss value expected in each year was obtained by integration of the loss at each RP rainfall E_{L_T} multiplied by the probability of the RP rainfall as given by the LP3 probability density function (pdf). However, the loss at each RP rainfall E_{L_T} has further uncertainty arising from rainfall estimate/forecast. E_{L_T} is thus further 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 while being 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 Gaussian distribution as shown schematically in Figure 4.5(a) and its loss L_{i_T} . The AEL, E_L is then computed with summation replacing integration as shown in Equation ((4.8)).

$$E_L = \sum_{j=0}^m \left(\sum_{i=0}^n L_{i_T} \cdot f_T(R_{i_T}) \cdot \Delta R_T \right) f(R_j) \cdot \Delta R \quad (4.8)$$

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

where

E_L - annual expected loss-AEL

L_{i_T} - i^{th} loss value with a pdf $f_T(L_{i_T})$ at RP T

$f_T(R_{i_T})$ -pdf (Gaussian distribution) of the uncertain RP rainfall R_{i_T} at each RP T

$f(R_j)$ -pdf of RP rainfall representing natural randomness modelled by LP3 distribution

n - no of samples from pdf $f_T(R_{i_T})$

m -no of samples (RP) from pdf $f(R_j)$

ΔR_T -bin size used for summation over pdf $f_T(R_{i_T})$

ΔR -bin size used for summation over pdf $f(R_j)$

The performance values of criterion AEL for all six levee plans are shown in Table 4.1 along with values for other criteria discussed next in Section 4.1.2 to 4.1.3, and in Section 4.2.3. The standard deviation values of criteria are later used in the application of PROMETHEE.

Table 4.1 Performance values of criteria for six alternative levee plans – Current condition.

Levee Systems	AEL (Mill US\$)	G	C (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

Note: AEL - Annual Expected Loss

G - Graduality

C - Construction cost of levee plans

Net SEVI_A - Net Socio-Economic Vulnerability Index based on area ratio

Net SEVI_D - Net Socio-Economic Vulnerability Index based on depth ratio

Net SEVI - Net Socio-Economic Vulnerability Index

4.1.2 Graduality (G) with incorporation of uncertainty

De Bruijn (2004) defined the graduality (G) as an indicator of flood resilience, which measures the progressiveness of flood loss or the increase of impact with increasing

discharge. This is improved here to incorporate rainfall uncertainty and used as a MCDA criterion. G essentially represents the slope of the typical discharge-damage relationship. De Bruijn (2005) studied different ways of quantifying G and the percentile difference between damage and discharge was chosen as this was assessed to be more comparable across different rivers. In our case as the percentile discharge (Q') and percentile damage (S') are uncertain, the loss and discharge values are replaced with the expected loss and expected discharge to account for the rainfall uncertainty. The graduality (G) is computed 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 Equation ((4.9)). The expected values of loss and discharge is calculated by following the procedure as for AEL as described in Section 4.1.1. The maximum and minimum are kept being at 2 and 1000 year RP rainfall, respectively for both loss and discharge. The difference between the loss percentiles $E_L'{}_j$ and discharge percentiles Q' are calculated via Equations (4.10) and (4.11). Note that $E_L'{}_j$ and Q' are the expected values. The performance values of criterion G for all six levee plans are shown in Table 4.1.

$$G = 1 - \frac{\sum_{j=0}^m |\Delta Q'_j - \Delta E_{Loss}'{}_j|}{200} \quad j = 1, 2, 3 \dots m \quad (4.9)$$

$$\begin{aligned} \Delta E_L'{}_j &= E_L'{}_j - E_L'{}_{j-1} \\ &= \left[\frac{100(E_{Lj} - E_{Lmin})}{(E_{Lmax} - E_{Lmin})} \right] - \left[\frac{100(E_{Lj-1} - E_{Lmin})}{(E_{Lmax} - E_{Lmin})} \right] \end{aligned} \quad (4.10)$$

$$\begin{aligned} \Delta Q'_j &= Q'_j - Q'_{j-1} \\ &= \left[\frac{100(Q_j - Q_{min})}{(Q_{max} - Q_{min})} \right] - \left[\frac{100(Q_{j-1} - Q_{min})}{(Q_{max} - Q_{min})} \right] \end{aligned} \quad (4.11)$$

where

E_{Lmin} and Q_{min} – at 2-year rainfall RF

E_{Lmax} and Q_{max} - at 1000-year rainfall RF

As defined, G 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 in Equation (4.9) for normalization to have G values between 0 and 1.

4.1.3 Levee construction cost

In the above sections the severity of the flood and the uncertainty in the forecasted rainfall were reflected in the calculated AEL and G values and used as criteria in the MCDA decision framework. On the other hand, the expense of levee systems should have equal importance in the flood mitigation decision making.

The construction cost (C) for the levees was adopted from a study by Cho et al. (2007). Figure 4.6 shows levee construction cost for unit length for Orleans, USA. All six plans were considered, and levee heights set separately in HEC-RAS. The levee heights at each river cross-section was extracted and gross levee construction cost was calculated using the relationship shown in Figure 4.6. The net construction cost is finally obtained by deducting the construction cost of Plan 0 (i.e. current existing levees). C was then used as a criterion in the MCDA frame work and the criteria values are shown in Table 4.1 for all six levee plans.

Figure 4.6 Construction cost (C) of levee per foot from Orleans. (Source: (Cho et al., 2007))

4.2 SEVI development and integration within MCDA

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 extent. The data used to define the index are thus location dependent as well as dependent on the flood mitigation measure being considered. Here we describe the approach developed to determine such an index for the central basin in Jakarta.

4.2.1 Development of socio-economic vulnerability index (SEVI)

Socio-economic data for Jakarta were available from 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 the larger provincial level (Jakarta Province) and comprise imports and exports data, 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)). It is noted that the central basin being studied here spanned parts of North, South, East, West and Central Jakarta all these being part of Jakarta Province.

The data items were analysed carefully to avoid duplicative 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 as listed in Table 4.2. 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 and the literacy rate as these reflect the ability to respond during an emergency. The number of beds represent the hospitalization capacity of the area which indirectly reflects the preparedness to recover. The vulnerability is therefore 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. The last reflects the preparedness with vulnerability being indirectly proportional.

Table 4.2 Selected social and economic variables for analysis

Social component	Economic component
Population density (P_D)	Per capita Gross Regional Domestic Product (G_P)
Population growth (P_G)	Unemployment (U)
% population young (Y)	Local and foreign investment (I_v)
Poor population (P_P)	% of monthly expenditure for insurance and taxes (I_n)
Number of beds per 1000 people (B)	
Literacy rate (L)	

The Pearson correlation test was next conducted to quantitatively assess the duplication effects among the selected variables with results shown in Table 4.3 (a) & (b). The correlation coefficient is calculated following Equation (4.12) with $|r|$ values closer to 1 reflecting a strong linear dependence of the variables are tested. A cut-off value of 0.7 (following Balica and Wright (2010)) is used to remove correlated variables.

$$r = \frac{\sum_{n=1}^N (x_n - \bar{x})(y_n - \bar{y})}{(N-1)s_x s_y}, (-1 \leq r \leq 1) \quad (4.12)$$

Table 4.3 Correlation between variables

Table 4.3 (a) Correlation between social variables

Social Variables	P_D	P_G	Y	P_P	B	L
P_D	1.000					
P_G	0.096	1.000				
Y	0.877	-0.320	1.000			
P_P	-0.157	-0.140	-0.009	1.000		
B	0.815	-0.381	0.847	-0.090	1.000	
L	0.139	0.416	-0.190	-0.774	-0.013	1.000

Table 4.3 (b) Correlation between economic variables

Economic Variables	G_P	U	I_v	I_n
G_P	1.000			
U	-0.461	1.000		
I_v	0.382	-0.649	1.000	
I_n	-0.169	0.119	0.098	1.000

Among the social variables, the number of beds per 1000 people B , % population young Y and population density P_D are significantly correlated with each other, since the planning of hospitals is strongly driven by population measures such as density P_D and the % population young Y . The literacy rate L , as expected, is 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 4.4 for year 2014 at district level (if available) and otherwise at Jakarta provincial level

where the values shown are further normalized spatially by the number of districts (as available) and temporally over years 2005-2014 using Equation (4.13). In the equation, variables with vulnerability being directly proportional [D] and indirectly proportional [ID] are normalized separately in order to get positive normalized values.

$$I_{m,n[D]}^t = \frac{x_{m,n}^t - x_{nmin}}{x_{nrank}} \text{ and } I_{m,n[ID]}^t = \frac{x_{nmax} - x_{m,n}^t}{x_{nrank}} \quad (4.13)$$

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

$x_{nrank} = x_{nmax} - x_{nmin}$

$x_{nmax} = \max(x_{m,n}^t)$; $x_{nmin} = \min(x_{m,n}^t)$ i.e. the maximum / minimum over districts and years (m number of districts and t number of years) for variable n

The social and economic dimensions of vulnerability are combined as one criterion for the later MCDA. For this, a SEVI is first calculated as the weighted sum of normalized social (S) and economic (E) variables from Table 4.4 separately using Equation (4.14) for each of districts as contributing to the central basin of Jakarta as well as for Jakarta as a whole, and then added via Equation (4.15). The values for $SEVI_m$ shown in Table 4.4 assumed equal weighting. Values from year 2014 are used as they are most representative of the current status.

Table 4.4 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

Note: The variables G_P and I_n are only available at a provincial scale thus assumed constant across five districts.

$$SEVI_{m(S,E)} = \frac{\sum_{n=1}^N I_{m,n} \times w_n}{\sum_{n=1}^N w_n} \quad (4.14)$$

$$SEVI_m = SEVI_{m(S)} + SEVI_{m(E)} \quad (4.15)$$

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

4.2.2 SEVI variable weightage

The effect of unequal weightage for social and economic variables is also assessed. The magnitude gradient provides a ready indication of the significance of each variable and is used as an indication of its weight as done 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 via Equation (4.16) 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 is shown in Equation (4.17) and is the derivative of the vulnerability functions. This is calculated, then normalized and averaged over years 2005-2014 with results shown in Table 4.5. As seen, the resulting values have almost equal magnitudes indicating that each of the seven social and economic variables has approximate equal importance in defining the SEVI. Thus, equal weights are mainly used in the subsequent analysis.

