

Uncertainty quantification of flood damage estimation for urban drainage risk management

Masaru Morita and Yeou KOUNG Tung

ABSTRACT

This paper presents a method of quantifying the uncertainty associated with inundation damage data for an urban catchment when undertaking stormwater drainage design and management. Usually flood damage is estimated by multiplying the inundated asset value by the damage rate corresponding to the inundation depth. The uncertainty of the asset value and the damage rate is described by probability distributions estimated from an analysis of actual flood damage data from a national government survey. With the inclusion of uncertainty in the damage rate and asset value, the damage potential curve defining the damage-frequency relationship is no longer a deterministic single-value curve. Through Monte Carlo simulations, which incorporate the uncertainty of the inundation damage from the damage rate and asset value, a probabilistic damage potential relation can be established, which can be expressed in terms of a series of curves with different percentile levels. The method is demonstrated through the establishment of probabilistic damage potential curves for a typical urban catchment, the Zenpukuji river basin in Tokyo Metropolis, under two scenarios, namely, with and without a planned flood control reservoir.

Key words | asset values, damage rates, Monte Carlo, probabilistic flood damage curves, uncertainty

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INTRODUCTION

Flood damage estimation, together with flood inundation calculations, are two essential processes in risk-based design and management of flooding in urban areas. In these estimation and calculation processes, uncertainty of various kinds exist (NRC 2000; Pappenberger & Beven 2006; Apel *et al.* 2008). Yen & Ang (1971) classified the uncertainty into two types: objective and subjective uncertainty. The former is associated with any random process that can be deduced from statistical samples. The latter is attributed to the lack of available quantitative information for the phenomena and processes. In flood damage estimation, reliable flood damage statistics should be used, if available, to carry out the flood risk assessment for a more defensible design and to inform decision making.

Flood inundation damage is generally calculated by the stage-damage curves and loss functions (Smith 1994).

Procedures have been provided for flood damage evaluation (FLOODsite 2007). The various parameters used in damage estimations, such as asset value and damage rate, are based on flood damage statistics and they often possess uncertainty that is greater than in hydraulic inundation calculations. The uncertainty with regards to hydraulic parameters affecting depth of flooding are widely discussed (Pappenberger *et al.* 2005). However, data and models to represent the exposure and damage parameters have generally been unquestioned (Chatterton *et al.* 2014).

Several studies have been undertaken to analyze the uncertainty in flood inundation calculations and flood damage estimations (De Moel & Aerts 2011; Bates *et al.* 2014). However, very few studies deal with uncertainty quantification of flood damage estimates based on actual flood damage statistics. Thus, it is the objective of this study to focus on the uncertainty quantification of flood damage estimates based on a national survey of flood inundation damage in Japan (PWRI 1995).

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doi: 10.2166/wst.2019.297

FLOOD DAMAGE ESTIMATION METHOD

The method used to estimate flood inundation damage in this study follows the procedure developed by Morita (2011). Figure 1 outlines the estimation procedure, in which storm hyetographs are transformed into inundation depths prior to estimating the corresponding flood inundation damage in monetary terms using a flood damage prediction model. In the study, a set of design storm hyetographs of different return periods or rainfall intensity-duration-frequency (IDF) curves are used as the input storm data. Finally, the flood damage prediction model produces a damage potential curve that defines the relationship between design storm return period and the monetary value of the inundation damage.

In the study, a geographic information system (GIS)-based flood damage prediction model is used. The model consists of two modules: Module-1 for calculating inundation depths from rainfall hyetographs and Module-2 for estimating flood inundation damage corresponding to the inundation depths provided by Module-1.

Flood damage prediction model

In Module-1, this study used the XP-SWMM 1D/2D model to calculate the inundation depths over an urban catchment under a given hyetograph. XP-SWMM is a stormwater modelling software that is widely used to deal with complex hydrologic, hydraulic and water quality problems in urban catchments (Phillips *et al.* 2005). Any other flood inundation simulation models with capabilities that are comparable to XP-SWMM can also be used. The numerical inundation simulation in the study adopted a 50 m × 50 m grid to match the mesh system in the Tokyo Metropolitan

Government asset database. The modelling accuracy can be improved by adopting a much smaller grid size, which is now computationally feasible, to capture more accurately the local features that may have impacts on inundation depth and flood damage.

