Flood catastrophe model for designing optimal flood insurance program: estimating location specific premiums in the Netherlands.

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ABSTRACT

As flood risks grow worldwide, a well-designed insurance program engaging various stakeholders becomes a vital instrument in flood risk management. The main challenge concerns the applicability of standard approaches for calculating insurance premiums of rare catastrophic losses. This paper focuses on the design of a flood-loss sharing program involving private insurance based on location-specific exposures. The analysis is guided by developed integrated catastrophe risk management (ICRM) model consisting of GIS-based flood model and a stochastic optimization procedure with respect to location-specific risk exposures. To achieve the stability and robustness of the program towards floods with various recurrences, the ICRM uses stochastic optimization procedure, which relies on quantile-related risk functions of a systemic insolvency involving overpayments and underpayments of the stakeholders. Two alternative ways of calculating insurance premiums are compared: the robust derived with the ICRM and the traditional average annual loss approach. The applicability of the proposed model is illustrated in a case-study of a Rotterdam area outside the main flood protection system in the Netherlands. Our numerical experiments demonstrate essential advantages of the robust premiums, namely that they: 1) guarantee program's solvency under all relevant flood scenarios rather than one average event; 2) establish a tradeoff between the security of the program and the welfare of locations; 3) decrease the need for other risk transfer and risk reduction measures.

Keywords: Flood risk, loss-sharing programs, spatial catastrophe model, quantile-related stochastic optimization, The Netherlands.

1. INTRODUCTION

A significant part of world population lives in flood prone coastal and delta areas. About 23% of the world population residing coastal zone and 10 % of the population living in low-lying areas [39], are threatened by floods. For example, damages from coastal storms and floods in the USA in 2012 accounted for almost $54 billion of estimated overall losses [40]. Particularly, the Netherlands are vulnerable to a rising sea level and increasing frequency of river flooding. About 60 to 70% of the country's population and economic value is concentrated in areas that are at risk of flooding from the sea and/or rivers. The situation may be further threatened by climate change affecting in particular the sea level rise. Coastal and delta areas were historically developed due to their proximity to marine and river transportation. Further developments are attracted to historic centers by agglomeration forces as well as by rich environmental amenities. As a result, exposure and vulnerability in coastal areas rapidly increase due to the clustering of population and growth of property values in flood-prone areas [26]. As a matter of fact, urban developments are capital intensive and are highly path-dependent [9], which means that where and how much of coastal and riverfront properties get developed depends on a series of previous decisions, e.g. location of past developments and past flood risk management (FRM) policy.

Worldwide governments develop FRM policies that aim to reduce flood risk. It can be reduced by decreasing either probabilities of the hazard, i.e. through structural engineering solutions such as dikes or beach nourishments, or the damages, i.e. through zoning, financial measures to distribute risk across stakeholders, proper land-use planning, or flood-proofing buildings.

Flood insurance is considered to be a vital element of a FRM policy [38]. A well-designed flood insurance program: (i) spreads risks across actors, locations and time and assures funds available for loss coverage [35], (ii) increases public awareness of flood risks [36], (iii) often leads to price discounts [7], (iv) promotes damage mitigation measures [8], and (v) improves the efficiency of use of scarce land [43]. A multi-layer disaster insurance program (MLDIP) in a form of a public-private partnership (PPP) [5], [8], [17], [20], [33] may include, e.g., a layer of private insurance, a risk transfer layer through reinsurance or/and catastrophe bonds and credits, and a layer of government contribution. A MLDIP requires the analysis of mutually dependent risk exposures of the involved stakeholders. For example, if an insurer wants to decrease the chances of bankruptcy, he may decrease the chances by imposing higher premiums or decreasing coverage, take reinsurance or buy a catastrophe bond. The burden of losses is shifted away from the insurer but may be unevenly redistributed among other stakeholders, i.e., individuals, government, reinsurance companies, and can lead to their instability or ruin. Thus, the success of a loss-sharing program depends on the mutual (systemic) stability of the involved heterogeneous stakeholders. This requires the analysis of complex multivariate joint probability distributions of losses dependent on decisions of various agents and hazards leading to the development of region-specific catastrophe flood models.

