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Discussions

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Statistical model for economic damage from pluvial flood in Japan using rainfall data and socio-economic parameters

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Abstract

The assessment of flood risk is important for policy makers to evaluate damage and for disaster preparation. Large population densities and high property concentration make cities more vulnerable to floods and having higher absolute damage per year. A number of major cities in the world suffer from flood inundation damage every year. In Japan, approximately JPY 100 billion in damage occurs annually due to pluvial flood only. The amount of damage was typically large in large cities, but regions with lower population density tended to have more damage per capita. Our statistical approach gives the probability of damage following every daily rainfall event and thereby the annual damage as a function of rainfall, population density, topographical slope, and gross domestic product. Our results for Japan show reasonable agreement with area-averaged annual damage for the period 1993–2009. We report a damage occurrence probability function and a damage cost function for pluvial flood damage, which makes this method flexible for use in future scenarios and also capable of being expanded to different regions.

1 Introduction

The assessment of the available water resources and their temporal and spatial distribution, as well as the analysis of flood and drought risk are of great importance for the health of human societies and environmental systems (Lehner et al., 2006). A world bank report (Dilley et al., 2005) marked that earthquake, floods and drought like natural hazards continue to cause tens of thousands of deaths, hundreds to thousand injuries, and billions of dollar in economic losses every year around the world. Flooding is one of the major causes of physical losses in the world and continually increasing in trend. Globally flood damage had increased from an average seven USD 7 billion yr^{-1} in 1980s to more than USD 20 billion yr^{-1} at the end of 2000s (Kundzewicz et al., 2013). Thirty-five percent of physical losses over the past 40 years in the Asia–Pacific region

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were due to flooding (Asian Development Bank, 2013). Moreover occurrence of floods was the most frequent among all natural disaster (Jha et al., 2011). Recent large scale and record breaking flooding events in terms of physical losses have provided serious attention to world leaders and policy makers toward proper planning and management of flood control infrastructure and formulating future adaptation strategies. China in 2010 experienced the largest flood damage of USD 51 billion in one single year and the 2011 flood in Thailand caused the most expensive insurance loss ever, worldwide, with total liability estimated at around USD 15 billion (Kundzewicz et al., 2013). Flooding events in Germany and central Europe in May and June 2013 were the most expensive, costing around USD 16 billion (Wake, 2013). Economic losses due to floods are higher in developed countries, whereas the economic losses expressed as proportion of gross domestic product are much higher in developing countries (Handmer et al., 2012). Even a huge investment for improvement of flood control infrastructures was made, flooding remains a serious problem throughout the Europe (Kundzewicz et al., 2013) and the case of Japan is also similar. Annual expenditure for flood control in government budget in Japan is nearly USD 10 billion (about JPY 1 trillion) as reported in Kazama et al. (2009). The high potential of flood damage in Japan is basically due to the fact that approximately 9 % of its land is flood prone; but contains 41 % of population and 65 % of the national assets (Kundzewicz et al., 2013).

Flooding related to rainfall usually divided into large-scale floods due to high discharge of rivers and stream (Fluvial flood), and local or urban floods that occur due to excessive rainfall that overwhelms local drainage capacity (Pluvial flood) (Bouwer, 2013). Even often published flood damage events were from fluvial flooding, the share of pluvial flooding cannot be under estimated. Pluvial flood damage, particularly in densely populated urban areas and areas with poor drainage facilities were recorded very high not only during heavy rainfall but also at moderate to low rainfall events. Rapid urbanization with inadequate engineered in-city drainage infrastructure promotes the damage not only to economy but also to human lives (Kundzewicz et al., 2013). The Ministry of Land, Infrastructure, Transport and Tourism (MLIT) of Japan had shown

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that 86 % of total economic flood damage in the Tokyo metropolitan during 1998–2007 was only due to pluvial flood (MLIT, 2008b). The flood damage in Kochi in September 1998 (Yamamoto et al., 1999) was largely due to pluvial flood and also failure of inner drainage systems led to the higher flood damage in 2000 Tokai flood (Ikeda et al., 2007). Average annual economic damage for residential property attributable to pluvial flood in Japan was approximately JPY 100 billion (about 45 % of annual flood damage of same kind) during 1993–2009 (MLIT, 2009). Figure 1 shows the historical total national fluvial and pluvial flood damage for general property in Japan. Here general properties imply housing, household appliances, depreciable business properties, business inventory properties, depreciable agriculture/fisheries and agriculture/fisheries inventory property. The figure reveals that annually pluvial floods cause significant damage and efforts for pluvial flood damage control seem ineffective. Even a well-prepared city in terms of flood defence infrastructures, like Tokyo, suffers frequent pluvial flood damage. Rapid urbanization with aging population, decline in preparedness of local communities to fight flood disaster, increase in new exposed facilities make cities more vulnerable than before (Ikeda et al., 2007). Smaller cities and towns are typically more severely affected by pluvial floods; perhaps due to less developed flood defences as pluvial flood damage per capita on those areas were reported higher than bigger cities. Pluvial flood impacts on UK and many European cities were also recorded very high in recent years (Morris et al., 2009; Van Riel, 2011; Spekkers et al., 2013). The scenarios in the present warn us for future as well since small changes in rainfall intensity can led to a rapid increase in losses in urban areas due to the highest concentration of capital (Bouwer, 2013; Morita, 2011; Zhou et al., 2012). Pluvial floods seem very serious and contribute to high physical losses all over the world; however, relatively a few studies on this issue were reported for present and also in future climate (Seneviratne et al., 2012).

In regard to the above discussion, a proper way of assessing pluvial flood damage amount for each hazard event in local to global scale for present and future is a demanding task for scientific communities. An accurate estimate of economic damage is

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now indispensable for decision makers so that economic viability of proposed infrastructure development, mitigation and/or adaptation plans for flood defence could be justified and could be used in overall flood risk management strategies (Lavell et al., 2012; Merz et al., 2010).

A wide range of methodologies had been developed and applied for assessing flood damage risk over the last few years, however most of these models were developed for fluvial flooding. A diverse approach had been applied for flood risk assessment by many researchers and organizations. Many conceptual models which provided the different vulnerability or risk indices for spatial comparison were developed for local to global scale. Some popularly known indices are event based disaster risk index (DRI) (UNDP, 2004), Hazard index for Mega cities (HIM) (Munich Re, 2004), Prevalent vulnerability Index (PVI) (Inter-American Development Bank, 2007), Discharge Probability Index (DPI) (Yoshimura et al., 2008), Flood Vulnerability Index (FVI) (Hara et al., 2009) and Advance flood risk index (AFRI) (Okazawa et al., 2011). Each index has their own criteria and spatial resolution (local to global scale) for calculating indices for risk or vulnerabilities. These index based approach might be suitable for assessing relative risk distribution; however as discussed earlier, a decision maker requires an absolute damage amount in monetary term so that economic viability of a proposed infrastructure development plan for flood defence could be justified.