For flood damage prediction, flow velocity could be another factor which influences flood damage. However, in urban areas, the influence of inundation depth on flood damage estimation is more significant than that of flow velocity (Kreibich *et al.* 2009).

The monetary value of inundation damage is estimated by Module-2 as a function of the inundation depth (Morita 2009). Flood damage can be tangible and intangible. Tangible damage is evaluated on a monetary basis, and can be categorized into direct damage and indirect damage (Penning-Rowsell *et al.* 2005). Direct damage refers to physical damage to houses, household articles, offices, retail outlets, corporate assets and other items due to direct contact with floodwater. In this study, direct damage due to inundation was divided into 11 damage types, of which four types relate to building structures and seven types relate to movable items (see shaded cells in Figure 2). Indirect damage is due to business losses caused by direct damage to shops leading to service disruption and by damage to public infrastructure and utilities. Limited consideration of indirect damage was given in this study and is described later. Floods can also cause intangible damage, which cannot be expressed in monetary terms; examples include psychological trauma, loss of life, social unrest, public health issues, etc. In this study, the focus is on direct tangible damage to buildings and their contents, with limited consideration given to indirect damage. Flood induced intangible damage is not considered in the current study.

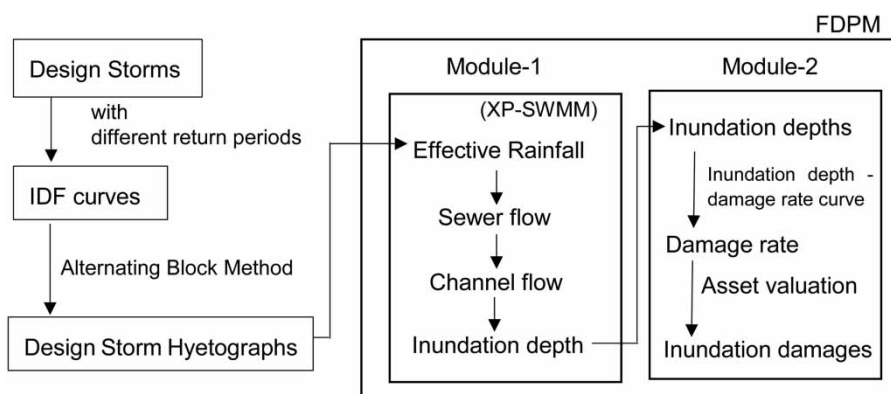


Figure 1 | Flowchart of flood damage prediction model.

Types	Direct damage		
	Structure	Movables	
private house	wooden	household articles	
	non-wooden		
business building	wooden	depreciable assets	manufacturing
			commercial
			service
	non-wooden	inventory assets	manufacturing
			commercial
			service

Figure 2 | Classification of the 11 types of direct damage

Flood damage statistics

In this study flood inundation damage in a urban catchment mainly focuses on direct damage caused by physical contact with floodwater for 11 damage types (see Figure 2) including houses, household articles, business buildings (factories, offices, retail outlets), corporate assets and others. The direct damage for household articles is calculated by multiplying the estimated asset value of an article by a damage rate which is a function of inundation depth computable from Module-1. The damage rate herein is the percentage of value of household articles damaged by floodwater. Module-2 for inundation damage estimation follows in general the manual published by River Bureau of the Ministry of Land Infrastructure Transportation and Tourism (2005).

For flood damage estimation, data on damage rates and asset values were obtained from a nationwide flood damage survey in Japan conducted by the Public Works Research Institute of the Construction Ministry from 1993 to 1995 (PWRI 1995). The inundation damage survey covered asset value, monetary damage, damage rate, inundation depth, sedimentation depth, inundation duration, building structure type, and number of floors for each exposure. Hundreds of flood damage samples in the Tokyo Metropolitan area were used as a database for the flood damage estimation.