It is further noted that as defined, ∇V which is the gradient of V with each variable reflects the importance of that variable when compared to the rest. In the variable selection process, the minimum of variables is selected with consideration of information content, data availability and the need to reduce the duplicative effects. As such the variable selection process itself is likely the reason for the resulting ∇V values being almost equal.

$$V_S = \left[\frac{P_D \times P_G}{L} \right] \text{ and } V_E = \left[\frac{G_P \times U \times I_v}{I_n} \right] \quad (4.16)$$

$$\nabla V_S = \begin{bmatrix} \frac{P_G}{L} \\ \frac{P_D}{L} \\ -\frac{P_D \times P_G}{L^2} \end{bmatrix} \text{ and } \nabla V_E = \begin{bmatrix} \frac{U \times I_v}{I_n} \\ \frac{G_P \times I_v}{I_n} \\ \frac{G_P \times U}{I_n} \\ -\frac{G_P \times U \times I_v}{I_n^2} \end{bmatrix} \quad (4.17)$$

Table 4.5 SEVI variable 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

4.2.3 Compiling SEVI with engineering framework within MCDA

It is noted that the SEVI as developed in Section 4.2.1 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, in which uncertainty in forecasted rainfall is included. Two different methods denoted as Method 1 and 2 are 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 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 (Figure 3.1) to the expected discharge at the river mouth. Here, 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 via Equation (4.18) where the summation of $SEVI_m$ over the districts is performed as weighted with the inundation area ratio for each of six different levee plans to arrive at the $Net\ SEVI_{A_i}$ for levee plan i . The approach incorporating the depth effect is reflected by Equation (4.19). 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 *Net SEVIs* was thus used together as independent criteria in the MCDA to assess the effect on the outcome. Their values for the different levee plans are listed in Table 4.1.

$$Net\ SEVI_{Ai} = \sum_{m=1}^5 \frac{Population\ in\ expected\ inundated\ area_{i,m}}{Total\ Population_m} \times SEVI_m \quad (4.18)$$

$$Net\ SEVI_{Di} = \frac{Expected\ over\ flow\ to\ the\ central\ basin_i}{Expected\ discharge\ at\ the\ mouth} \times SEVI_J \quad (4.19)$$

where

$SEVI_m$ - *SEVI* for district m

$SEVI_J$ - *SEVI* for whole Jakarta

$Net\ SEVI_{Ai}$ - *Net SEVI* based on area ratio for plan i

$Net\ SEVI_{Di}$ - *Net SEVI* based incorporating depth for plan i

Method 2

It is noted that 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 which are 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. 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 (c.f. Equation (4.13)) for each alternative plan. The $SEVI_m$ shown in Table 4.4 was re-calculated with Equation (4.14) and (4.15) for all the districts m and plans i as $SEVI_{m,i}$, and the $Net\ SEVI_i$ was obtained from Equation (4.20) as the summation of $SEVI_{m,i}$ over the districts for each plan i separately.

$$Net\ SEVI_i = \sum_{m=1}^5 SEVI_{m,i} \quad (4.20)$$

Methods 1 and 2 above were used as alternate forms of the socio-economic criterion along with the criteria of AEL, G and C. The performance values of socio-economic criteria are given in the Table 4.1.

4.3 Rainfall projections under climate change

The impact of climate change in rainfall variation is analysed here and the uncertainty from GCMs are quantified. The MCDA criteria AEL, G and Net SEVIs are also calculated with future rainfall conditions for different emission scenarios. However, the GCM projections had to be downscaled before application on hydrology and flood models. In this section the methodologies for downscaling calculation, uncertainty assessment and criteria computations are described in detail.

4.3.1 Comparison of LARS-WG, SDSM and NEX-GDDP projections

The SD models, LARS-WG and SDSM, and the downscaled gridded dataset, NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) are used for the comparative analysis for both annual and seasonal (wet, December-March, and dry, June-September) rainfall extremes. Figure 4.7 shows the GCM grids used in SDSM and NEX-GDDP data coverage over the study region of Jakarta. The red lines in Figure 4.7 represent the CanESM2 GCM grid which have a spatial resolution of 2.7906° (latitude) and 2.8125° (longitude) used in SDSM. The green shaded area in Figure 4.7(b) denotes the Jakarta DKI region. The different combinations of GCMs and future scenarios and downscaling methods used as shown in Figure 4.8 allows us to investigate the relative importance of different sources of uncertainties. LARS-WG uses SRES emission scenarios and SDSM and NEX-GDDP are based on AR5 RCPs. All three methods cover historical and future time periods with only slight difference. Characterization of the

variability in the changes of future rainfall across these approaches will be useful in interpreting climate change impacts.

Figure 4.7 Map of the western Maritime Continent. (a) showing the study area of Jakarta (filled red square) and CanESM2 grids and (b) map of Jakarta showing the rain gauges used and the NEX-GDDP grids.

Figure 4.8 Methodology flowchart showing the framework comparing historical and future daily rainfall RP curves via three different components: LARS-WG, SDSM, and the NEX-GDDP gridded data.

Observed daily rainfall data from four gauging stations (Halim, Priuk, Ciliduk, and Depok – Figure 4.7) for the period of 1984-2006 are available (DPU, 2009) and used for this study. Based on the recorded data, the regional averages of annual rainfall and annual maximum daily rainfall are 1983mm and 112 mm/day, respectively.

Using LARS-WG requires input weather variables such as the daily solar radiation and the maximum and minimum temperature. Data for the four stations are obtained from the Global Weather Data for Soil and Water Assessment Tool (SWAT) website (<https://globalweather.tamu.edu/>). The three major steps in LARS-WG described in Section 2.3.3 are followed here. For the analyses, 100 independent sequences of synthetic daily rainfall, each with length of 23 years were produced using observations from 1984 to 2006. Similarly, 100, 23 years long sequences of future rainfall series were produced for emission scenarios A1B (15 GCMs) and B1 (11 GCMs) over the period of 2046–2065. The length of each sequence was chosen to match with the length of the observed record, and 100 sequences were produced in order to characterize the uncertainty. In the above it is noted that the calibration of the LARS-WG model identifies the best random seed. This random seed is then used to generate a 2300 years long daily precipitation record for each GCM and emission scenario combination. Finally this 2300 year record is separated into 100 independent sequences, each 23-year duration.

SDSM, which formed the second component of the methodology, is used to examine changes in rainfall extremes under the newer RCP scenarios defined in AR5. While three GCMs are available with the earlier AR4 emission scenarios, only one GCM, the second generation Canadian Earth System Model (CanESM2), is available with the AR5 RCP scenarios. Hence this study used SDSM 4.2.9 to generate the future daily rainfall under the RCP 4.5 and RCP 8.5 as available with the CanESM2 GCM. SDSM needs two types

of inputs data comparing daily rainfall (local predictands) and CanESM2 predictors (large-scale regional predictors) from the GCM grid box that covers the study area. CanESM2 predictors (Table 4.6) were obtained from the Canadian Climate Data and Scenarios for each station from the corresponding grid box (<http://ccds-dscc.ec.gc.ca/?page=pred-canesm2>).

The use of SDSM requires selection of a predictor set. Mahmood and Babel (2013) developed a predictor screening procedure using correlation matrix, partial correlation and significance indicator values was used to finalise the predictor selection. This approach adapted here. The correlations r_i between the predictand rainfall and 26 predictors were computed ($i \in [1, n]$, n – number of available predictors as listed in Table 4.6, and the one with the highest correlation (r_k) was selected as the first predictor for each of the rainfall stations (Table 4.7). Then, the partial correlations r_{p_j} between the remaining predictors (i.e., $j \neq k$) and the predictand rainfall, conditioned on the presence of the previously selected predictor, were obtained. The percentage reduction in correlation (PRC) was then calculated for these remaining predictors as follows:

$$PRC = \left(\frac{r_i - r_{p_j}}{r_i} \right); (1 \leq j \leq n; j \neq k) \quad (4.21)$$

The predictor which had the minimum PRC was selected as the second predictor. Subsequent predictors were selected by repeating the above steps (i.e., computing partial correlations and selecting the one with the least PRC). The first predictor selected through the above procedure is referred to as the super predictor (SP) and together with two next predictors selected at each station are listed in Table 4.7. Mostly, one to three predictors were sufficient to explain the predictand without multicollinearity (Mahmood and Babel, 2013). The correlation coefficients for super predictors were found to be 0.15, 0.21, 0.11, and 0.09 for Halim, Priuk, Ciliduk, and Depok stations, respectively.

Table 4.6 CanESM2 large scale predictors used in screening process

Predictor	Description	Predictor	Description
ceshmslpgl	Mean sea level Pressure	ceshp8_fpgl	800hPa wind speed
ceshp1_fpgl	1000hPa wind speed	ceshp8_upgl	800hPa zonal velocity
ceshp1_upgl	1000hPa zonal velocity	ceshp8_vpgl	800hPa meridional velocity
ceshp1_vpgl	1000hPa meridional velocity	ceshp8_zpgl	800hPa vorticity
ceshp1_zpgl	1000hPa vorticity	ceshp8thpgl	800hPa wind direction
ceshp1thpgl	1000hPa wind direction	ceshp8zhpgl	800hPa divergence
ceshp1zhpgl	1000hPa divergence	ceshp500pgl	Relative humidity at 500hPa
ceshp5_fpgl	500hPa wind speed	ceshp850pgl	Relative humidity at 850hPa
ceshp5_upgl	500hPa zonal velocity	ceshprcpgl	Total rainfall
ceshp5_vpgl	500hPa meridional velocity	ceshs500pgl	Specific humidity at 500hPa
ceshp5_zpgl	500hPa vorticity	ceshs850pgl	Specific humidity at 850hPa
ceshp5thpgl	500hPa wind direction	ceshshumpgl	Surface-specific humidity
ceshp5zhpgl	500hPa divergence	ceshtempgl	Mean temperature at 2m height

Table 4.7 List of CanESM2 predictors selected for downscaling.

Halim	Priuk	Ciliduk	Depok
<i>ceshp1_vp</i> gl	<i>ceshp1_vp</i> gl	<i>ceshp1_vp</i> gl	<i>ceshp1_vp</i> gl
ceshp1_zp	ceshp1zhp	ceshp1_up	ceshshump
ceshp8thp	ceshp1thp	ceshp8thp	ceshp1thp

Once the predictors were selected, the monthly empirical relationships were derived within SDSM using the following sub models: ordinary least squares for optimization, the fourth-root transformation to account for non-normality (Huang et al., 2011; Khan et al., 2006), and conditional scenario. Ordinary least square optimization method was used as it was much faster than the dual simplex method with the results being comparable (Huang et al., 2011). It was necessary to use transformation for daily precipitation as the distribution is skewed unlike for temperature where it is normally distributed (Khan et al., 2006). The conditional scenario was suitable for dependent climate variables such as precipitation and evaporation (Mahmood and Babel, 2013). As in LARS-WG, 100 realizations of 23 years long daily time series of rainfall were generated for all four stations for the historical (1984–2006) and future (2046–2068) time periods under scenarios RCP 4.5 and 8.5. Note that as only one GCM was used here for analyses, therefore climate model uncertainty cannot be assessed.