The direct flood damage estimating models so far developed basically utilizes two different sub-models: first, to evaluate hydrological parameters (e.g. flood velocity, flood duration and flood depth) based on some physically based hydrologic modelling techniques (hydrological models), and second to evaluate absolute/relative damage amount based on a susceptibility function usually derived from empirical analysis (loss models), which relate the hydrological parameters to damage amount. The basic features of hydrological models are to estimate hydrological parameters for a hazard event generally defined by its exceedance probability (return period). On the other hand, a loss model is a central idea for flood damage estimation (Merz et al., 2004) and the most common way of estimating direct damage amount is the use of depth-damage

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functions often termed as susceptibility function or vulnerability function (Dutta et al., 2003; Glade, 2003; ICPR, 2001; Jongman et al., 2012a; Kazama et al., 2009; Kelman and Spence, 2004; Kreibich et al., 2010; Rodda, 2005; Schmidt-Thomé et al., 2006; Smith, 1994; Ward et al., 2013). Some loss models are multi-parameters models based on several hazard parameters (flood depth, flow velocity, contamination etc.) and resistance parameters (flood prone object type and/or size, mitigation measures etc.) for example HAZUS-MH (FEMA, 2003), Model of multi coloured manual (Penning-Rowsell et al., 2005), FLEMOps (Apel et al., 2009), and FLEMOcs (Kreibich et al., 2010).

Flood damage assessment methodology and their results further depend on the defined spatial boundary (Apel et al., 2009). To date several studies had been done from very local municipal level (Baddiley, 2003; Grünthal et al., 2006), catchment scale (Dutta et al., 2003, 2006; ICPR, 2001), national scale (Hall et al., 2005; Kazama et al., 2009; Rodda, 2005), regional scale (Schmidt-Thomé et al., 2006) to the global scale (Jongman et al., 2012b; Ward et al., 2013). Winsemius et al. (2013) also provided a framework for global river flood risk assessment. Due to the increasing need of national scale and even larger scale flood damage assessment (Winsemius et al., 2013), a macro-scale studies are getting much popular.

Most of the damage assessment models so far discussed were primarily developed for fluvial flooding; however loss model could be a common component for both fluvial and pluvial flood damage assessment. A few studies on pluvial flood and its associated damage were also reported. Zhou et al. (2012) described a framework for economic pluvial flood risk assessment considering future climate change which quantifies flood risk in monetary term as expected annual damage in different return period of rainfall. Escuder-Bueno et al. (2012) presented a methodology for assessing pluvial flood risk using two different curves; one for societal risk and other for economic risk; however both were limited to a local scale.

The flood damage assessment models to dates contain a number of uncertainties in both hydrological and loss models. Hydrological models possess uncertainties regarding extreme value statistics used, stationary and homogeneity of data series, consid-

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eration of physical properties (e.g. dikes and drainage systems) of a location and calibration and validation of model output etc. (Apel et al., 2009). But the largest sources of uncertainties in damage modelling were associated with prescribed depth-damage functions (Apel et al., 2009; Hall et al., 2005; Jongman et al., 2012a; Merz et al., 2004, 2010; Moel and Aerts, 2010). A reason for uncertainty in loss models is its crude assumption of relationship between damage with flood depth only in most cases. Moreover, these models generally developed for some specific location using past flood records and its validation are always a critical issue for its temporal and spatial transferability. Uncertainty related with the property types and their values are also critical in many cases. There is still a need of better understanding of different processes lending to damage so that they can be modelled appropriately (Meyer et al., 2013). A special report of the Intergovernmental Panel on Climate Change (IPCC), often called IPCC SREX (IPCC, 2012) also focused a need of more empirical and conceptual effort to develop robust damage assessment methodology.

In regard to the present situation, this study is motivated towards a development of a simple but robust statistical model as integral of hazard, vulnerability and exposure based on historical database in Japan for pluvial flood damage assessment that could be used for all regions irrespective of their individual characteristics of pluvial flooding. Moreover the model describing in this paper overcome several uncertainties regarding both hydrological and vulnerability models and capable for estimating total annual damage in national scale in simple and rapid way. Our method for damage assessment is a macro-level statistical model, that focuses on pluvial flood and considers all daily precipitation events in a year and thereby calculate annual damage. In this study, each daily rainfall event is characterised by its exceedance probability based on the Gumbel distribution. We report two different functions namely damage occurrence probability function and damage cost function. The former represents the relationship of exceedance probability of rainfall and its corresponding damage probability, and latter represents the relationship of exceedance probability of rainfall to relative damage cost of a particular location. These two functions are further used to calculate

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annual damage and thereby average annual damage (AAD) for entire Japan due to pluvial flooding. We also examined uncertainties associated with daily damage data and its preparation. A popular bootstrap method was applied for uncertainty analysis. We believe this model helps decision makers to estimate annual damage for short term planning and to estimate average annual damage for long term planning with reasonable level of confidence. As a macro-level study, we use readily available data, including population density, elevation, and national annual gross domestic product (GDP) which make this method more flexible to use for future climate scenarios and also extendable to global assessment. The next section describes the methodology, including forcing data and theory. The subsequent section presents the results for annual damage along with uncertainty analysis. The final section concludes the paper.

2 Methodology

2.1 Data

2.1.1 Precipitation data

Daily precipitation data were used as an external forcing for hazard in this study since it is a strong external loading for pluvial flood (Zhou et al., 2012). Daily precipitation data were obtained from the Auto Meteorological Data Acquisition System (AMeDAS), which cover all areas of Japan at an interval of about 20 km on average. High density of observation stations and having longer observation periods led us to use AMeDAS dataset. Daily precipitation data for the period 1976–2009 were utilized. Approximately 1300 Japan Meteorological Agency (JMA) rain gauges were sampled, and data were interpolated using the inverse distance method for its simplicity and much appropriate for relatively dense gauge network (Dirks et al., 1998; Mouri et al., 2013; Yoshimura et al., 2008) to assign a value to each grid point in a $0.1^{\circ} \times 0.1^{\circ}$ grid. For each 0.1° grid, the surrounding rain gauges were averaged with a weighting of $1/d^2$, where d

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is the distance from the centre of the grid to the rain gauge. The annual maximum daily precipitation data were computed from daily precipitation data for each grid and thereby calculated the exceedance probability of annual maximum daily rainfall, which will be explained later.

2.1.2 Population density data

Population size of a location has strong influence to flood risk (Kundzewicz et al., 2013). Increasing population in a flood prone zone increases exposure and thereby total damage amount increases with increasing population (Moel et al., 2011; Morita, 2011). The case of Japan is even more serious as a large number of population live in relatively small flood prone area (Kundzewicz et al., 2013). However, population size is not a sole component for determining flood risk. Resident of small cities or towns are often far more vulnerable to disaster than residents of megacities (Cross, 2001). Three population density classes (low: 0–250, medium: 250–2000, and high: > 2000 persons km^{-2}) were prepared to analyse the damage occurrence probability and vulnerability in different population densities. For this purpose, annual population data for 1993–2009 were used from the Gridded Population of the World, version 3 (GPWv3), and these data were interpolated onto a $0.1^{\circ} \times 0.1^{\circ}$ grid. The global data were adjusted based on the Japan national census so that the population of each prefecture was properly given. The prefectural population data were taken from the Statistics Bureau, Ministry of Internal Affairs and Communications (MIC), Government of Japan.