Flood damage estimation

To calculate the value of direct structural damage, the asset value is multiplied by the damage rate determined by the inundation depth. The same method was adopted for the damage to movable items in buildings. The direct damage for structures, DS , movables in the domestic households, $DM1$, and movables in business buildings, $DM2$, are estimated for each $50\text{ m} \times 50\text{ m}$ grid cell using

the following equations:

$$DS(i) = \Sigma \alpha(i, j) \cdot A(i, j) \cdot VS_k \cdot R_k(h_i) \quad (1)$$

where in any grid cell i , $DS(i)$ = direct structural damage; $\alpha(i, j)$ = reciprocal of the number of floors of building j ; $A(i, j)$ = total area of the floor space of building j ; VS_k = asset valuation per unit floor area of damage type k ; $R_k(h_i)$ = damage rate of type k determined by inundation depth h_i .

$$DM1(i) = \Sigma \alpha(i, j) \cdot VM1 \cdot A(i, j) \cdot R_k(h_i) \quad (2)$$

where $DM1(i)$ = direct movable damage for households in grid cell i ; $VM1$ = valuation of domestic articles per unit floor area.

$$DM2(i) = \Sigma \alpha(i, j) \cdot NM2_k \cdot A(i, j) \cdot VM2_k \cdot R_k(h_i) \quad (3)$$

where $DM2(i)$ = direct movable damage for business buildings in grid cell i ; $NM2_k$ = number of employees of a business building per unit floor area of damage type k ; $VM2_k$ = asset valuation of a business building per unit employee of type k .

In Equations (1)–(3), the variables $\alpha(i, j)$, $A(i, j)$, and damage type k ($k = 1$ –11) are obtained from the GIS database of the Tokyo Metropolitan Government. The other variables, VS_k , $VM1$, $NM2_k$, and $VM2_k$ are extracted from the statistics of the Tax Bureau of Tokyo Metropolitan Government. The total damage of each grid cell i is obtained by summing the damage to all buildings within the grid cell.

In order to estimate the monetary value of inundation damage using Module-2, GIS data of the private and corporation assets within the study catchment are utilized in flood damage calculations by overlaying the assets data and the calculated inundation depth for each building. In the study, the GIS assets data of the Tokyo Metropolitan Government were used. Figure 3 shows a map superposing