The third and final component employed the NEX-GDDP dataset. One of the main limitations of SDSM is the lack of multiple GCMs for the AR5 RCPs. To gain insights into climate model uncertainty for different RCPs, we employed the NEX-GDDP data (<https://cds.nccs.nasa.gov/nex-gddp/>, accessed on September 25, 2016). This global dataset comprises 0.25° resolution, bias-corrected, spatially disaggregated, and daily temperature and precipitation series from the 21GCMs (Table 4.8) of the Coupled Model

Intercomparison Project Phase 5 (CMIP5) covering historical (1950-2005) and future (2006-2100) time periods. Details on the bias correction methodology can be found in (Thrasher et al., 2012), and a description of spatial disaggregation approach and the list of 21 GCMs can be found in the NASA technical note (<https://nex.nasa.gov/nex/resources/365/>, accessed on October 5, 2016). To facilitate comparison with LARS-WG and SDSM analysis, we selected NEX-GDDP grids that covered the rain gauge locations of the study domain (Figure 4.7). We selected 40 years of historical data, 1961-2000, to overlap the observed record and future projections, covering 2031-2070, to overlap the future time periods of LARS-WG and SDSM. Note that only 20 GCMs were used in this study as the ACCESS-0 GCM gave unrealistic values for annual maximum daily rainfall (~1000mm/day) and was discarded.

The performance of LARS-WG and SDSM models were analysed with the daily rainfall statistics and frequency analyses with standard probability distribution LP3. The future rainfall projections from GCMs and emission scenarios/pathways were compared within and between the models, LARS-WG, SDSM and NEX-GDDP. The percentage change in the annual and seasonal daily rainfall extremes were calculated with its GCM and ensemble uncertainties where ever applicable. The NEX-GDDP data which contained AR5 emission pathways with 20 GCM projection was used in further climate change uncertainty analyses. The results from LARS-WG, SDSM and NEX-GDDP are discussed in the results Chapter 5 on rainfall projection.

Table 4.8 GCMs in NEX-GDDP data

	GCM model	Original Resolution (Lat×Lon)		GCM model	Original Resolution (Lat×Lon)
1	ACCESS1-0	1.875×1.25	12	INMCM4	2.0×1.5
2	BCC-CSM1-1	2.8×2.8	13	IPSL-CM5A-LR	3.75×1.8
3	BNU-ESM	2.8×2.8	14	IPSL-CM5A-MR	2.5×1.25
4	CanESM2	2.8×2.8	15	MIROC-ESM	2.8×2.8
5	CCSM4	1.25×0.94	16	MIROC-ESM- CHEM	2.8×2.8
6	CESM1-BGC	1.4×1.4	17	MIROC5	1.4×1.4
7	CNRM-CM5	1.4×1.4	18	MPI-ESM-LR	1.9×1.9
8	CSIRO-MK3-6- 0	1.8×1.8	19	MPI-ESM-MR	1.9×1.9
9	GFDL-CM3	2.5×2.0	20	MRI-CGCM3	1.1×1.1
10	GFDL-ESM2G	2.5×2.0	21	NorESM1-M	2.5 × 1.9
11	GFDL-ESM2M	2.5×2.0			

4.3.2 Temporal change factor

The temporal change factor (CF) is defined here as the normalized change in the daily rainfall extremes from a historical to future time period. The CF for each GCM ‘*g*’ at

the T year RP was calculated using the normalized difference in the daily rainfall R of future and historical periods following Equation (4.22). The daily rainfall projections from NEX-GDDP data set was used to calculate the CF for the period from 1961-2000 to 2031-2070 and for the emission pathways RCP 4.5 and 8.5 separately for the three grids (Ciliduk, Priuk, and Halim and Depok) covering the study area.

$$CF_{T,g} = \left[\frac{R_{T_F,g} - R_{T_H,g}}{R_{T_H,g}} \right] \quad (4.22)$$

where

$CF_{T,g}$ - Temporal change factor (CF) of GCM g at RP T

$R_{T_F,g}, R_{T_H,g}$ -daily rainfall of future/historical time period with GCM g at T years of RP

4.3.3 Uncertainty from GCM

The uncertainty across GCMs (in this study 20) implied uncertainty in the final CF. Here, an expected CF at each RP T denoted as CF_T , was defined as the weighted sum over the CFs from the 20 GCMs calculated using Equation (4.23). The distance from the median raised to power d was used as a weightage ($W_{T,g}$) for GCM g as based on the inverse distance method (Caers, 2011). Three different d values of 0.5, 1, 2 were tested and found to be having minor effect on expected change CF_T as shown in Figure 4.9. Thus, the constant d was set to be 1 to avoid infinite values for the weightage, a constant value of unity was added to the absolute difference of $CF_{T,g}$ and $\widetilde{CF_{T,g}}$ as shown in Equation (4.24). The three CF_T s for grid cells covering Ciliduk, Halim/ Depok and Priuk stations were then averaged to yield a constant value over the region.

$$CF_T = \sum_{g=1}^{20} CF_{T,g} \times W_{T,g} \quad (4.23)$$

$$W_{T,g} = \frac{\frac{1}{(|CF_{T,g} - \widehat{CF_{T,g}}| + 1)^d}}{\sum_{g=1}^{20} \frac{1}{(|CF_{T,g} - \widehat{CF_{T,g}}| + 1)^d}} \quad (4.24)$$

where

$W_{T,g}$ -weightage of GCM g at RP T

$\widehat{CF_{T,g}}$ = median of $CF_{T,g}$ over GCMs at RP T

Figure 4.9 Sensitivity of constant d of GCM weightage equation in CF calculation

4.3.4 Incorporating Climate change uncertainty with MCDA

The variation in the rainfall due to climate change will have an impact on the loss value and flood mitigation decisions. The impact of climate change was included in the MCDA decision framework by re-computing the criteria AEL, G and Net SEVIs with changed annual maximum daily rainfall. Projections from emission pathways RCP 4.5 and 8.5 were analysed separately.

The CFs calculated in the previous section was applied to the observed rainfall from stations Ciliduk, Halim and Priuk to obtain the projected point rainfall for the future time period. Thus, the rainfall at the T year RP for the future was calculated by simply multiplying the current rainfall (from observed data) with CF. Here the temporal changes of the daily rainfall in the point scale was assumed to follow GCM's grid scale temporal changes.

The loss values for the projected expected rainfall were read from the curves developed in Section 3.4 as before and criteria calculated by the procedure developed for current condition (Section 4.1 and 4.2) but where now the inner summation was replaced by corresponding loss value for projected expected rainfall in AEL Equation (4.8). This is because the uncertainty in the climate change is already accounted via expected CF. This was similarly done for G and Net SEVI.

The Jakarta population projection from Hoornweg and Pope (2013) was further used for the 2050 population in the criteria calculations since 2050 is the midyear of rainfall projection period considered. In particular the Net SEVI under future conditions accounts for the population growth in the expected population in the inundation area. The criteria values under the future rainfall conditions are summarized in Table 4.9. Note that the basin parameters other than population were kept at current 2009 land use in this table. Basin parameter projections for the future are analysed in Section 4.4.

In the MCDA framework (see Figure 4.4) the difference between current and future values of the criteria were used to represent effect of future conditions. This better reflects the severity of climate change than using the raw values of criteria. Thus, the difference in AEL, G and Net SEVIs were calculated for each of the levee plans. The five criteria from the current condition and four criteria comparing future minus current were used in MCDA. One more levee plan (Plan 6) with the protection level of 400 years of current rainfall RP was added to the MCDA analysis (see Table 3.1) as under climate change the best option moved to higher plans as will be discussed latter in Section 6.2. Thus higher protection level plans need to be added in order to better span the decision space.

Table 4.9 Performance values of criteria for eight alternative levee plans – Future rainfall condition

Levee Systems	Current condition					Future rainfall and current urban condition							
	C	AEL	G	Net SEVI _A	Net SEVI _D	RCP 4.5				RCP 8.5			
						AEL	G	Net SEVI _A	Net SEVI _D	AEL	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	0.5098	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	5.1600	0.1421	0.0024	0.0199	8.9103	0.0069	0.0013	0.0111	12.7386	0.0513	0.0022	0.0084

4.4 Projected urbanization and land use change

Jakarta is known to be a rapidly urbanizing city over the last two decades and thus the effect of land-use changes need to be considered when considering future conditions. Here the future urban extent was projected from historical records. The urban growth and its impact on the flood extent were analysed and considered in the flood decision making process. The methodology used to obtain the future urban extent and procedures to couple the urbanization effect in the MCDA framework are described in this section.

4.4.1 Classification

Landsat Thematic Mapper (Landsat TM) (<https://earthexplorer.usgs.gov/>) was obtained for Jakarta covering the period of 1989-2009 (18 years, 3 years of missing data over years 2001-2003) and used for land classification. Comparatively cloud free images were selected from each year and image for 1989 and 2009 are shown in Figure 4.10. In the Figure 4.10, the green shade shows the urban area and red indicates the vegetation extent. It is readily see that the urban land is growing from downstream to upstream. Also in 2009 the whole DKI region was almost fully urbanized.

Interactive supervised classification tools from ArcGIS 10.0 were used to categorize the land use classes comprising of urban, bare land, water body and vegetation and with a further class of cloud. The maximum likelihood (ML) classification technique was employed, and the ArcGIS tool uses all seven available bands in the layers. The ML classification is a statistical approach for pattern recognition. The probability of a pixel falling into a land use class is calculated and assigned to the class with highest probability (Rawat and Kumar, 2015; Tso et al., 2009). The accuracy of the classification depends on the quality of the training samples. Here each of the land use class was trained with 50-100 samples each year.