2.1.3 Damage data

Damage data are always a critical issue in flood damage assessment. Lacking of reliable, consistent and comparable data is a major obstacle (Hall et al., 2005; Handmer, 2003; Handmer et al., 2012; Kundzewicz et al., 2013; Merz et al., 2010; Meyer et al., 2013) to formulate a robust methodology and to validate it. Moreover the level of uncertainties in damage estimation are mainly depended on available data (Escuder-

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Bueno et al., 2012; Handmer, 2003). Several international flood damage database which archive the flood damage data from all over the world along with duration (start and end date) and location exist for example EM-DAT, Dartmouth flood observatory, Munich Re and Swiss Re etc. Since all databases have their own criteria of damage recording, local scale small damages (Meyer et al., 2013) and in some cases big damages were often not recorded because of which total annual damage recorded in these database were much smaller than that recorded in respective national damage database. However such national level damage databases are only available for a few developed countries. In this study, daily damage data due to pluvial flood for the period 1993–2009 based on economic damage to tangible general property (housing, household appliances, depreciable business property, business inventory property, depreciable agriculture/fisheries property, agriculture/fisheries inventory property) from MLIT's flood disaster statistics were used. The various characteristics of this database are well described in Mouri et al. (2013). These data include the name of the city or town where a disaster happened, type of disaster (Fluvial or Pluvial), type of damaged assets, start and end date of flooding, and total damage amount. Further disaggregation of these data into temporal and spatial resolution was really a big challenge. For this study, the first day of damage onset was considered the damage day and total recorded damage amount was given to that single day. These damage data were further interpolated onto the $0.1^{\circ} \times 0.1^{\circ}$ grid based on the geometric centre of the city (Mouri et al., 2013; Yoshimura et al., 2008). The geometric centre of each city was calculated using an address-matching service developed by the Centre for Spatial Information Science, The University of Tokyo (CSIS UT, 2013). Obviously above assumptions for spatial and temporal breakdown of damage data produce some uncertainties. Yoshimura et al. (2008) examined the various criteria of spatial and temporal breakdown of the recorded damage data and found that the above consideration works better for simulating daily damage amount for Japan. Better damage data recording techniques for both spatial and temporal scale are indispensable for developing a ro-

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bust damage model. Nevertheless area-averaged annual national damages were well calculated by the proposed methodology showing its performance capability.

2.1.4 Gross Domestic Product (GDP) data

Assets value is another important component of economic damage assessment. Currents models for economic flood damage estimation possesses high uncertainties regarding the assets value used (Jongman et al., 2012a; Moel and Aerts, 2010). For regionalization of a model, integrated asset value which has a uniform definition for all regions is essential. Far a macro-scale study, an aggregated asset value is more appropriate to make it flexible for expanding to any other region (Merz et al., 2010) and in the absence of real assets data in present situation, GDP can be a powerful candidate in this regard (Jongman et al., 2012a). GDP data were used as an asset value and macro-economic vulnerability is defined as the ratio of damage to GDP at a location which will be described more in later section. National annual GDP data for 1993–2009 were taken from the International Monetary Fund (IMF) world economic outlook database of April 2012. Prefectural GDP data were taken from the statistics bureau, ministry of internal affairs and communications (MIC), government of Japan. These data, shown in Fig. 2 reveals that the GDP of each prefecture is approximately proportional to the population (these data are for 2003, but the trend was similar in other years). The national level annual GDP was hence distributed onto each grid proportional to the grid population (Chan et al., 1998; Jongman et al., 2012b; Ward et al., 2013) as given in Eq. (1).

$$\mathrm{GDP}_{\mathrm{grid}} = \mathrm{GDP}_{\mathrm{nation}} \cdot \frac{\mathrm{Population}_{\mathrm{grid}}}{\mathrm{Population}_{\mathrm{nation}}} \tag{1}$$

2.1.5 Slope data

Many geological and topographical characteristics contribute to the flood risk (Kundzewicz et al., 2013). The topographical characteristic fundamentally determines

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the flooding extent, its depth and velocity which ultimately govern flooding impact at a location. In most of the reported methodology (Dutta et al., 2003; Kazama et al., 2009; Zhou et al., 2012) topographical slope was implicitly used in their hydrological model. In some model direct elevation data were used to estimate flood water depth for example in Feyen et al. (2012). We also evaluated the topographical dependency in damage occurrence at a location. To preserve the impact of topographical characterises in flooding, we used slope as one of the parameter in our damage occurrence probability function, the details of which will be described later. Topographical slope data were prepared based on GTOPO30 datasets (USGS, 1996). GTOPO30 is a global digital elevation model (DEM) with horizontal grid spacing of 30 arcsec (approximately 1 km). The maximum slope at each grid point was compared with the slope in the surrounding eight grids, and the mean of the maximum slopes in each grid was used for the 0.1° grid data.

2.2 Theory

2.2.1 General definition of flood risk

Extreme events interacting with exposed human resources and economic activities can lead to disaster. To this end, various definition of risk can be found in different literatures. Smith (1996) defined the risk simply as a probability of a specific hazard occurrence. Davidson (1997) further elaborated the risk as a product of hazard, exposure, vulnerability, capacity and measures. Hall et al. (2005) specifically defined flood risk as the product of the probability of flooding and the consequential damage, summed over all possible flood events. As per the definition of United Nation International Strategy for Disaster Reduction (UNISDR) (UNISDR, 2009), disaster risk is a product of hazard, vulnerability and exposure and hence can be simply written as:

$$\text{Risk} = \text{Hazard} \cdot \text{Vulnerability} \cdot \text{Exposure}. \quad (2)$$

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IPCC (2012) broadly defined the disaster risk as the likelihood over a specified time period of severe alternations in the normal functioning of a community or society due to hazardous physical events interacting with vulnerable social condition, leading to wide spread adverse human, material, economic, or environmental effects that require immediate emergency response to satisfy critical human needs and that may require external support for recovery. In fact definition of risk is still not clear and often controversial (Okazawa et al., 2011). In this study, we define damage risk as a product of disaster occurrence probability and corresponding vulnerability due to a hazard event at a location. Vulnerability is defined as the conditional relative damage amount with respect to the GDP (assets) and termed as damage cost function. Figure 3 shows the conceptual framework for the different components and their interrelationship for damage assessment in this study. Here, the damage risk can simply be written as:

$$\text{Damage risk} = \text{Damage Occurrence Probability} \cdot \text{Damage Cost function}. \quad (3)$$

Each daily rainfall data was characterized by its exceedance probability. In general, an exceedance probability is a probability that an event of specified magnitude will be equalled or exceeded in any defined period of time, on average and generally calculated and expressed as one in year. These exceedance probabilities were further relate with the probability of damage occurrence at a location in one hand (referred as damage occurrence probability) and average cost of damage due to this event on the other hand (referred ad damage cost function). Flooding and flood damage are two different phenomena (Mouri et al., 2013) and hence for better understanding flooding and its associated damage, we defined flood damage occurrence probability and damage cost function separately. The division of total damage risk into two components enhanced to judge the contributing factors (exposure and susceptibility) of damage risk by defining each risk components independently. The probable cost of damage was then obtained with the product of these two components. The calculation procedures of each component are described in the following sub-sections.