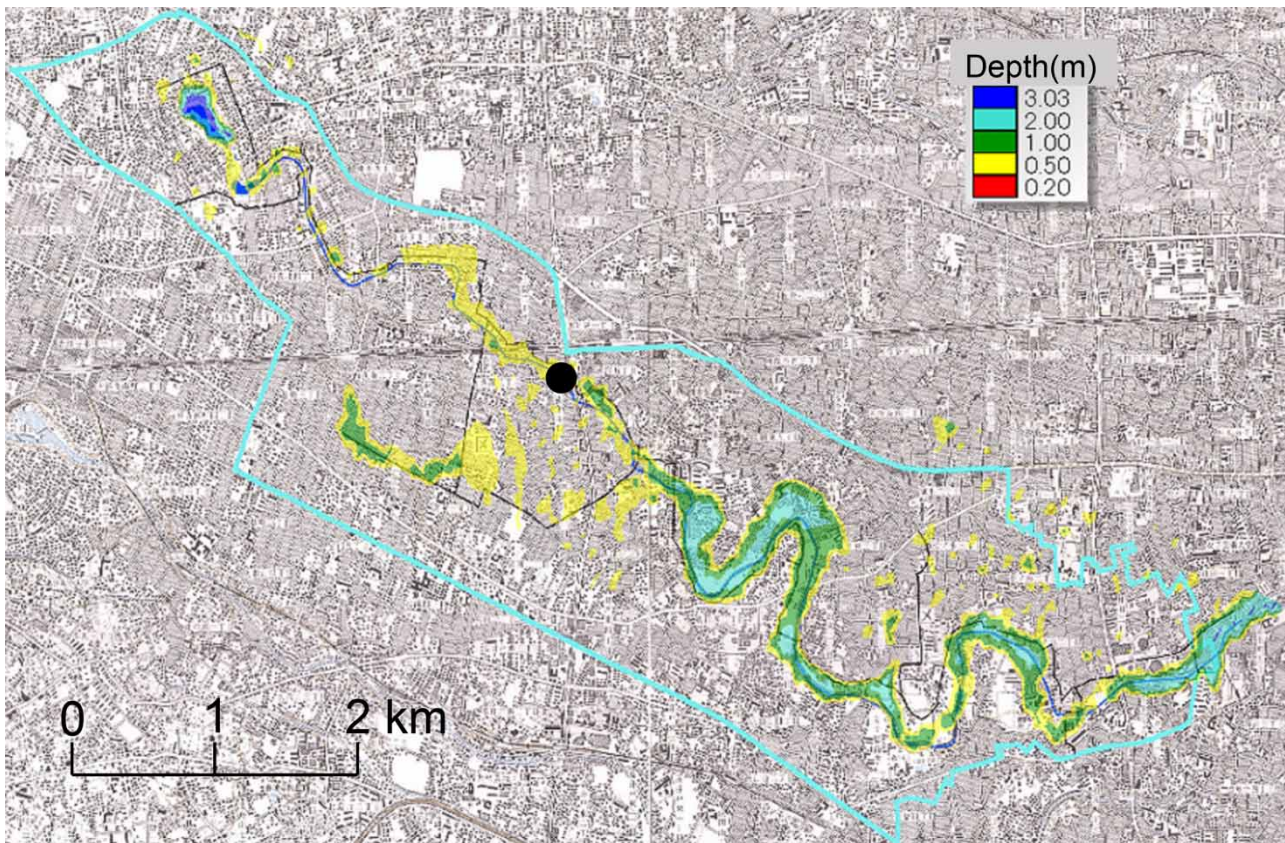


Figure 3 | Calculated inundation depth for a 30-year storm superposed with GIS data (• indicates planned flood control reservoir).

calculated inundation depths and GIS data in the study area with $50\text{ m} \times 50\text{ m}$ grid cells.

In damage calculations, the relationships between damage rate and inundation depth of damage type k in grid cell i are described by $R_k(h_i)$, which defines damage rate as a function of inundation depth. The curves were obtained for the 11 direct damage types (see Figure 2) according to inundation damage statistics (PWRI 1995). As an example, Figure 4 shows the survey data of damage rate versus inundation depth for the household articles in a private home. The two curves in Figure 4 are defined by the logistic functions obtained by means of unconstrained least square (ULS) method and constrained least square (CLS) method. Note that the curve by the ULS method (the dashed line) produces a damage rate–inundation depth (y vs. x) relation which is a poor representation of the data, especially when the inundation depth x is very shallow or very deep. The logistic curve obtained by the CLS method (the solid line) is a better representation of the data, although there remains a high scatter of data in comparison with the curve. The logistic function was adopted for its amenability to describe damage rate–inundation

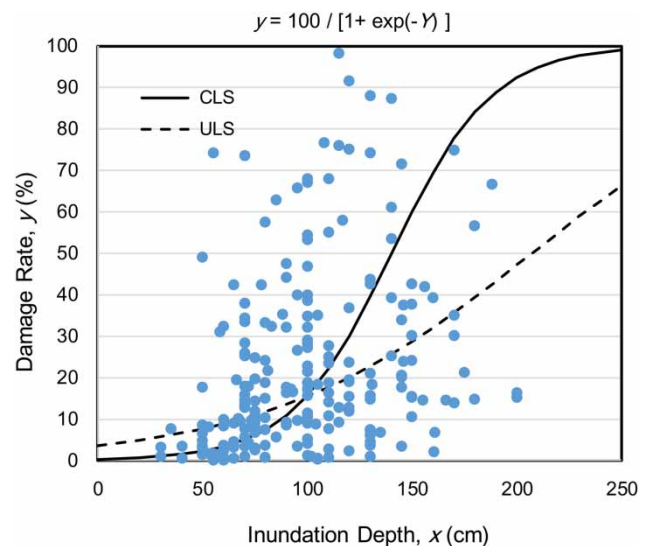


Figure 4 | Comparison of the damage rate–inundation depth relation for household articles obtained by the ULS and CLS methods.