Figure 4.10 Landsat TM image for Jakarta region with false colour code (a) 1989 (b) 2009

4.4.2 Urban extent projection

The urban area was extracted from the classified layer annually over the period of 1989-2009. It is noted here that the urban area was highly uniform all over the downstream Jakarta basin while the upstream areas were less urbanized. Thus, urban extent was studied for three regions comprising upstream, midstream and DKI Jakarta as shown in Figure 4.11. The Ciliwung catchment upstream of the Katulampa ‘bottle neck’ was considered upstream, the DKI Jakarta region considered downstream, and area in between considered midstream. The percentage urban area (%) was calculated for each year and for all three regions as plotted in Figure 4.12. There are fluctuations in the

trends as mainly due to data quality (presence of clouds) and human subjectivity in the classification process.

Figure 4.11 Three urban growth regions-Jakarta

Figure 4.12 Percentage urban extent for three of upstream, midstream and downstream (DKI Jakarta)

The percentage urban area was projected by fitting the data with an exponential form that asymptotes to an upper bound. However, the upstream was showing little or negligible changes in urban extent with a maximum of 4.4% (Figure 4.12). Thus, the upstream urban extent was kept constant at the current condition. The highly urbanised downstream DKI Jakarta for the year 2009 had its percentage urban as 87.6% (Figure 4.12) and this was set as the upper boundary for the future projection. A fitting in Equation (4.25) was assumed with constant α determined using the curve fitting package LAB-Fit V7.2.49 for DKI Jakarta and midstream separately.

$$U_t = (87.6 - U_{1989})(1 - e^{-\alpha(t-1989)}) + U_{1989} \quad (4.25)$$

where

U_t , U_{1989} -percentage urban area at year t , 1989

$\alpha = 0.03788$ (DKI Jakarta - D) and 0.01477 (midstream -M)

The final forms are then given by:

$$[U_t]_D = (47.889)(1 - e^{-0.03788(t-1989)}) + 39.711 \quad (4.26)$$

$$[U_t]_M = (82.679)(1 - e^{-0.01477(t-1989)}) + 4.921 \quad (4.27)$$

The fitted urban area results are shown in Figure 4.13. The projected percentage urban extent for the year 2050 (2030) for DKI Jakarta and midstream area are 82.8% (77.5%) and 54.0% (42.5%) respectively. Budiyo et al. (2016) reported that urban area within DKI Jakarta in 2009 was 82.4% and projected to reach to 84.92% in 2030. The Landsat data based results here are therefore comparable with 75.3% urban extent in 2009 and projected to reach 77.5% in 2030 for DKI Jakarta.

Figure 4.13 Future projection of percentage urban area (%) for Jakarta

4.4.3 Flood model simulation for year 2050 and MCDA analyses

The percentage impervious which closely follows the percentage urban area was adjusted to reflect the projected urban extent condition in 2050. The percentage impervious area in year 2050 was calculated by direct scaling with the urban area as shown by Equation (4.28) for all the sub basins falling in DKI Jakarta [D] and midstream [M] regions.

$$[I_i^{2050}]_{(D,M)} = [(U_i^{2050} - U_i^{2009}) + I_i^{2009}]_{(D,M)} \quad (4.28)$$

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 HEC-HMS was re-ran for the 2050 basin conditions and the loss curves shown in Figure 3.8 updated. The MCDA criteria were re-computed again with the current condition and future rainfall conditions separately with the updated loss curves as shown in Table 4.10 and Table 4.11 respectively. The seven levee plans were then analysed with PROMETHEE, MCDA for two separate cases (a) current rainfall and 2050 urban

extent and (b) future rainfall and 2050 urban extent. The latter case thus represents the most severe case but reflects the future condition the best.

The MCDA results are discussed in Chapter 6. Specifically, the current condition is analysed for cases (a) baseline and (b) with socio-economic factors and the future condition is with cases (a) future rainfall and current urban, (b) current rainfall and future urban and (c) future rainfall and future urban (c.f. Figure 4.4).

Table 4.10 Performance values of criteria for eight alternative levee plans – Future urban extent (2050) and current rainfall condition

Levee Systems	E_L	G	Net SEVI _A	Net SEVI _D
Plan 0	85.0685	0.8507	0.0350	0.0448
Plan 1	26.7824	0.7290	0.0139	0.0146
Plan 2	20.7150	0.7343	0.0104	0.0110
Plan 3	22.1480	0.7343	0.0118	0.0117
Plan 4	14.4902	0.6418	0.0077	0.0072
Plan 5	5.1052	0.4909	0.0033	0.0025
Plan 6	3.1210	0.4461	0.0018	0.0013

Table 4.11 Performance values of criteria for eight alternative levee plans – Future rainfall condition and 2050 urban extent

Levee Systems	RCP 4.5				RCP 8.5			
	E_L	G	Net SEVI _A	Net SEVI _D	E_L	G	Net SEVI _A	Net SEVI _D
Plan 0	129.0613	0.8791	0.0544	0.0686	154.5481	0.8259	0.0648	0.0828
Plan 1	49.2688	0.8056	0.0228	0.0231	66.5103	0.7714	0.0311	0.0334
Plan 2	33.5725	0.7390	0.0167	0.0171	52.1374	0.7867	0.0237	0.0262
Plan 3	41.3629	0.8047	0.0199	0.0175	57.9478	0.7974	0.0269	0.0275
Plan 4	26.4548	0.7307	0.0128	0.0132	40.3704	0.7508	0.0180	0.0194
Plan 5	11.1876	0.5996	0.0061	0.0048	21.1893	0.7360	0.0097	0.0088
Plan 6	6.1994	0.5174	0.0034	0.0027	12.5455	0.6268	0.0060	0.0058

Chapter 5

Rainfall Projections and SD models Comparison

This chapter presents SD model validation and comparison and its rainfall projections which is used in the CF calculation to account for climate change variability in the with MCDA criteria. The methodology used is described in the Section 4.3.1 on rainfall projections from LARS-WG, SDSM and NEX-GDDP under different emission scenarios. Further the rainfall temporal CF results from NEX-GDDP as formulated in Section 4.3.2 is shown here for all three rainfall stations.

5.1 LARS-WG validation

The daily mean, standard deviation, and maximum rainfall were computed for each month over the 100 realizations at each station of Ciliduk, Halim, Priuk and Depok. Figure 5.1 shows a comparison of statistics obtained for the synthetic series against the observed record. In general, the statistics from the synthetic series agree quite well with those observed. The interquartile range of 100 realizations captures the statistics of the observed record for a majority of months and for all four stations. The observed data used here are for 23 years over 1984–2006 (with one year of data gap at Depok). The boxplots shown in Figure 5.1 are derived from 100 independent realizations of a 23-year-long LARS-WG generated data. Whiskers indicate minimum and maximum out of 100

realizations. The average percentage error over the months for the mean and maximum daily rainfall in the generated series is shown in Table 5.1. The maximum error for daily maximum rainfall is at Depok station (15%). With the exception of maximum daily rainfall at Depok, the percentage error was high during the dry months as arising from the smaller number of rainy days available for calculating the daily statistics. For example, the highest percentage error in maximum daily rainfall was 33.4% in June (average rainy days of 5.3 days) and 32.9% in August (average rainy days of 3.7 days) at Halim and Priuk, respectively. A similar pattern was observed in mean and standard deviation of daily rainfall.

Figure 5.1 Comparison of observed mean (a), standard deviation (b), and maximum daily rainfall (c) with LARS-WG generated rainfall sequences at the four stations.

Table 5.1 Percentage error in daily mean and maximum rainfall averaged over 12 months.

Station	LARS-WG		SDSM	
	Mean	Maximum	Mean	Maximum
Halim	3.3	5.6	19.7	11.1
Priuk	7.1	9.4	15.8	12.7
Ciliduk	5.4	6.2	11.7	11.5
Depok	10.1	15.0	16.9	30.6

The annual maximum daily rainfall for each of the 100 realizations from synthetic series was also fitted with the LP3 probability distribution for all four stations and plotted in Figure 5.2 where whiskers indicate minimum and maximum rainfall obtained from 100 realizations. As seen the RP curves from the synthetic series closely follow the observed RP curves except at higher RPs, where they deviate slightly. These differences at higher RPs are expected as arising from a sample size of 23 years. Larger discrepancies between RP curves of observed and synthetic annual maxima are seen for Depok, which can be attributed to higher differences between observed and synthetic daily rainfall time series at this station (Figure 5.1 and Table 5.1). In addition, Depok has larger fitting uncertainty compared to other stations (Figure 3.2).

The overall comparison of basic statistics (Figure 5.1) and RP curves (Figure 5.2) indicates that synthetic series generated from the LARS-WG model is satisfactory. Hereafter, these 100 realizations of LARS-WG generated synthetic data is used as the historical values when analysing changes between historical and future daily rainfall extremes.

Figure 5.2 Comparison of RP curves obtained from observation with those from LARS-WG generated rainfall.

5.2 SDSM Validation

A comparison of daily rainfall statistics for observed and SDSM generated rainfall is shown in Figure 5.3. The boxplots are obtained from 100 realizations of a 23-year-long SDSM generated data and the whiskers indicate minimum and maximum of the 100 realizations. Table 5.1 also shows the percentage error for mean and maximum daily rainfall as averaged over the months. The maximum error is observed at Depok (30.6%) for maximum daily rainfall as was the case with LARS-WG. Similarly, the maximum percentage error in SDSM simulations mainly occurs during dry months. The fitted daily RP curves (Figure 5.4) show that the RP curves at Halim and Priuk closely follow those derived from the observed record. Here whiskers indicate minimum and maximum rainfall from 100 sequences. However, they deviate noticeably for Ciliduk and Depok stations. This is partly attributed to the fact Ciliduk and Depok stations are in one CanESM2 GCM grid while Halim and Priuk lie in adjacent grids but close to boundary

(Figure 4.7). The correlation between the predictors and the predictand was higher for Halim and Priuk than for Ciliduk and Depok (see Section 4.3.1).

Figure 5.3 Comparison of observed mean (a), standard deviation (b), and maximum daily rainfall (c) with SDSM generated rainfall sequences at the four stations.

Figure 5.4 Comparison of RP curves obtained from observations with those from SDSM generated rainfall data.

Overall, it is observed that the percentage errors are higher in the SDSM analysis compared to LARS-WG (Table 5.1). That LARS-WG is capable of producing historical synthetic data better than SDSM is because LARS-WG is a weather generator that produces synthetic series as based on actual observed data while SDSM is a SD approach that depends on the empirical relationships developed between the predictors of the GCM CanESM2 and predictand (rainfall here). Furthermore, the CanESM2 predictors used in SDSM have a coarse resolution ($\sim 2.81^\circ$) when compared to the point-level predictands. However, SDSM has an advantage of being able to generate future rainfall time series for AR5 emission scenarios as described earlier in Section 4.3.1.