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2.2.2 Exceedance probability of rainfall (w)

Annual maximum daily rainfall was assumed to follow a Gumbel distribution. The annual maximum daily rainfall data for the period 1976–2009 were used to calculate the Gumbel parameters. Gumbel distribution is one of the extreme value statistical distributions which were widely adapted for hydrological events (Hirabayashi et al., 2013; Mouri et al., 2013; Ward et al., 2013; Yoshimura et al., 2008). Mouri et al. (2013) showed the applicability of Gumbel distribution for AMeDAS daily precipitation for entire Japan using standard least-square criterion (SLSC). We also evaluated the goodness of fit of Gumbel distribution to annual maximum daily rainfall using the Probability Plot Correlation Coefficient (PPCC) (Hirabayashi et al., 2013; Vogel, 1986) test which revealed that about 94 % of grids have PPCC value greater than the critical PPCC (0.95532 for 34 samples) corresponding to 5 % significance level prevailing its applicability. Based on the Gumbel distribution extreme value theory, the cumulative distribution function for the annual maximum daily precipitation, x, can be written as:

$$F(x) = e^{-\exp(-a(x-b))}, \tag{4}$$

where a and b are the Gumbel parameters, calculated based on the annual maximum daily precipitation value from 34 years (1976–2009) precipitation data set for each grid point. The parameters a is a scale parameter, and was calculated from

$$a = \frac{\sqrt{6}\pi}{6\sigma}, \tag{5}$$

where σ is the standard deviation of the annual maximum daily precipitation rate. The parameter b is a location parameter and was calculated from

$$b = \mu - \frac{0.5772}{a}, \tag{6}$$

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where μ is the mean annual maximum daily precipitation rate, and 0.5772 is Euler's constant. The exceedance probability of each daily precipitation can be defined as

$$w = 1 - F(x). \tag{7}$$

In this study, all daily rainfall was characterized by its exceedance probability using Eq. (7) hence each grid possesses different amount of daily rainfall with same return period. Defining rainfall by its exceedance probability makes the homogenous condition of rainfall events to each location i.e. each grid.

2.2.3 Damage Occurrence Probability (DOP)

The damage occurrence probability (DOP) is the probability of damage at a given location (i.e. grid point) in response to a rainfall event. To calculate damage occurrence probability at each location, some "bins" of exceedance probability were prepared. The width of each bins were fixed as per their sensitivity regarding number of daily rainfall events and number of damaging events. Several trials were performed to fix the bin size especially for lower exceedance probability bin. The number of damaging events for each bin for all three population density classes are shown in Fig. 4a. The figure reveals that the number of damaging events were very few in smaller exceedance probability bin (i.e. higher return period), however the number of damaging events in higher exceedance probability bin (i.e. smaller return period) were surprisingly higher. The damaging events in frequent rainfall events were often neglected in previous damage modelling technique, although these damages could have a considerable share in total damage amount. The DOP was calculated as a ratio of damaging events (n) in relation to the total number of events (N) within a specified exceedance probability "bins" using recorded damage data as in relation Eq. (8) below.

$$\mathrm{DOP} = \frac{n}{N}. \tag{8}$$

Three population density class (low: 0–250, medium: 250–2000, and high: $> 2000\,\mathrm{km}^{-2}$) were prepared to evaluate the dependency of population density on dam-

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age occurrence probability at a location due to daily rainfall event using Eq. (8). The recorded damage in each grid for the years 1993–2002 were used to calculate damage occurrence probability. As seen in Fig. 4a, the exceedance probability bin of 0–0.01 (large return period) obviously had smaller number of events thereby smaller number of damaging events. Only 12 (out of 120 events), 23 (out of 56 events), and 13 (out of 19 events) number of damaging events were recorded in this bin for low, medium and high population density class respectively. The damage occurrence probability as a function of exceedance probability of daily rainfall for all three population density class are shown in Fig. 5. The figure prevails that higher population density had higher damage occurrence probability than lower populated area. The figure clearly shows the dependency of damage occurrence probability on the exposure of the location. Since topographical slopes have strong influence on drainage of water from a location and can contribute to pluvial flooding, the relationship of damage occurrence probability and topographical slopes were also analysed for all population density classes based on the damage recording data for the period 1993–2002 in each grid. For this, at least three topographical slope sub-classes were prepared based on the available data. Different slope sub-classes for each population density class were prepared to manage the number of damaging event. For example, high population density class was subdivided into three slope sub-classes (0–0.5 %), (0.5–1 %) and (1–25 %). The smallest exceedance probability bin (0–0.01) belonged only 8 (out of 9), 3 (out of 5), and 2 (out of 5) number of damaging events produces DOP of 0.889, 0.600, and 0.400 respectively. An uncertainty related to small number of data remain especially for this bin, however the size of lower exceedance probability bin was optimized so that it produced better results in both calibration and validation period. Figure 6 shows an example of topographical dependency for high population density class with different slope sub-classes. The figure reveals that lower topographical slope exhibits higher damage occurrence probability perhaps due to the poor natural drainage of water. For slopes with gradients greater than 25 %, no damage was recorded (even in populated areas). We implemented a multi-regression fitting algorithm for the probability of damage as

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a function of exceedance probability (w) and the topographical slope (S) for different population density classes to produce an equation for damage occurrence probability as given in Eq. (9). For slope higher than 25 %, no probability of damage presumed.

$$\left.\begin{array}{ll} \mathrm{DOP}(w,S) = e^{c\ln\left(\frac{1}{w}-1\right)+d\cdot(S\ \mathrm{in}\ \%)+d'} & \text{for } S < 25\,\% \\ \mathrm{DOP}(w,S) = 0 & \text{for } S \geq 25\,\% \end{array}\right\} \tag{9}$$

The parameters c, d, and d' in the above relationship were computed for all population density classes using damage data for the period 1993–2002 and Eq. (8). The calibration of these parameters was performed to produce the reasonable national annual damage during 1993–2002. The calibrated parameter values are tabulated in Table 1.

2.2.4 Damage cost function

The damage cost function describes the degree of damage associated with each daily rainfall event and hence also can be termed as vulnerability. As described earlier, the most common way of estimating direct damage amount so far was the use of a depth-damage function. A depth-damage function shows the relationship between flood depth and relative damage associated with it. Total damage amount due to a flood event is not only depended on water depth but also other factors like flow velocity, duration of inundation, sediment concentration etc. (Kundzewicz et al., 2013; Merz et al., 2004), resistance parameters (type, size, shape and property of objects) (Kreibich et al., 2010) and the level of preparedness of a society (Merz et al., 2004). Another main issue related to depth-damage functions is its spatial and temporal non-transferability especially for national level and global level damage assessment, because they were often developed from local municipality scale or catchment scale. Also asset values at a location always create a large uncertainty which are largely depend upon various building characteristics. In this study, we introduce a damage cost function that relate the exceedance probability of rainfall to the average damage per GDP (DpG) for each population density class. The GDP was taken as asset value which indicates asset irre-

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spective of the individual characteristics of a location and hence widen its applicability to all regions.