Catastrophe models comprise several modules: a hazard generator, vulnerability and financial modules. Catastrophe models use rich spatial data and evaluate premiums based not only on historical observations but also considering various socio-economic and climatic scenarios [(1), (23), (25)]. However, in many of these models the pricing of catastrophe risk is based on the Average Annual Loss (AAL) without explicit accounting for goals and constraints of the involved stakeholders. A risk load is often expressed in terms of standard deviation and administrative costs load [(34)], or only in AAL [(1)]. Due to the skewedness of catastrophe risks as well as spatial dependencies of losses on policies, this approach may appear to be misleading [(2), (5)]. Mean and standard deviation alone cannot serve as appropriate indicators for catastrophe risk pricing. They characterize normal risks and do not capture specifics of heavy-tailed catastrophic loss distributions. In contrast, quantile-based, in particular, Value-at-Risk (VaR, [(42), (47)]) and Conditional Value-at-Risk (CVaR) indicators, gain popularity in determining catastrophic insurance policies [(2), (41)]. In particular, geographically-detailed ICRM[1] model incorporating quantile-related risk functions and stochastic optimization (STO) procedures allows proper capturing of spatio-temporal profiles of catastrophe risks for designing robust insurance and involved stakeholders arrangements [(2), (17), (18)].

The goal of this paper is to develop an ICRM-based approach to evaluate location specific robust insurance policies and compare them with traditional AAL pricing in outside dikes in the Rijnmond-

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[1] A general ICRM model has been developed and studies at International Institute for Applied Systems Analysis (IIASA). For the description see e.g. Ermolieva, T., Ermoliev, Y., Norkin, V. 1997; Ermolieva, T., Ermoliev, Y. 2012; Amendola, A., Ermolieva, et al. 2012 and further references therein.

Drechtsteden (RiD) area around Rotterdam, the Netherlands. We design the region-specific ICRM model combining a HIS-SSM model (Highwater Information System – Damage and Casualties Module[31]) and a stochastic optimization procedure to generate flood loss scenarios and quantify robust insurance premiums and coverages for flood-prone locations outside main flood defense system, i.e. outside dike rings. Until recently insurance from river and coastal flooding did not exist in the Netherlands, leaving a post-disaster relief program as the only financial FRM instrument. The issue has been debatable since some consider it unfeasible [30], [32] while others argue it is feasible under various reinsurance schemes [1]. Yet, the first flood insurance contracts became available at the end of 2012[3] but only for areas protected by dikes. Although several studies exist on how to enhance flood insurance system in the Netherlands [1], [27], [28], [30], [32], they primarily analyze inside-dikes flood risks. For example, Aerts and Botzen [1] apply the AAL principle to derive flood-related insurance premiums for large dike-ring areas in the Netherlands.

This paper studies insurability of flood risks explicitly simulating insurance supply and demand balances. The robust balance substantially depends on the choice of coverages and premiums creating the capacity of insurance to sustain the floods and the willingness of individuals to pay the premiums. We use such economically-sound risk functions as overpayments by individuals and shortfalls of insurers to derive robust solutions.

The paper proceeds as follows. Section 2.1 presents a simple example illustrating misleading policy implications resulting from using AAL for collective damages. It shows the need for quantile-based approaches. Section 2.2 outlines a general ICRM multi-agent spatially-explicit model that is specified in section 3 for the case study region. The proposed model includes non-smooth stochastic risk functions to achieve a robust systemic solvency in the form of a probabilistic equilibrium between the insurance supply and the demand of insured. In the case of a single aggregated insurer (a catastrophe fund) and an aggregated insured (region) this equilibrium is reduced to a VaR type quantile-based constraints. Section 3 is also devoted to a detailed description of the case study region, including data availability and main ICRM modules. Numerical experiments in section 4 report on how ICRM allows designing a robust flood-loss sharing program in the RiD region by polling risks through a flood insurance relying on location-specific premiums including also potential risk transfer through a contingent credit for buffering the risk, and a partial government compensation. The section demonstrates that robust location-specific premiums compared to AAL, increase the stability of insurance and reduce the demand for other risk transfer measures. Involvement of the government and introduction of a credit increases the demand for the insurance and helps to fulfill its liabilities while avoiding insolvency. Concluding remarks are summarized in section 5.