5.3 Future Rainfall Projections with LARS-WG

The comparison of daily rainfall RP curves between the historical and future time series for emission scenarios A1B and B1 is shown in Figure 5.5. The medians from 100 realizations are calculated for each of the 15 GCMs (shown individually as thick grey

lines), and the overall median is compared with the median of the historical rainfall RP curves. Figure 5.5 also shows the overall GCM uncertainty (shown as shaded grey area) calculated by pooling together all 100 realizations of all 15 GCMs. All four stations experience an increase in daily rainfall at all RFs for the A1B emission scenario. The stations Halim, Priuk, Ciliduk, and Depok experience 2.4, 5.5, 6.3, and 5.7% increase in daily rainfall, respectively, at the RP of 25 years. It is evident that the climate model uncertainty has the major influence on the changes in annual maximum daily rainfall with the largest uncertainty at station Halim. The predictions with emission scenario B1 are lower than with A1B as expected, since the A1B scenario assumes a balanced emphasis on all energy sources while B1 assumes global solutions are developed to meet economic, social, and environmental stability (IPCC, 2000). The median for the B1 emission scenario also show an increased future rainfall, though smaller than with A1B and with the exception of Halim station where a decrease is observed.

Figure 5.5 Daily RP curves comparison between GCM predictions from emission scenarios A1B and B1 for future (2046–2065) and historical generated rainfall with LARS-WG.

5.4 Future Rainfall Projections with SDSM

The CanESM2 predictors and the empirical relationships developed at each station using the historical time period were used to obtain daily time series for a future time period of 2046-2068 under RCP 4.5 and RCP 8.5 emission scenarios. As with the historical

rainfall, 100 independent realizations of daily rainfall for the future period are generated, and the annual maximum daily rainfalls from each realization were fitted with LP3 probability distribution and median values calculated. Figure 5.6 compares the median values of historical and future daily rainfall maxima. All four stations show an increase in daily rainfall intensity under both future climate scenarios. The future daily rainfall under RCP 4.5 at 25-year RP increased by 3.2, 6.0, 7.3, and 13.7% at stations Halim, Priuk, Ciliduk, and Depok, respectively. The corresponding increases are 7.0, 9.9, 3.9, and 6.4% under the higher emission scenario RCP 8.5. Expectedly larger increases are seen at stations Halim and Priuk under RCP 8.5, but lower increases are seen for Ciliduk and Depok. As noted earlier, Ciliduk and Depok which lie on same CanESM2 grid cell had higher errors during the SDSM validation and had lower correlations with the predictors (cf. Section 5.2) and this have contributed to the predicted smaller increment.

Figure 5.6 Comparison between GCM predictions for future (2046–2068) and historical generated rainfall from SDSM for AR 5 emission scenarios RCP 4.5 and RCP 8.5.

5.5 Future Rainfall Projections with NEX-GDDP Data

The NEX-GDDP rainfall data from 20 GCMs for the historical (1961-2000) and future time period (2031-2070) are analysed. Figure 5.7 compares future RP curves for each GCM and emission scenario against the historical curves where the 20 GCM predictions

are indicated with thick grey lines. The median of future RP curves is always higher than the corresponding historical for all stations and for both emission scenarios. For example, the RCP 4.5 emission scenario results in 10%, 16.5%, and 12.2% increases at 25-year RP for the three grid cells that cover the four stations. The corresponding values are 17%, 17.6%, and 16.7% increase under RCP 8.5. Figure 5.7 also shows the large uncertainty across the 20 different GCMs.

Figure 5.7 Comparison of median historical and median future predictions with NEX-GDDP data comparing 20 GCMs under RCP 4.5 and 8.5.

5.6 Comparison across Models

The future prediction results from LARS-WG (15 GCMs), SDSM (1 GCM), and NEX-GDDP (20 GCMs) are compared here. Figure 5.8 shows the percentage change in the future daily rainfall compared to historical for RPs of 50, 100, and 250 years. Dark vertical bars denote 10th and 90th percentile values for all GCMs which for LARS-WG is for the medians from 100 realizations for each of the GCMs. The light vertical bars for LARS-WG denote 10th and 90th percentiles obtained by pooling 100 realizations across all GCMs. All three approaches show an increase in future daily rainfall with one exception being LARS-WG at station Halim under emission scenario B1 where it shows a decrease for all three RFs. This is attributed to AR4 B1 being an optimistic emission scenario while the other scenarios considered are typical (A1B, RCP 4.5) or less optimistic (RCP 8.5). Hence station Halim shows an average increase of 2.0% under LARS-WG with A1B, 2.2% (7.5%) under SDSM with RCP 4.5 (8.5), and 11.5% (17.0%) under NEX-GDDP with RCP 4.5 (8.5) in the 100-year RP daily rainfall. In general, the LARS-WG and SDSM indicate smaller changes in future rainfall compared to the NEX-GDDP. An exception to this behaviour is a 20.3% increase at Depok using SDSM under RCP 4.5.

Figure 5.8 Comparison of percentage change in the annual maximum daily rainfall for future time period using LARS-WG (2046–2065), SDSM (2046–2068), and NEX-GDDP (2041–2070) with different emission scenarios.

The median percentage change in rainfall between emission scenarios A1B and B1 ranges from 2.1 to 8.6% for the four stations. The GCM uncertainty as quantified using interpercentile range (10th–90th percentiles) is much higher, ranging from 12.5 to 42.2% and from 8.6 to 38.1% for LARS-WG A1B and B1 scenarios, respectively (Table 5.2).

The corresponding uncertainty for NEX-GDDP is 41.7 to 60.3% and 55.5 to 62.6% for RCP 4.5 and RCP 8.5, respectively. The uncertainty arising from the GCMs is smaller for LARS-WG compared to that of NEX-GDDP (Figure 5.8), which is mainly due to the former's use of the change factor approach to obtain future projections. More specifically, LARS-WG derives change factors from GCM output at their native scale ($\sim 2.5^0$) and imposes these further on historical input data to obtain future rainfall projections. On the other hand, NEX-GDDP data is downscaled from GCM native resolution to 25 km. It is also noted that LARS-WG model results are with 15 GCMs under SRES scenarios, whereas NEX-GDDP data has 20 GCMs under RCP scenarios.

Table 5.2 Comparison of median (50th) and interpercentile range (10th to 90th) of percentage changes in 100-year RP daily rainfall for LARSWG and NEX-GDDP.

Station	LARS-WG (AR4)				NEX-GDDP (AR5)			
	A1B		B1		RCP 4.5		RCP 8.5	
	50 th	10 th - 90 th range	50 th	10 th -90 th range	50 th	10 th -90 th range	50 th	10 th - 90 th range
Halim	2.2	42.2	-6.4	38.1	11.5	41.7	17.0	62.6
Priuk	4.2	13.8	1.2	8.8	16.7	60.3	18.5	61.5
Ciliduk	8.4	12.5	5.6	8.6	13.0	44.4	18.2	55.5
Depok	6.5	16.2	4.4	13.2	11.5	41.7	17.0	62.6

The above analysis was repeated for the wet (December to March) and dry (June to September) seasons. The future wet season daily rainfall is increasing for most of the cases (Figure 5.9). The percentage change in daily rainfall in the wet season and the corresponding GCM uncertainty are comparable to that of the annual scenario (Figure 5.8 and Figure 5.9), except for LARS-WG result at station Halim under emission scenario B1. The similarity between wet season and annual results is expected as most

of the annual daily maximum rainfall values are recorded during the wet season. For example, the percentage of annual daily maximum rainfall occurring during the wet season is 83% and 44% at Priuk and Ciliduk stations, respectively. For the dry season, the future daily rainfall shows less of a change or even a decrease (e.g., Priuk, Figure 5.10). Comparison of Figure 5.8, Figure 5.9 and Figure 5.10 indicates that the GCM uncertainty is the largest during the dry season. Larger GCM uncertainty during the dry season is because of fewer number of rainfall days available for analysis and lower daily rainfall maxima.

The median daily rainfalls from the 100 realizations across the different models are summarized in Table 5.3. The annual and the wet season daily rainfall values are quite comparable, and the dry season daily rainfall is much smaller with the exception of station Halim where a number of annual maximums occurred in the dry season. This is reflected in the LARS-WG simulation results where the annual projections are consistent with the dry season where other stations are consistent with wet season (Figure 5.8, Figure 5.9 and Figure 5.10).

Table 5.3 Daily rainfall from annual and seasonal analysis for historical and future time periods

Station	RP	Model	Historical			Future-A1B for LARS-WG/RCP 4.5 for NEX-GDDP		
			Annual	Wet	Dry	Annual	Wet	Dry
Halim	50	LARS-WG	189.7	164.0	209.8	193.6	177.2	212.2
		SDSM	227.1	206.5	156.6	231.4	208.2	159.7
		NEX-GDDP	100.2	101.0	51.9	113.1	113.5	49.1
	100	LARS-WG	202.9	176.1	239.3	207.3	191.7	241.3
		SDSM	248.3	230.3	179.9	253.9	228.2	182.0
		NEX-GDDP	108.7	109.7	56.4	121.2	123.0	52.2
	250	LARS-WG	221.8	190.8	278.6	226.6	209.1	280.7
		SDSM	272.6	260.3	207.7	282.1	259.3	213.5
		NEX-GDDP	120.0	119.8	59.6	130.7	131.5	57.1
Priuk	50	LARS-WG	214.1	215.9	88.3	225.3	225.6	82.5
		SDSM	208.7	208.1	112.7	223.5	220.7	101.7
		NEX-GDDP	94.5	96.4	39.2	111.8	112.1	39.3
	100	LARS-WG	233.9	238.0	91.6	243.8	244.9	86.4
		SDSM	229.6	231.4	132.4	250.8	251.7	115.2
		NEX-GDDP	103.5	106.1	43.9	120.8	121.4	42.1
	250	LARS-WG	260.2	261.3	95.5	268.9	273.1	90.0
		SDSM	258.7	262.7	159.1	295.0	295.8	133.5
		NEX-GDDP	115.9	119.6	47.8	132.3	132.3	45.7
Ciliduk	50	LARS-WG	163.0	168.5	133.9	176.2	178.5	132.9
		SDSM	228.0	203.4	178.3	241.2	225.5	174.8
		NEX-GDDP	96.9	97.0	55.5	109.7	111.0	53.2
	100	LARS-WG	170.9	181.4	140.5	185.3	191.3	138.6
		SDSM	252.7	224.1	199.5	264.0	249.6	197.0
		NEX-GDDP	104.1	103.3	58.6	117.6	118.6	56.8
	250	LARS-WG	180.3	197.9	147.9	196.1	207.4	147.5
		SDSM	284.0	254.2	230.0	298.6	281.2	227.5
		NEX-GDDP	116.4	114.4	62.7	124.3	125.8	62.6
Depok	50	LARS-WG	286.4	269.3	119.3	303.3	286.7	118.6
		SDSM	254.7	207.9	184.4	295.7	220.7	200.3
		NEX-GDDP	100.2	101.0	51.9	113.1	113.5	49.1
	100	LARS-WG	314.0	303.8	125.6	334.3	322.1	124.8
		SDSM	279.2	230.0	206.5	336.0	245.3	230.9
		NEX-GDDP	108.7	109.7	56.4	121.2	123.0	52.2
	250	LARS-WG	347.9	343.3	137.0	373.0	364.5	134.2
		SDSM	315.5	254.4	244.9	388.9	279.0	275.3
		NEX-GDDP	120.0	119.8	59.6	130.7	131.5	57.1

Figure 5.9 Same as Figure 5.8 but this is for wet season (December to March).