In this study, we prepared some exceedance probability bins, and mean DpG in each bin with different damaging evens were calculated for the period 1993–2002 for all three population density classes. Damage per GDP value showed very large variation within a bin as seen in Fig. 4b–d as boxplots for low, medium and high population density class respectively. The lower and higher end of box gives the 25th and 75th percentile value of the data, whereas red bars within each box show the median value of the data within each bin. Larger deviation in each bin is shown by whisker plot (dotted line) showing a range of 1.5 time of inner quartile. The green line joins the mean value of DpG in each bin. The figures (boxplots) reveals that there is a large deviation of damaging value with respect to its property even with similar hazard events. This large variation is partly due to bin size itself which constitute a large variation of hazard frequency, and partly due to the large uncertainty in damage amount even with same hazard event at a location. Moreover, the mean value of damage per GDP is significantly higher than its corresponding median value showing that a few number of damaging events causes larger share in total annual damage. We adopted an inverse power law to relate exceedance probability of rainfall (w) and damage per GDP (DpG) for mean value for each population density class as given in relation Eq. (10).

$$\mathrm{DpG} = p \cdot w^{-q}, \tag{10}$$

where, the parameters p and q were computed from historical data [1993–2002] for each population density class with least square fitting technique. Figure 7 shows the fitted damage cost function curves for all three population density class. The vulnerability parameters p and q in Eq. (10) were then estimated for mean DpG as tabulated in Table 2. The uncertainty related to the spatial and temporal averaging of damage per GDP in each exceedance probability bin was evaluated using Bootstrap method and will described in next section. The damage cost function is a crucial component required to calculate the absolute damage resulting from an event at a given location.

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This corresponds to the level of damage at a given location for each precipitation event. The damage cost function curves shown in Fig. 7 reveals that lower population density areas led to greater damage per GDP than higher population density area and shows higher vulnerability to pluvial flood damage perhaps due to less flood defence works.

2.2.5 Uncertainty analysis

As discussed before, a flood damage assessment model possesses a number of uncertainties which always limit its use for future projection. In this study, damage due to an event was computed using the Eqs. (9) and (10). Vulnerability parameters were calculated by fitting a power curve with mean DpG value, however as seen from Fig. 4b–d, the DpG values in each exceedance probability bin have large variation. The uncertainty related to very large variation of DpG in each bin was evaluated using Bootstrap Method (Efron, 1979). Using the Bootstrap technique of resampling for the data in each bin, 10 000 Bootstrap samples were generated and their means were calculated. 10th and 90th percentile values were taken for these mean values (10 000 in number) assigning lower and upper uncertainty range of the mean for each bin. The parameter values for Eq. (10) were also calculated for these 10th percentile and 90th percentile DpG along with mean DpG. The values of vulnerability parameter for these two percentile DpG are also tabulated in Table 2 along with computed parameter values for mean DpG. The former two hence gave the maximum and minimum limit of our damage estimation with probable confidence band of 80 % and latter produces total annual damage.

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2.2.6 Annual damage and average annual damage

Annual damage was calculated from the sum of the daily damage value due to each rainfall event in a year, which can be given as:

$$\text{Annual loss of each grid} = \sum_{1}^{365} \mathrm{DOP}(w_i, S)\mathrm{DpG}(w_i)\mathrm{GDP}. \tag{11}$$

The DOP and DpG (mean) for each rainfall event were calculated using Eqs. (9) and (10) for each grid, and summation of the damages from all daily rainfall events during a year was taken as the annual loss for the grid point as in Eq. (11). The summation of damage from all grids over Japan gave the annual national damage due to pluvial flood inundation. Average annual damage from a period seems to be a more appropriate representative value for a period because of the stochastic nature of damaging events. Moreover use of 90th percentile and 10th percentile DpG from Bootstrap means gave the highest and lowest limit of the annual damage which provides 80 % probable range of estimated annual damage.

2.2.7 Calibration and validation

Parameters in the DOP and the damage cost function were first computed using the damage data for the period 1993–2002. Damage data for 2003–2009 were used for validation purpose. Only DOP parameters were calibrated during the fine tuning process to estimate better annual damage variation and average annual damage during the periods. The average annual damage and its annual variation were observed while calibrating DOP parameters.

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3 Results

The results of proposed model were evaluated by its capability to produce the annual total national damage and average annual damage in both calibration and validation period using the damage occurrence probability function and the damage cost function with mean DpG. Along with total national damage, total annual damage for all three population density classes were also evaluated. Figure 8a–c show the annual variation of total calculated damage within low, medium and high population density class respectively along with the recorded damage variation. The total national pluvial flood damage (recorded and calculated) is shown in Fig. 8d. The upper and lower ranges of annual damage were calculated using parameters of damage cost function with 90th and 10th percentile of Bootstrap samples means as shown by shaded area in the figures. Annual variation in the calculated damage compared with the recorded variation in damage shows good agreement in most years, except for 1997 (in low population density class) and 1998 (in medium population density class). As these data were generated using spatial and temporal averaging, the large localised damage in some grids may have been underestimated. For example, the largest recorded damage in 1998 was due to the Kochi flood on 24 September 1998; however, as Iwasada et al. (1999) pointed out, the inundation of the Kochi flood resulted from overflowing water from a part of the Kasumi Levee (a traditional Japanese discontinuous levee) along the Kokubu river. This means that this particular inundation was unexpected, given the existing flood-mitigation measures. Thus, some of the recorded damage in pluvial flooding may be from river flooding and may therefore be over-recorded.

The annual variation in the total damage during the validation period shows good agreement with the recorded data, which may be due to the absence of any event causing extensive damage in this time period in a particular grid.

The computed average annual national damage (with the financial costs normalised to 2005 levels) during the calibration period 1993–2002 was JPY 94.12 billion, which is slightly lower than the recorded average annual damage over this period

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(JPY 111.45 billion). Computation of the average annual damage for 2003–2009 using this method gave JPY 84.54 billion, slightly higher than the recorded average damage in this period (JPY 76.39 billion). Fukubayashi (2012) also estimated the national average annual damage for flood inundation in Japan during 1993–2009 to be JPY 108 billion, but did not evaluate the annual variation in the damage.

Even though the model was calibrated and validated with bulk national damage data, the performance of the model with different population density classes were also very good as seen from Fig. 8a–c. This led us to present the spatial distribution of the average annual damage and average annual damage per GDP for the period 1993–2009 using Eqs. (9)–(11). The results are shown in Figs. 9 and 10, respectively. The average annual damage distribution reveals very large damage in big city areas, particularly Tokyo, Osaka, Nagoya, and Niigata, which is related to the large population density in flat lands. However, the spatial distribution of the average damage per GDP shows an inverse trend. In general, scattered small towns have higher damage per GDP than do big cities, perhaps due to less preparation for pluvial flooding.