depth relation because: (1) the value of damage rate is bounded between 0 and 100; and (2) damage rate at a given household location would, in general, increase

monotonically from near zero with shallow inundation to a certain high depth beyond which full damage would happen. The use of the logistic model would restrict the estimated value of damage rate to stay within [0, 100]. The methods using ULS and CLS to establish the damage rate–inundation depth relationship is detailed in Appendix A (available with the online version of this paper).

Indirect damage was calculated using a relation between the inundation depth and the number of business interruption days for each business entity. The indirect damage for business interruption was obtained by multiplying the number of days of interruption by the employees' added value per day of each business entity.

Although the proposed framework integrating GIS-based flood inundation simulation and flood damage estimation is applied to flood risk management in an urban setting, it can equally be implemented, with proper modification, to rural areas. Modifications for Module-2 include inundation damage information about farmhouses and agricultural crops. As for Module-1, any numerical inundation simulation models suitable for overland flow on farmlands would be suitable.

Damage potential curve

The monetary inundation damage costs are calculated by the flood damage prediction model under design storms of various return periods. The resulting damage–frequency relation is described as a damage potential curve. The damage potential curve shows the relationship between design storm return period and flood damage. By only considering inherent randomness of rainfall without accounting for uncertainty in other factors, such as asset values and damage rates, such damage potential curves in general will show only a one-to-one relationship between damage and return period that does not account for the underlying scatter in the damage data (see Figure 4).

ASSESSING UNCERTAINTY IN FLOOD DAMAGE ESTIMATION

Flood inundation damage can be estimated by multiplying the asset value by the damage rate, which is a function of the inundation depth obtainable from Module-1. The damage rate–inundation depth relation defined by the solid line in Figure 4 can be used for deterministic flood damage estimation without having regard to the scatter of the data. However, it is clearly revealed in Figure 4 that

the data variability is too significant to be ignored. Therefore, it is warranted to develop a probabilistic flood damage estimation model to capture the intrinsic variability of the damage rate and asset value.

Assessing uncertainty in the damage rate

To quantify uncertainty in the damage rate as shown in Figure 4, the scatter of the data around the estimated damage rate–inundation depth relation can be represented by using a suitable probability distribution. As mentioned above, the estimated value for the damage rate should be bounded within [0, 100]. A logistic model for the damage rate is a suitable choice for fitting the damage rate–inundation depth data such as Figure 4, that is,

$$y = \frac{100}{1 + \exp[-(a + bx)]} \quad (4)$$

where y = damage rate; x = inundation depth; and a & b = model coefficients. Equation (4) can be linearized as:

$$\ln\left(\frac{y}{100 - y}\right) = Y = a + bx \quad (5)$$

The best-fit model coefficients can be determined by linear regression using a least squares fit. Both ULS and CLS methods (described in Appendix A, available with the online version of this paper) are used to determine the best-fit model coefficients. The logistic curve (the solid line) shown in Figure 4 was derived by the CLS method. The constrained method allows the incorporation of damage rate–inundation depth characteristics for the study site, giving a more sensible relation (see Appendix A for comparing the results produced by the two least square methods).

Based on Equation (5), the residuals for $Y = \ln[(100 - y)/y]$ in the linearized model can be defined by:

$$\ln\left(\frac{y_i}{100 - y_i}\right) = Y_i = a + bx_i + e_i, \quad i = 1, 2, \dots, n \quad (6)$$

with e_i being the residual corresponding to the i -th observed data. According to linear regression theory (Kutner *et al.* 2003), the solid straight line in the linearized domain (see Figure 5) defines the mean response of Y conditioned on a specified inundation depth. To quantify the uncertainty in damage rate, a probability distribution for the residuals around the solid straight line in Figure 5 is sought. The validation of assumed distributions was carried out by the chi-square test for four theoretical distributions:

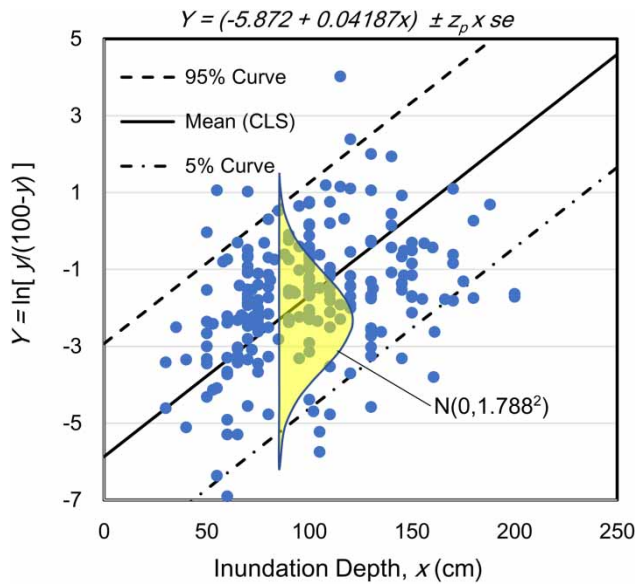


Figure 5 | Scatter of damage rates around the straight line for the CLS method. The scatter of the residuals can be represented by a probability distribution.

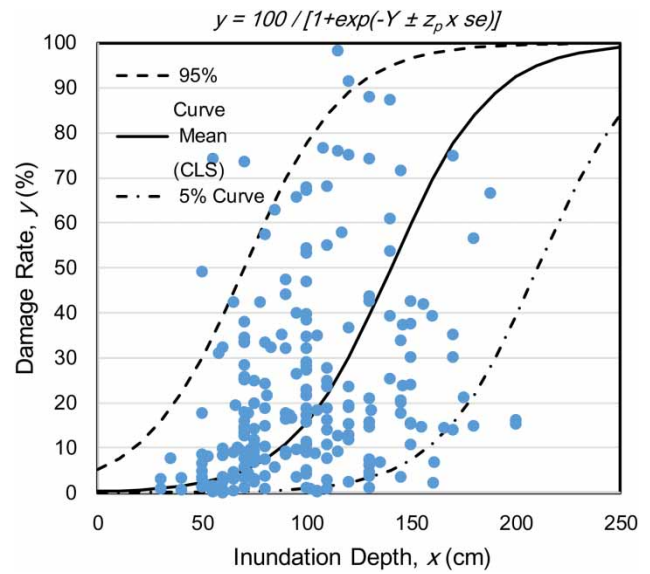


Figure 7 | Example damage rate–inundation curves (logistic curve) by the CLS method and at a 95% confidence interval for household articles.

normal, lognormal, triangular, and uniform distribution. The normal distribution was adopted herein to describe the dispersion, $e \sim N(\mu = 0, \sigma = 1.788)$, as shown in Figure 6. The solid line and the data (x, Y) in Figure 5 were retransformed into the logistic curve in x - y domain in Figure 7. The straight lines of $Y, Y + z_{0.95}\sigma, Y - z_{0.95}\sigma$ in Figure 5 correspond to the mean, the upper and lower bounds of 95% confidence intervals of the logistic curves in Figure 7, respectively.

Assessing uncertainty in the asset value

Not only the uncertainty of damage rates but also the scatter of asset value data should be assessed to quantify their

uncertainty with a probability distribution. The log-normal distribution was found to properly describe uncertainty in the asset value data residuals in the same way as presented in Figure 6. The uncertainties in both the asset value and the damage rate were thus incorporated in the inundation damage calculation. The monetary inundation damage can then be calculated by multiplying the probabilistic asset values by the probabilistic damage rates. In this study, a Monte Carlo simulation was applied to quantify the uncertainty of direct damage for the 11 damage types for households and businesses.