Figure 5.10 Same as Figure 5.8 but this is for dry season (June to September).

The projections with all three approaches show that the daily rainfall maximum increases in the Jakarta region with consequent implications for future flood potential. Uncertainty across GCMs is seen to be much higher than uncertainty from emission scenarios. Future seasonal daily rainfall maximum increases for the wet season, but the dry season did not exhibit a consistent increase or decrease across the models. GCM uncertainty is also higher in the dry season. The changes in wet season daily rainfall

maximum exhibit similar behaviour as the annual scenario, as the latter is mainly controlled by the wet season for this study region.

The average increase in 100-year RP rainfall can be as high as 20% in the future (see Figure 5.8). According to loss curves shown in Figure 3.8 for the central basin of Jakarta, this would lead to a significant increase in flood discharge (28%) and direct economic damage (42%). However, given the large GCM uncertainty, deterministic (e.g., from ensemble averaging) and probabilistic (e.g., specific percentile ranges) rainfall estimates can be propagated through the hydrologic/hydraulic modelling chain to assess the impact of climate change on future flooding.

Based on the above results the NEX-GDDP data was selected to be used for rainfall projection for Jakarta hydrology and flood mitigation studies. This is because NEX-GDDP contains 20 GCMs with the most recent emission pathway projections AR5 compared to LARS-WG and SDSM. Further it has much longer record of data (~40years ref Figure 4.8) used in the analysis.

The CF from the period from 1961-2000 to 2031-2070 was calculated for 20 GCMs at T year of RPs using NEX-GDDP data. Figure 5.11 shows the computed expected CF, CF_T using Equation (4.23) for RCP 4.5 and 8.5. In the case of RCP 4.5, the CF is decreasing when the RFs are increasing for the grid cells covering Halim and Ciliduk with Depok, while the cell covering Priuk is showing only small variations except for extreme RFs which shows a slight increase.

It is noted that uncertainties in regional or local precipitation rather than in the GCMs have large implications on flood mitigation decisions. Here the 20 GCMs as downscaled to 0.25° (~25km) in the NEX-GDDP dataset are assessed for their variability (Section

5.5) and via the rainfall Change Factors applied to generate future point rainfall (see later Section 6.3.1).

Figure 5.11 CF (1961-2000 to 2031-2070) from NEX-GDDP data. (a) RCP 4.5, (b) RCP 8.5

Chapter 6

MCDA Results and discussion

The results of developed PROMETHEE, MCDA framework on flood levee decision making for current and future conditions (c.f. Figure 4.4) are presented here. The MCDA criteria calculated from Sections 4.1, 4.2.3, 4.3.4 and 4.4.3 reflecting the impacts driven from climate change, socio-economic features, urbanization and related uncertainties are analysed in the decision framework and the results are discussed in this Chapter.

6.1 Analysis under current conditions

6.1.1 Baseline – Uncertainty from rainfall frequency analysis

As a baseline, the case accounting for uncertainty from rainfall frequency analysis under current conditions were first considered. The six alternative levee plans (Plan 0-5, Table 3.1) for flood mitigation in the central basin were analysed with PROMETHEE MCDA using the performance values for first three criteria of AEL, G and C as listed in Table 4.1. As a baseline case, only three these traditional engineering criteria were used while the socio-economic criteria were not. Current rainfall and land use conditions were used here. The criteria AEL and C were minimized while the criterion G was maximized. Uncertainty in rainfall frequency analysis was incorporated in AEL and G. The

preference indexes calculated using Equation (4.4) with the results tabulated in Table 6.1 for all the possible pairs were calculated based on the Gaussian preference function with the inflexion point set via the standard deviation of performance values of each criterion (see Table 4.1). The net outranking values were obtained by applying PROMETHEE, MCDA technique with the criteria equally weighted as following the methodology described in Chapter 4.

The net outranking values (Table 6.2) indicate that the alternative Plan 1 (protect Cengkareng and Ciliwung/WBC for 50yrs RP rainfall discharges) is the best plan of the 6 plans considered. Plan 2 (protect Ciliwung with WBC up to 50yrs RP rainfall & Cengkareng up to 100yrs RP rainfall) is the second best with its net outranking index being close to Plan 1. When moving from one plan to the next higher protection plan, the AEL loss reduction for Ciliwung River is more significant than for Cengkareng (Table 3.1) because of the higher area of exposure and denser population. Similarly, C is larger for Ciliwung due to its longer reach at equal level of protection. The rank values are highly sensitive to the criteria AEL compared to other two (G and C).

It is noted that the selection of the preference function parameters and the criteria weights are the key parameters which should be assessed via sensitivity analyses. A sensitivity analysis was conducted using a range of 0.5-1.5 times the inflexion point of the preference function of each criterion to assess the effect of preference function shape. Plan 1 was the best plan for more than 89.4% of the time and Plan 0 was for 10.6% of the time.

Table 6.1 Preference index and outranking flows - Baseline

Levee Systems	Plan 0	Plan 1	Plan 2	Plan 3	Plan 4	Plan 5	π^-
Plan 0	0.000	0.303	0.307	0.310	0.320	0.325	0.313
Plan 1	0.236	0.000	0.001	0.003	0.020	0.045	0.061
Plan 2	0.259	0.003	0.000	0.001	0.013	0.035	0.062
Plan 3	0.426	0.129	0.103	0.000	0.008	0.027	0.139
Plan 4	0.509	0.235	0.199	0.062	0.000	0.006	0.202
Plan 5	0.655	0.545	0.529	0.423	0.281	0.000	0.487
π^+	0.417	0.243	0.228	0.160	0.128	0.088	

Table 6.2 Net outranking index and rank values- Baseline

Levee Systems	Net outranking index	Rank
Plan 0	0.104	3
Plan 1	0.182	1
Plan 2	0.166	2
Plan 3	0.021	4
Plan 4	-0.074	5
Plan 5	-0.399	6

6.1.2 Impact of socio-economic conditions

The baseline case with socio-economic criteria are next analysed with the net outranking value of six alternative levee plans shown in Table 6.3 The criteria comprising AEL, G, C are tested with the Net SEVI criterion/criteria from Methods 1 (inundation area and depth effect applied to all the variables) and Method 2 (inundation area effect applied to all the variables directly get influenced) separately (see Section 4.2.3). Plan 2 (i.e., protect Ciliwung/ WBC up to 50 years and Cengkareng up to 100-year 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 (it is best for the baseline case), while Plans 0 and 5 are 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 remain the worst two.

The above ranking of the plans is qualitatively explained as follows. The criterion, C and severity and exposure criteria (AEL, G, Net SEVIs) are comparatively higher compared with the rest for Plans 5 and 0, respectively. This resulted in Plans 5 and 0 being the worst two plans in both Methods 1 and 2. The C for a given protection level in Ciliwung is higher than in Cengkareng due to its longer reach. Moving from Plan 1 (50-year RP rainfall protection for both Ciliwung and Cengkareng) to Plan 3 (100-year RP rainfall protection for Ciliwung and 50 years for Cengkareng) has a higher C than moving to Plan 2 (50-year RP rainfall protection for Ciliwung and 100 years for Cengkareng). Conversely, the reduction in severity and exposure criteria (AEL, G, Net SEVIs) for Ciliwung is more significant than for Cengkareng for a specific protection level, e.g., larger loss reduction results when moving from Plan 1 to Plan 3 than to Plan 2 (ref Table 4.1). Overall, River Ciliwung thus has more significant impact on the ranking than Cengkareng. For Ciliwung, the C increment is larger than reduction in severity and exposure criteria (AEL, G, Net SEVI). This resulted in Plans 1 and 2 (Ciliwung with 50-year RP rainfall protection level) to be ranked in the top and Plans 3 and 4 (Ciliwung with 100-year 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 population in the inundated area. The PROMETHEE results are hence expected to be similar with Method

1 if only Net SEVI_A (area effect) is used as socio-economic criteria; this being confirmed as indicated as Method 1a in Table 6.3. In Table 6.3, 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 and only the worst plans are interchanged in ranking. A further comparison between Methods 1 and 1a has only the best two plans switched in ranking. Compared to Method 1a, the higher protection level Plan 2 is ranked first in Method 1 where the socio-economic criteria are captured with both inundation area and depth effect. As inundation depth effect is also play an equally role as inundation area in deciding on the best plan. Thus, the Method 1 for Net SEVI calculation scaled via area and depth effect is adopted for the rest of the PhD study.

Table 6.3 Net outranking index and rank values- with socio-economic criteria

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 variable weights calculated in Table 4.5 via the derivative method is next applied in calculating SEVI variables (see Equation (4.14)). The Net SEVI is re-computed for the PROMETHEE outranking analysis. While the performance values from using equal (Table 4.1) and unequal (Table 6.4) weights as expected differ, the difference in the

criteria performance values (see Equation (4.1)) between plans is comparable, resulting in the final ranking being unchanged across the plans. This is also expected as the variable from the derivative method produced almost equal weightage (see Section 4.2.2).