A MLIT report (MLIT, 2008a) described a significant increase in the daily precipitation rate in Japan over the last 100 years, as well as increases in short-term heavy rainfall over the past 30 years as also revealed in Utsumi et al. (2011). The report further revealed based on different studies that future annual precipitation and summer precipitation will increase in most part of Japan. This is expected to decrease the return period of an event and thereby increase the probability of damage and the size of the damage for a given event. Practical guidelines for strategic climate change adaptation planning for flood disaster prevention (MLIT, 2010) focuses on three main strategic areas: socio-economically developed and urbanised areas, alluvial plains, and regions where flood control measures are currently underdeveloped. The guidelines also highlights the importance of economic damage assessment. The average annual damage estimation for pluvial flood and its regional distribution could be valuable data for any future adaptation or mitigation planning. We believe that our methodology and results can be applied in such studies.

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4 Discussion and conclusion

We have described a method to calculate annual pluvial flood damage based on daily precipitation data, socio-economic and topographical data. Using this method, we can compute the damage from every event in a year, many of which are typically excluded when computing damage from a low-frequency event only. We observe a significant contribution of high-frequency low-magnitude events in total annual damage, which is included in this method via the probability of damage. The probability of damage at a given location depends on the population density and the topographical slope of the landscape. The damage occurrence probability is higher for high population density area because of large concentration of properties.

The damage cost function curves show that damage per GDP was lower in highly populated areas than in areas of low population density at a given frequency of rainfall events. We believe that the damage per GDP in highly populated urban areas reflects the ability to withstand the disaster. The spatial variation in the total damage cost and the damage per GDP across Japan were computed for each grid point using simple relationships. The rapid and simple way for calculating annual damage and average annual damage due to pluvial flood with some uncertainty range will be a very useful tool for decision makers for planning, policy making, budgeting, and management of urban drainage systems. We believe the damage occurrence probability function and damage cost function will be applicable in addressing future climate and socio-economic changes and can also be applied to other areas or countries. However a precise optimization of parameters might be needed for other nations. The functions and results presented here also provide some insight for the improvement of present integrated physical hydrological modelling technique for flood damage assessment which might have capability to assess flood damage associated with even shorter rainfall duration (sub-daily scale) which now much difficult to incorporate in presented model due to temporal and spatial scale of present damage recording technique.

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Table 1. Damage Occurrence parameter values for Japan in all three population density classes.

Population density class	Population density	c	d	d'	R^2
Low	0–250 km^{-2}	0.55	−0.01100	−4.1218	0.38
Medium	250–2000 km^{-2}	0.52	−0.01194	−2.8861	0.48
High	> 2000 km^{-2}	0.40	−0.04374	−1.7125	0.42

Table 2. Vulnerability parameters values in Japan for all three population density classes. The upper and lower values were derived from 90th percentile and 10th percentile of 10 000 bootstraps samples mean in each probability exceedance bin respectively.

Population density class	Population density	p Upper	Mean	Lower	q Upper	Mean	Lower	R^2 Upper	Mean	Lower
Low	0–250 km^{-2}	0.002142	0.001535	0.001000	0.311	0.295	0.241	0.56	0.56	0.47
Medium	250–2000 km^{-2}	0.000769	0.000510	0.000251	0.377	0.381	0.385	0.47	0.54	0.74
High	> 2000 km^{-2}	0.000101	0.000070	0.000041	0.761	0.720	0.589	0.74	0.72	0.58

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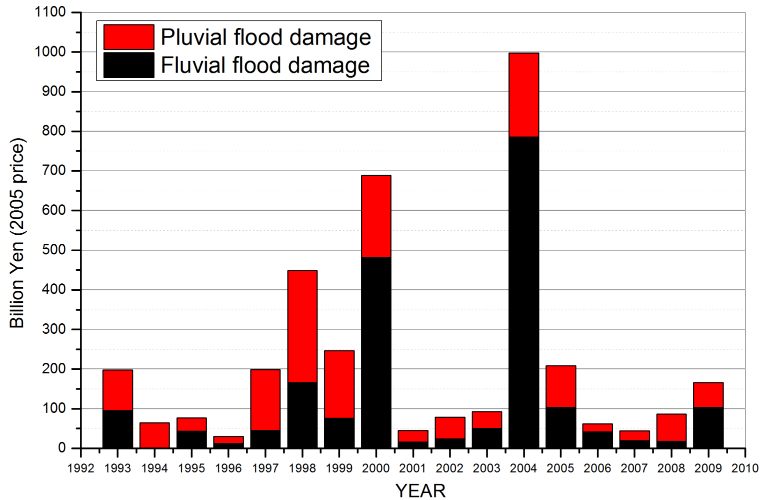

Figure 1. Historical general property damage due to pluvial and fluvial flood in Japan for the period 1993–2009. The fluvial flood damage showing its high fluctuation annually, however pluvial flood damage is much constant over the period.

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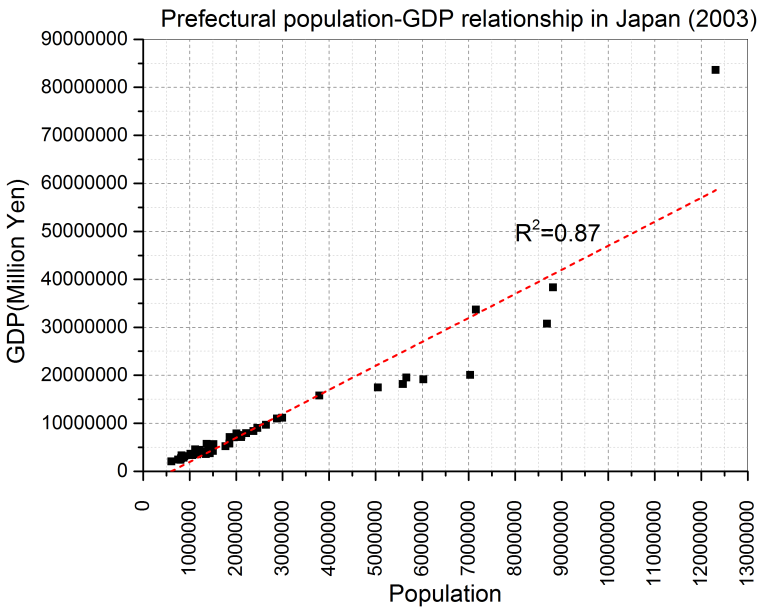

Figure 2. GDP as a function of prefectural population in Japan for the year 2003. The data shows population–GDP relation follows linearly except in few cases.