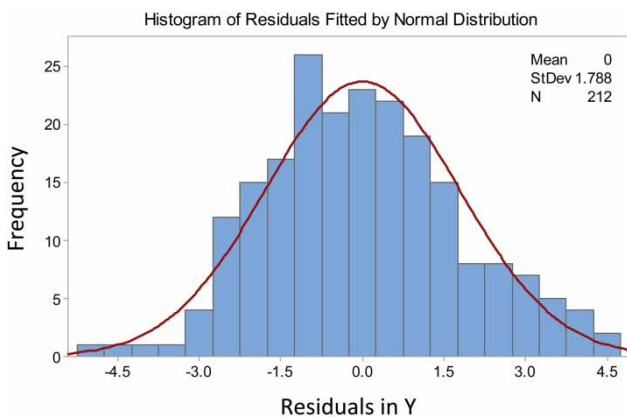


Figure 6 | Frequency distribution of residuals from the CLS method.

RESULTS AND DISCUSSION

Application of flood damage prediction model to urban drainage area

The flood damage prediction model was applied to a typical urban catchment located in the Zenpukuji River basin in Tokyo Metropolis. The catchment has an area of 18.3 km² and is densely populated with a high concentration of private houses and business buildings. In the catchment, flood control reservoirs were constructed in the 1980s and 1990s to reduce the flood inundation damage. At the present time, a new reservoir with a storage capacity 200,000 m³ (denoted by the dark spot in Figure 3) is being planned and is expected to work effectively for flood control. In

this study, two probabilistic damage potential curves were developed with and without the proposed reservoir.

Inundation calculations were carried out for every 50 m × 50 m grid cell within the study catchment for each design hyetograph. As an example, Figure 3 shows the flood inundation map for a 30-year storm under the present catchment condition. The calculated results were superimposed with GIS data developed by the Tokyo Metropolitan Government. The database includes asset data organized for a 50 m × 50 m grid cell, which is identical to the calculation grid used in this study.

Quantification of uncertainty in flood damage estimates

To quantify the uncertainty in flood damage estimates, a Monte Carlo simulation was undertaken using Crystal Ball software. For each design storm of a chosen return period 1,000 Monte Carlo repetitions were carried out where the asset values and the damage rates were randomly generated. The random damage rate and asset value were treated as statistically independent. The flood damage was estimated for 24-hour rainstorms with 14 different return periods, i.e. 1.2 years, 2 years, 3 years, 4 years, 5 years, 7.5 years, 10 years, 15 years, 20 years, 30 years, 50 years, 100 years, 150 years and 200 years. The input hyetographs were created based on rainfall IDF curves published by the Tokyo Metropolitan Government with the 14 return periods considered using the alternating block method (Chow *et al.* 1988). The total flood damage in the Zenpukuji River basin was described as a relationship between flood damage percentile and the return period (see Figure 8 without the planned flood control reservoir and Figure 9 with the planned flood control reservoir).

In Figure 8, the probabilistic damage potential relation is represented by a series of curves, each associated with a different percentile level. The damage potential curve associated with the p -th percentile indicates the non-exceedance probability level of the flood damage amount. The heavy solid curve in the middle of Figure 8 denotes the median value (50th percentile) of flood damage for different return periods. The uncertainty of flood damage potential can be expressed as a confidence band, such as 20%, 40%, 60%, or 80%, centred around the median curve. The width of the confidence band increases with the confidence level. Figure 8 also shows that the width of the confidence band is narrower for small return periods and becomes broader as the return period increases. This can be attributed largely to the smaller scatter of damage rates for the lower inundation depth as shown in Figure 4.