Table 6.4 Net SEVIs with variable weight in it and net outranking indices

Alternative levee Plans	Net SEVI _A	Net SEVI _D	Net outranking index	Rank value
Plan 0	0.0070	0.0557	-0.310	6
Plan 1	0.0022	0.0132	0.152	2
Plan 2	0.0021	0.0102	0.154	1
Plan 3	0.0014	0.0093	0.085	3
Plan 4	0.0011	0.0065	0.039	4
Plan 5	0.0003	0.0018	-0.120	5

The developed PROMETHEE-MCDA framework is further used to assess the importance of the socio-economic criteria relative to other criteria by adjustments of the criteria weights w_k in Equation (4.4). Three different cases are compared in Table 6.5, where the socio-economic criteria were assigned weights of 0 (no consideration, i.e. baseline case analysed in Section 6.1.1), 1 (equal weightage) and 2 (socio-economic criteria having double weightage), denoted as Cases 0, 1, 2, respectively in Table 6.5. Case 1 results correspond to those shown in Table 6.5 where equal weights were used. Comparison between Cases 0 and 1 shows that best plan moves to the next higher protection level (Plan 2) where the socio-economic criteria are included. Furthermore Plan 0, the third rank plan in Case 0 is now ranked the worst in Case 1. In this, it shows that Plan 0 is particularly sensitive to the socio-economic criteria, Net SEVIs. This is because Jakarta has a huge socio-economic vulnerability with a reported economic exposure of 6.7 Million USD/km² (Muis et al., 2015). Going from baseline (i.e. w/o

socio-economics) to current (i.e. including socio-economics) thus introduced a new large change in vulnerability which is maximized for Plan 0, the do-nothing plan. The overall rank values of plans are changed by introducing the socio-economic criteria; and in particular the best two plans' ranks are switched. However, the ranking in Cases 1 and 2 is 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 as described in Section 4.2.1. The robustness of the ranking to the year of the data used is tested via using the next most recent year's data of 2013. No changes in the ranking resulted. Therefore, socio-economic criteria of Method 1 are used here after.

Table 6.5 Net outranking index and rank values with increasing weights in the socio-economic criteria

Alternative Levee Plans	Case 0		Case 1 (Method 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

6.2 Accounting for higher protection levee systems

Current conditions, specifically in rainfall and socio-economic conditions are used in Section 6.1. The 50-100 years RP of levee protection (Plans 1 & 2) are chosen as the best alternatives as dependent largely on whether social and economic conditions are included. The best plans are however expected to shift further towards higher protection levels when future conditions of increased rainfall are considered. Based on the analysis

of Chapter 5 the projected future rainfall projections results have the current 200 and 400 year RP of rainfall being shifted to 100 year RP in future (2031-2070) under RCP 4.5 and RCP 8.5 respectively as shown in Figure 6.1. In addition, the rapid urbanization in Jakarta would increase the severity, specifically the AEL and G due to the increased impervious surface. Therefore Plan 6 with the protection level of 400 years of RP in both rivers (ref Table 3.1) is added as additional plan in the MCDA analysis to provide a wide range of alternative levee plan options.

The MCDA analysis was repeated with the earlier six now plans extended Plan 6 but keeping the inflection point of Gaussian preference function unchanged to be consistent. The net outranking index with the rank values are listed in Table 6.6. The rank order remains same for current condition cases (baseline and with socio-economic) as seen comparing Table 6.2, Table 6.3 and Table 6.6.

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% used, see Section 4.1). This is tested by re-computing performance values in Table 4.9 and the net outranking values in Table 6.6 using a 90% confidence interval. While the maximum percentage change over the individual criteria values is substantial at 51.4%, the resulting net outranking values are comparable with a maximum percentage change of 2.9% when compared to using the 99.7% confidence interval. The ranks as shown in Table 6.6 are further unchanged for both the base line and current condition cases.

Table 6.6 Net outranking index for eight levee plans – Current condition

Alternative levee plans	Baseline		With Socio-economics	
	Outranking Index	Rank values	Outranking Index	Rank values
Plan 0	0.143	3	-0.290	7
Plan 1	0.251	1	0.170	2
Plan 2	0.239	2	0.176	1
Plan 3	0.119	4	0.125	3
Plan 4	0.033	5	0.085	4
Plan 5	-0.260	6	-0.056	5
Plan 6	-0.526	7	-0.209	6

6.3 Analysing future conditions

6.3.1 Impact of climate change

The observed rainfall values were projected with the calculated expected CFs (average of CFs from Ciliduk, Halim and Priuk for RCP 4.5 and RCP 8.5 (Figure 6.1) as calculated in Section 0. The increase in the daily rainfall for 50, 100 and 250 years of RP are shown in Table 6.7. To further test the sensitivity of the CF development procedure, a grid rainfall was obtained by combining using the station year method and the subsequent procedures were followed to calculate one CF for the entire Jakarta. The daily rainfall projected are very close to the original case shown in Table 6.7.

Figure 6.1 Rainfall projections using CFs.

Table 6.7 Percentage change in the annual daily rainfall from 1961-2000 to 2031-2070

Case	RCP	50 years	100 years	250 years
Via expected CF (Used in further analysis)	4.5	7.7	7.5	7.2
	8.5	15.4	16.2	17.4
Sensitivity test case via station year method	4.5	7.7	7.3	7.0
	8.5	15.1	15.8	16.8

The five criteria (Table 4.1) for current conditions and the four criteria representing the difference between the current and future criteria values (Table 4.1 and Table 4.9) were used to analyse seven alternative levee plans with MCDA PROMETHEE. Note that Net SEVIs from Method 1 was analysed as used as described in Section 6.1.2. Further the population projected for the year 2050 was used for loss calculations but the basin features (land use and roughness) were kept at current condition.

Table 6.8 Net outranking index and rank values- with future rainfall conditions

Alternative Levee Plans	RCP 4.5		RCP 8.5	
	Outranking Index	Rank	Outranking Index	Rank
Plan 0	-0.238	7	-0.337	7
Plan 1	0.048	4	0.034	5
Plan 2	0.109	2	0.050	4
Plan 3	0.177	1	0.071	2
Plan 4	0.073	3	0.109	1
Plan 5	0.011	5	0.058	3
Plan 6	-0.180	6	0.016	6

Plan 3 (Ciliwung with WBC up to 100yrs & Cengkareng up to 50yrs RP rainfall discharges) is the best option where the rainfall is assumed to follow RCP 4.5 climate projection (see Table 6.8). Plan 2 is the second best and Plan 0 is the worst option. In the case with RCP 8.5 climate projection, the best plan moves even further towards higher protection levee, where Plan 4 is chosen to be the best and Plan 3 is second best. Plan 0 remains as the worst option.

The best plans are moving higher levee protection levels due to increased severity of flood as driven by the increased rainfall. In both RCP cases the severity of the flood is much higher than the current condition. The criteria ΔAEL and ΔG became dominant over the construction cost C . Thus, shifting the best plan to higher protection levels. The Plan 0, the current levee system is the worst option in all three future condition cases where the criteria AEL is high compared to other plans.

6.3.2 Impact of urbanization

The 18 years of Landsat data in the period of 1989-2009 were used to classify the land use classes of urban, bare land, vegetation and water body as described in Section 4.4.1. The percentage urban area was calculated (see Figure 4.12) for three regions upstream, midstream and DKI Jakarta. The midstream and DKI Jakarta show an increasing urbanization trend but the upstream region exhibited very less/no change in urban area. The percentage urban area gradually increases with maximum recorded urban extent of 75.3%, 43.3% and 4.4% in the time period 1989-2009 for DKI Jakarta, midstream and upstream regions respectively. The upstream region shows 0.72% urban area change in average; thus it was treated as unchanged from 2009 in the future projections.

The projected percentage urban area for year 2050 was updated in the flood simulations. The seven plans analysed with criteria calculated for current rainfall condition and 2050 urban extent (Table 4.10) in MCDA PROMETHEE. The outranking index with the rank values are listed in Table 6.9 . Plan 2 is the best alternative which is identical to the current condition case with socio-economics features (Sections 6.1.2 and 6.2). Plan 0 is the worst option which is similar to all the current and future cases discussed previously. Comparing Table 6.8 and Table 6.9 the impact of increasing rainfall due to climate change has a greater effect on flood levee plan decision than increased urban/impervious land cover due to urbanization. The urban growth in the midstream is much faster than DKI Jakarta the region reaching the saturation urbanization point. The major part of river Cengkareng is in the midstream region and as such the risk increases rapidly with urbanization. Thus Plan 4 (protects Ciliwung up to 50years and Cengkareng up to 100years RP rainfall) is prioritized over Plan 3 (Ciliwung up to 100years rainfall and Cengkareng up to 50years RP rainfall) as the second best.

Table 6.9 Net outranking index and rank values- under future urban conditions

Alternative Levee Plans	Outranking Index	Rank
Plan 0	-0.364	7
Plan 1	0.074	4
Plan 2	0.118	1
Plan 3	0.082	3
Plan 4	0.090	2
Plan 5	-0.006	6
Plan 6	0.007	5

6.3.3 Impact of climate change and urbanization

Results from the case analysing future rainfall (RCP 4.5 and RCP 8.5) with 2050 urban condition are discussed here. The seven levee plans were analysed in MCDA with the performance values calculated and shown in Table 4.11 and net outranking results are listed in Table 6.10. In these extreme cases the Plan 5 (protect up to 250years RP rainfall in Cengkareng and Ciliwung) is selected as the best under both RCPs and the 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 second-best option than for the case RCP 4.5 due to the increased severity of flood. Plan 0 is the worst option as all the current and future cases discussed. As described in the Section 6.3.2, Plan 2 is prioritized over Plan 3 due to the rapid urbanization in the Cengkareng basin. Comparison between all three future condition cases (see Table 6.8, Table 6.9 and Table 6.10) it is readily seen that the climate change is the driving force pushing the best plan to higher protection levels due to the increased severity.

It is noted that the current 250 years of RP rainfalls is shifted to ~120 and ~60 years RP for RCP 4.5 and 8.5 respectively (see Figure 6.1). Thus, the suggested levee protection option Plan 5 with the protection level of 250 years of RP for the future circumstance (in terms of future RP) is comparable with the current condition best plans Plan 1 and 2.