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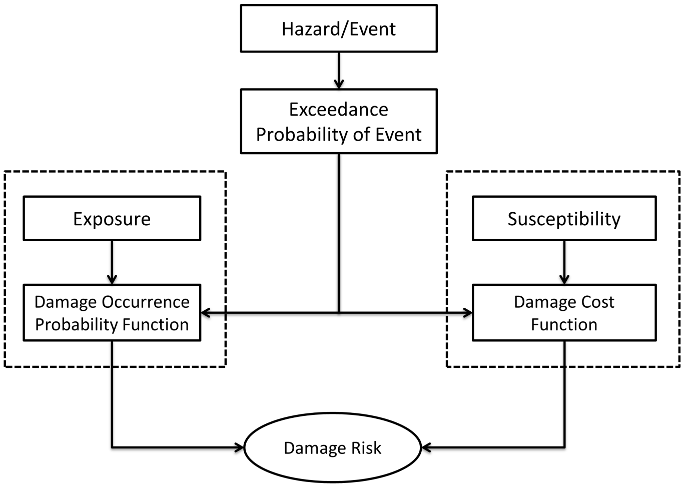

Figure 3. Different components of damage assessment and their interrelationships. Damage occurrence probability appears to be more depended on exposure, whereas damage cost seems to be depended on susceptibility in a particular location.

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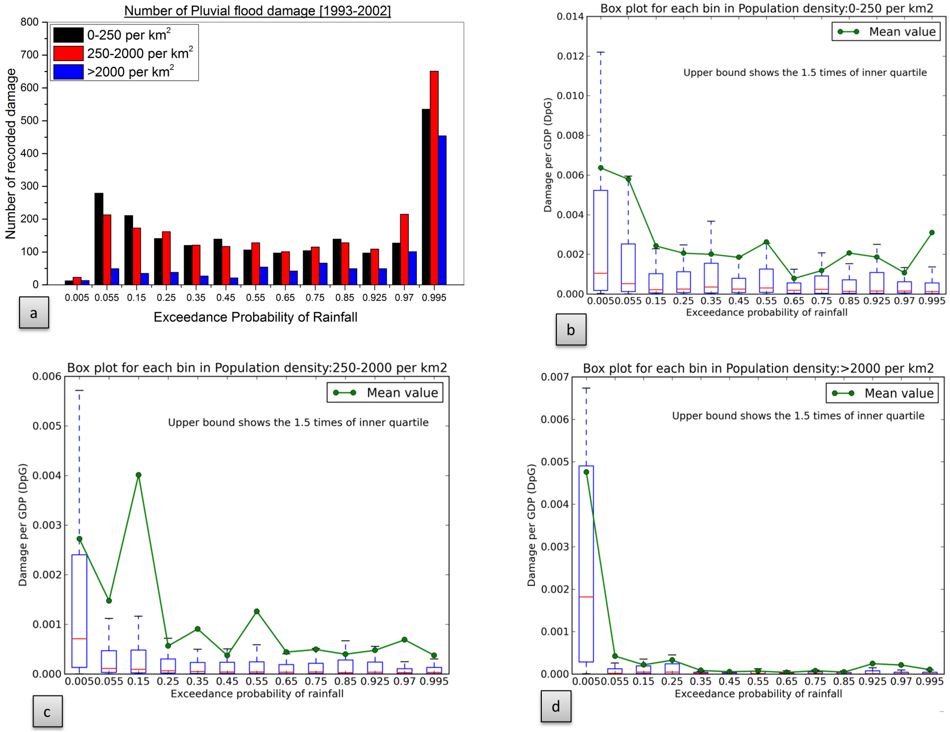

Figure 4. (a) Number of total recorded damage in each exceedance probability bins and distribution of DpG in each exceedance probability bin for **(b)** low population density class, **(c)** medium population density class, and **(d)** high population density class. The number of damaging events were in higher exceedance probability bins in all three population density class as seen in **(a)**. However, the amount of damage was associated with lower exceedance probability bins as seen in **(b)**, **(c)** and **(d)**.

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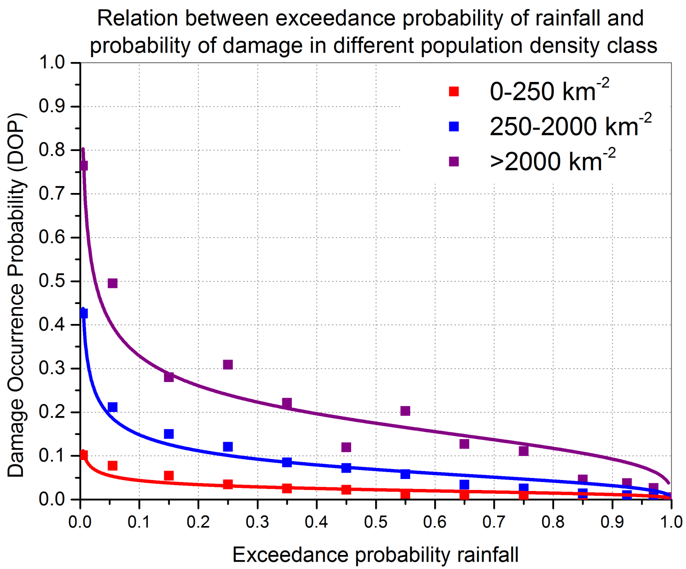

Figure 5. The damage occurrence probability as a function of the exceedance probability of rainfall for different population density classes. Higher population density exhibits higher damage occurrence probability and vice-versa.

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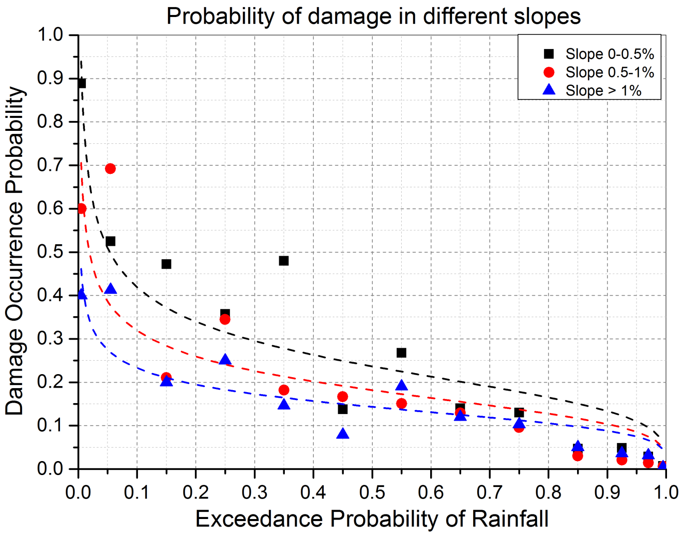

Figure 6. The damage occurrence probability as a function of the exceedance probability of rainfall for different topographical slopes for population density class > 2000 persons km^{-2}. Lower slopes area shows higher damage occurrence probability than higher slopes.