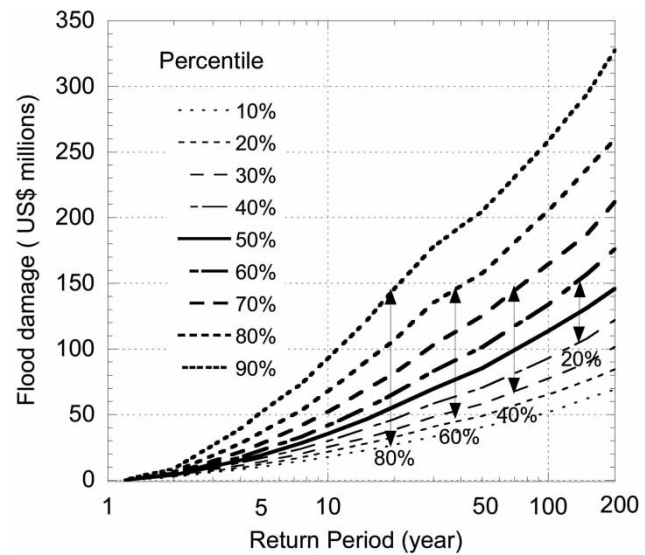


Figure 8 | Probabilistic damage potential curves under the present condition (without flood control reservoir).

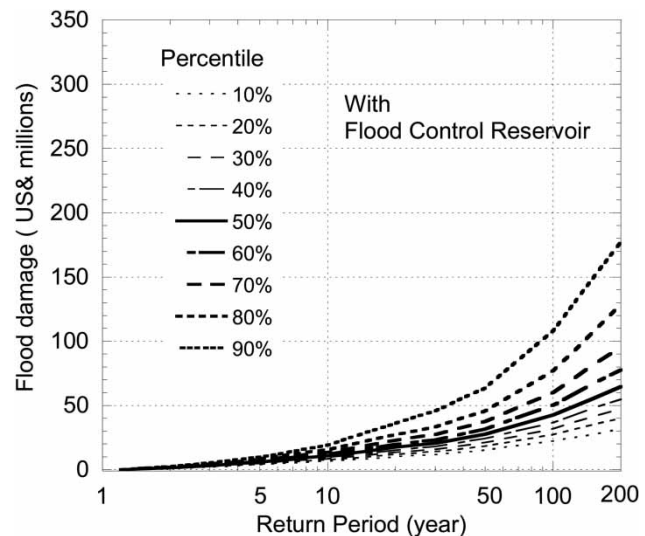


Figure 9 | Probabilistic damage potential curves with the planned flood control reservoir.

When the planned new reservoir is in service, the damage potential curves for the river basin are expected to shift downward as shown in Figure 9. This is because the presence of the flood control reservoir will reduce the inundation depth downstream of the reservoir and will reduce flood damage. The comparison between the two sets of potential damage curves enables the effectiveness of the planned reservoir to be assessed taking into account the uncertainty of flood damage estimates.

Multiplication of the damage potential curve and storm probability curve yields a risk density curve, and the integration of the risk density curve produces the risk cost or annual expected damage (AED) (Morita 2011, 2013). The AED, along with the uncertainty of the construction cost, can be then used in risk-based decision making for flood control planning and management (Morita 2009). When the damage potential relation is a single curve, without considering uncertainty in the damage rate and asset value, the determination of the risk density curve and risk cost is quite straightforward. However, the process for determining risk cost becomes more cumbersome when the damage potential curve is probabilistic, as shown in Figures 8 and 9.

CONCLUSIONS

A framework which integrates a GIS-based flood damage prediction model and flood damage estimation uncertainty is presented in this paper. A constrained logistic regression analysis was implemented to establish a probabilistic damage rate–inundation depth model for various damage types to houses, household articles and business buildings from actual surveyed flood inundation damage data for Metropolitan Tokyo. Based on the probabilistic damage rate–inundation depth relationships and probabilistic relation for the asset value, Monte Carlo simulations were undertaken to develop probabilistic damage potential curves. With the inclusion of uncertainty in the damage rate and asset value, the damage potential is no longer a single-value curve, but is subject to uncertainty. In a numerical example for an actual urban watershed in Metropolitan Tokyo, its probabilistic flood damage potential can be expressed in terms of a series of curves, each corresponding to different percentile levels. The probabilistic flood damage potential curve can be transformed into the flood damage area chart with stipulated reliability values for flood risk management in urban areas. Because probabilistic damage potential curves are not unique, additional treatment is needed to obtain the AED for evaluating the effectiveness of a flood control project when including uncertainty in the flood damage estimates.

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First received 12 April 2019; accepted in revised form 16 August 2019. Available online 29 August 2019