Table 6.10 Net outranking index and rank values- under future rainfall and urban conditions

Alternative Levee Plans	RCP 4.5		RCP 8.5	
	Outranking Index	Rank	Outranking Index	Rank
Plan 0	-0.547	7	-0.542	7
Plan 1	0.052	6	0.013	6
Plan 2	0.082	4	0.090	4
Plan 3	0.079	5	0.038	5
Plan 4	0.120	2	0.115	3
Plan 5	0.124	1	0.167	1
Plan 6	0.090	3	0.119	2

The cases analysing the current conditions, baseline and with socio-economic results in Plan 1 (Table 6.2) and Plan 2 (Table 6.3) as best levee systems which are low in flood protection level. The case with future urban condition but under current rainfall results in a similar best plan the case with socio-economics (Table 6.9). However future rainfall projections have a great influence in the levee plan choice. Plan 3 and Plan 4 are the best levee option for the case with future rainfall and current urban conditions under RCP 4.5 and 8.5 respectively (Table 6.8) while Plan 5 is selected for the extreme case of future rainfall and future urban condition under both RCP 4.5 and 8.5 (Table 6.10).

Chapter 7

Conclusion

A developed flood mitigation decision making framework using MCDA PROMETHEE is developed which accounts for socio-economic features, uncertainty in rainfall estimation and a changing future. The research highlights have the following findings.

7.1 Future rainfall projections

The impact of changing climate on local-scale annual and seasonal maximum daily rainfall using different downscaling models were assessed (see Section 4.3 and Chapter 5). The future daily rainfall was generated with LARS-WG and SDSM at four stations in Jakarta, and the RP curves were compared against the observed. While 15 GCMs were used for LARS-WG analysis under AR4 SRES A1B and B1 emission scenarios, only one GCM under AR5 RCP 4.5 and 8.5 scenarios was available and used in the SDSM simulations. 20 GCMs were used from the gridded NEXGDDP data also under RCP 4.5 and 8.5. The projections with all three approaches show that the daily rainfall maximum increases in the Jakarta region with consequent implications for future flood potential. Uncertainty from GCMs is seen to be much higher than uncertainty from emission scenarios. Future seasonal daily rainfall maximum increases for the wet season but the dry season did not exhibit a consistent increase or decrease across the models. GCM

uncertainty is also higher in the dry season. The changes in wet season daily rainfall maximum exhibit similar behaviour as the annual scenario as the latter is mainly controlled by the wet season for this study region. The projections with all three approaches show the average increase in 100-year RP rainfall can be as high as 20% in the future in the Jakarta region with consequent implications for future flood potential. The study showed that the uncertainties arising from the use of different GCMs are predominant compared to those arising from different statistical downscaling approaches and emission scenarios. Given the large GCM uncertainty, deterministic (e.g., from ensemble averaging) and probabilistic (e.g., specific percentile ranges) rainfall estimates can be propagated through the hydrologic modelling chain to assess the impact of climate change on future flooding which was addressed in Section 4.3.4 and 6.3.1). The analysis reported here facilitates decision regarding interpretation of model results across different spatial scales and emission scenarios. While this study examined local-scale changes in the seasonal and annual maximum daily rainfall in Jakarta, the results are broadly applicable to other near equatorial regions in Southeast Asia due to similarities in climatology.

7.2 SEVI and uncertainty in rainfall in MCDA PROMETHE framework

A SEVI capturing socio-economic factors in flood vulnerability is developed (Sections 4.2 and 6.1.2) to represent the social and economic factors as based on available reported social and economic data, and the SEVI is further scaled into a Net SEVI that accounts for the socio-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 reported measures of flood vulnerability (e.g., PVI and FVI) that provide only a general assessment without accounting for the specific mitigation measure being evaluated.

Thus, the practical utility of this work lies in the incorporation of socio-economic effects into a flood mitigation decision framework via the use of the SEVI as demonstrated within a MCDA PROMETHEE framework for assessing flood levee options for a central basin in Jakarta, Indonesia. The final ranking process is also shown to be robust to equal or unequal weights assigned to the variables used in defining the SEVI. It is also robust to the scaling process of converting to 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 six levee plans considered, it is shown that the best 2 plans (Plan 1 - protect up to 50yrs RP rainfall (Cengkareng and Ciliwung with WBC) and Plan 2 - protect Ciliwung with WBC up to 50yrs RP rainfall & Cengkareng up to 100yrs RP rainfall) remain the same best 2, though their order may be 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 socio-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 for flood levee protection level is general in that it accounts for socio-economic factors and with uncertainty in the rainfall incorporated.

7.3 Future projections in MCDA PROMETHEE framework

The uncertainty of future projections arise from GCMs (see Section 4.3) and urban extent projections (see Section 4.4) were incorporated in MCDA and seven levee plans were ranked (see Section 6.3). The 20 GCMs from NEX-GDDP data were used to develop temporal CF and the future point rainfall projections obtained by multiplication with observed rainfall. The land use pattern was classified using ArcGIS for the period

of 1989-2009 and the percentage urban area was projected for the year 2050. The MCDA PROMETHEE criteria under the future conditions was used to assess the levee plans.

Three different cases were studied here with the decision framework to assess the future conditions (see Figure 4.4). The Plan 3 (protect Ciliwung with WBC up to 100yrs rainfall & Cengkareng up to 50yrs RP rainfall) and Plan 4 (protect up to 100yrs RP rainfall (Cengkareng and Ciliwung with WBC)) were chosen as the best plan for RCP 4.5 and 8.5 respectively. These plans at higher protection level than the cases with current conditions. The climate change increases the severity of the flood which was reflected by the criteria. The extreme climate scenario RCP 8.5 has the plan with 100 year rainfall RP protection for both rivers being ranked first in terms of rainfall, this corresponds to ~30year rainfall RP protection level in future conditions. The future urban and current rainfall case results the best plan similar to the case with socio-economics factors. Compared to the case with future rainfall projections, the urban projections cases are less severe. Cengkareng river basin is urbanizing faster than Ciliwung as Ciliwung is already reaching the saturation point. Thus the Plan 4 (protect up to 100yrs RP rainfall (Cengkareng and Ciliwung with WBC)) results second in the ranking when future urban extent, but current rainfall is considered. The most extreme cases with future rainfall and urban condition results Plan 5 as the best for both RCP 4.5 and 8.5 scenarios. The severity of the climate change and urbanization together shifted the best plan towards the higher protection level (Plan 5 - 250 years of rainfall RP in both rivers). It is noted that this current 250 year of protection level corresponds to ~120 and 60 year future rainfall RP conditions for RCP 4.5 and 8.5 respectively.

This PhD work developed a flood mitigation decision framework incorporating socio-economics, uncertainty and climate change in order to aid in decision making and supporting sustainable development. This forms one of the few reported studies that

include such diverse factors along with inclusion of associated uncertainties and represents the novelty of the work. The SEVI and Net SEVI developed are also advancements to couple widely studied social and economic vulnerability into an engineering framework for risk management. It is further noted that the developed decision making framework is general and can be readily adapted to other urban areas prone to flooding.

7.4 Future work

In terms of future work, the methodology used to obtain geometric average of CF over GCMs can be improved to better account for the variability arising from the GCMs such via taking ensemble averages. The rainfall projection could be substituted with dynamically downscaled projection as an alternative, but this will require more computational resources. Land use projection models can further be used to better project the urban extent. The dynamic changes of socio-economic variables in the historical record also clearly indicate a time dimension in such vulnerability. Thus, the SEVI can be improved with future projections of social and economic variables beyond that based on population projections as performed here. *The MDCA framework itself can be improved by adding more levee plan alternatives, or even replacing the MCDA-PROMOTHEE decision framework with more recent evolutionary-based approaches that yield non-dominated optimal solutions, known as Pareto optimal solutions (Su et al., 2018).* This approach treats the levee protection level as a continuously varying design variable to be optimized, rather than as the selection of a best plan amongst a fixed number of alternatives.

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Appendix A

Hydrologic Engineering Centre – Hydrologic Modelling System (HEC-HMS)

HEC-HMS is a 1-D model designed by US Army Corps of Engineering in 2001 to simulate precipitation runoff process. HEC-HMS can account for the following components in its simulations (USACE, 2000):

1. Historical precipitation or frequency based hypothetical precipitation possible at a given location.
2. Loss models which used to estimate the effective rainfall.
3. Direct runoff models which account for overland flow, storage and energy losses while water runs into the streams.
4. Hydrologic routing models which account for storage and energy flux.
5. Models of confluences and bifurcations of rivers and channels.
6. Model water control measures.

There are various options to choose among the standard models on runoff volume, direct runoff, base-flow, and routing model. Each sub-basin is further evaluated with individual geo-meteorological features. HEC-HMS adopts semi-distributed modelling which achieved through the use of sub-catchment and channel routing concepts (Joo et al., 2014). Detailed information on the use of HEC-HMS can be found in Hydrologic Modelling system HEC-HMS Technical Reference Manual (USACE, 2000).

Previous studies using HEC-HMS include Markus et al. (2007) who assessed the relative changes in peak flows with respect to the changes in rainfall, and Ali et al. (2011) and Du et al. (2012) to study land-use effects on streamflow. Meenu et al. (2013) indicated that HEC-HMS is ideally suited to analyse hydrologic systems as changes in parameters are handled efficiently. Even though there are a number of newer rainfall-runoff

software packages available, the freely available HEC-HMS which has the ability to simulate the land-use changes and design-rainfall precipitation in flood peak flows in used in the Jakarta Flood Model of Chapter 3.

Hydrologic Engineering Centre - River Analysis System (HEC-RAS)

The US Army Corps of Engineers Hydrologic Engineering Centre - River Analysis System (HEC-RAS) is a 1-D hydraulic model that can provide four different analysis specifically steady flow, unsteady flow, moveable boundary sediment computation and water quality analysis. The steady flow model is able to simulate subcritical, supercritical and mixed flow regimes. Calculations are based on energy equations and momentum equation where water surface rapidly varies. Flow with obstructions (culvert, bridges, weir, drop structures etc.) and change in levees and channel improvements can also be accommodated. The unsteady flow model is developed for subcritical flows along with simulate storage area (USACE, 2010). Detailed information on the use of HEC-RAS can be found in River Analysis System Hydraulic Reference Manual (USACE, 2010).

HEC-RAS is particular useful in simulating the effects of control structures on water surface profiles. Such structures are specified through boundary conditions in the flood routing (Mujumdar and Nagesh Kumar, 2012). Yerramilli (2012) used HEC-RAS integrated with Arc-GIS and the results indicate that the model has capability of simulating flood event. The feature is of particular utility in the Jakarta Flood model and this PhD work where various levee plan are evaluated.

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