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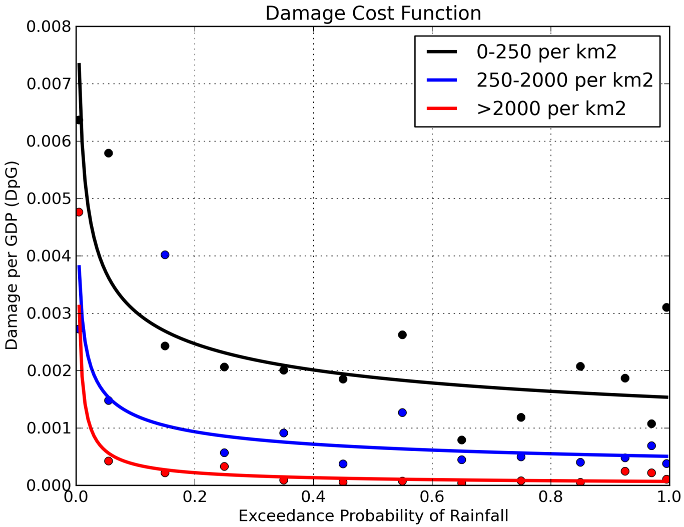

Figure 7. The damage cost function for different population density classes as a function of the exceedance probability of rainfall derived using mean DpG. The vulnerability varies with population density and lower populated area exhibits higher vulnerability.

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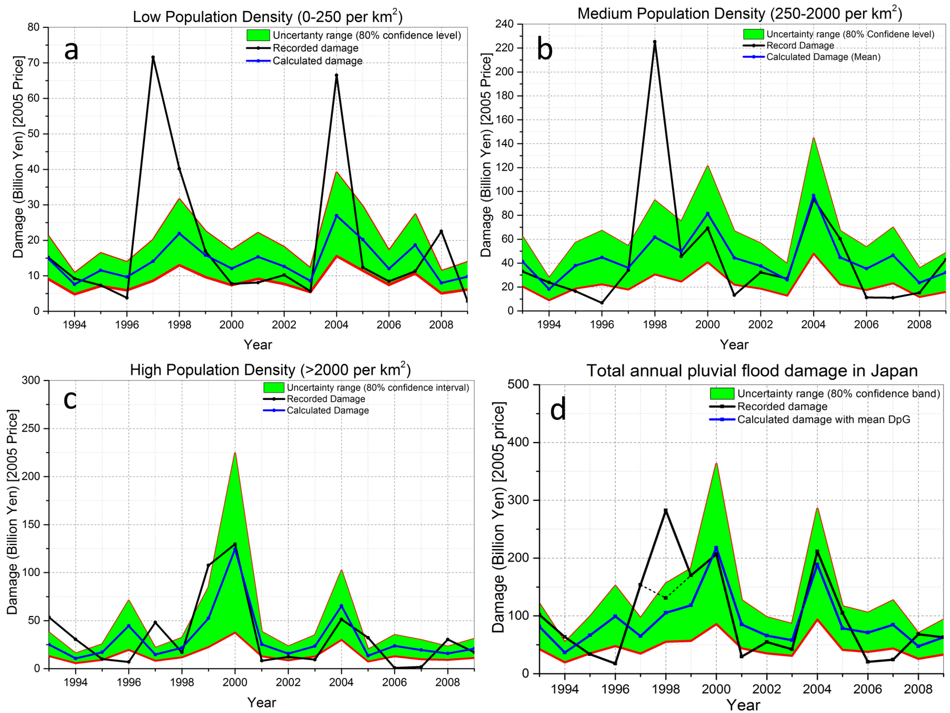

Figure 8. Total annual pluvial flood damage variation in **(a)** low population density class, **(b)** medium population density class, **(c)** high population density class, and **(d)** whole nation. The period 1993–2002 was used for calibration and 2003–2009 for validation. T he dotted line for 1997–1999 in **(d)** shows the highest recorded damage excluding the Kochi flood in 1998. The shaded area spreads from 10th percentile (lower panels) to 90th percentile (upper panels) of 10 000 bootstrap samples mean values which shows the 80 % confidence band of damage estimation using proposed methodology. The data were normalized to 2005 levels.

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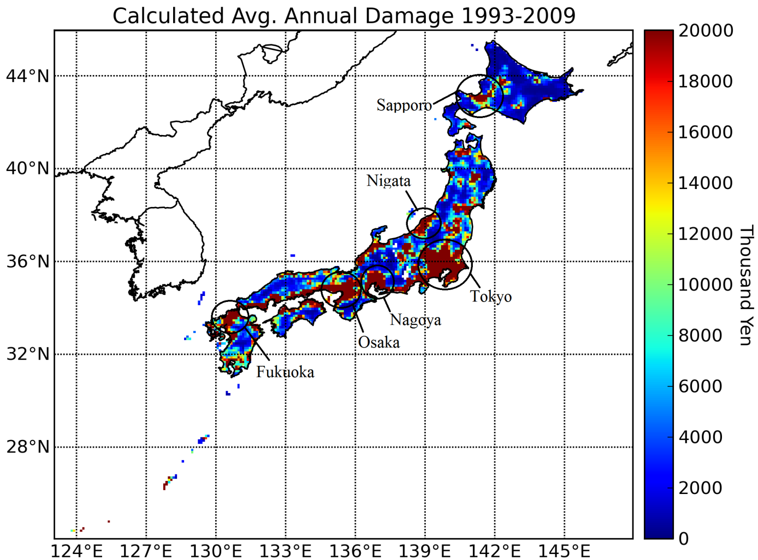

Figure 9. Spatial distribution of average annual damage 0.1° grid (1993–2009) over Japan. More highly populated areas had higher absolute damage value.

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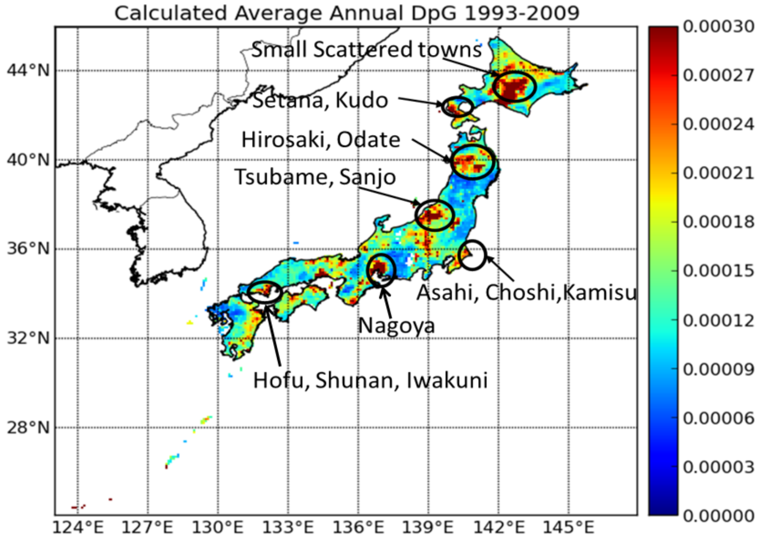

Figure 10. Spatial distribution of average annual damage per GDP per 0.1° grid for 1993–2009 over Japan. Many areas with smaller population densities exhibited larger damage per GDP.

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