2. INTEGRATED CATASTROPHE MANAGEMENT MODEL

2.1 Insurability of catastrophic risks

In the Netherlands, flood safety standards in protected areas vary between 200 and 10000 year floods return periods [29]. Although floods may happen rarely, their abrupt occurrence in time and space comes as "spikes" that cannot be properly modeled "on average", say a 100-year flood may occur any year in the future. For example in Dordrecht, a flood with a return period of 2000 years may cause damage of about 1.5 billion euro. According to the AAL approach an expected damage is 0.75 million euro per year including damage to private (households and businesses) and governmental actors. This is a reasonable affordable amount except that this damage is not going to occur in small annual portions – all 1.5 billion will come at once. Thus, annualization of expected damages and evaluation of insurance premiums based on that average may be misleading and could undermine the financial stability of an insurance program and overall FRM.

Catastrophic losses challenge the applicability of standard approaches using actuarially fair premiums (expected losses). Catastrophes occur as "spikes" in time and space. In this case, as it is well known, mean values and standard deviations are not robust indicators of collective interdependent losses.

Example (Interdependent collective vs independent individual losses). Expected loss doesn't distinguish the case of catastrophic collective loss. A key issue is the use of proper indicators for collective losses. In a sense, we often have to show that $100 >> \overbrace{1+1+...+1}^{100}$. Assume that each of 100 locations has an asset of the same type. An extreme event destroys all of them at once with probability 1/100. Consider also a situation without the extreme event, but with each asset still being destroyed independently with the same probability 1/100. From an individual point of view, these two situations are identical: an asset is destroyed with probability 1/100, i.e., individual losses are the same. Collective (social, catastrophic) losses are much higher.

In the first case 100 assets are destroyed with probability 1/100, whereas in the second case 100 assets are destroyed with probability 100^{-100}, which is practically 0. In both cases, expected losses are equal, while probabilities of collective interdependent losses 1/100 and independent 100^{-100} are strikingly different. Analyzing insurability of interdependent location-specific catastrophic losses requires developing an ICRM model and STO methods enabling to simulate collective damages to design a robust portfolio of coverages and premiums. This creates a systemic solvency preventing in a probabilistic sense shortfalls of insurers and overpayments by locations.

2.2 Stochastic Integrated Catastrophe Risk Management Model

This section introduces a basic geographically-explicit ICRM model(17), (19), (21) that is specified in section 3 for a case study in the Netherlands. To account for multiple risk management stakeholders, the study region is subdivided into sub-regions or locations $j=\overline{1:m}$. Locations may correspond to a collection of households, flood-protection zone, municipality, etc. For example in (1) the locations correspond to dike-protected areas. We assume that for each location j an estimation W_j of the property value or "wealth" of this location exists, which includes values of houses, lands, factories, etc.

Suppose that n agents, $i=\overline{1:n}$, (insurers, governments, re-insurers, funds) are involved in the loss sharing program. They may have contracts with locations to cover their losses. Each agent i has an initial fund or a risk reserve R_i^0 that in general depends on magnitudes of catastrophic events. Assume that the planning horizon covers $t=0,1...$ time intervals. The risk reserve R_i^t at each t is calculated according to the following formula:

$$R_i^{t+1}=R_i^t+\sum_{j=1}^{m}(\pi_{ij}^t-c_{ij}^t(q_{ij}^t))-\sum_{j=1}^{m}L_j^t(\omega_t)q_{ij}^t\ , \qquad (1)$$

where q_{ij}^t is the coverage of a company (insurer) i in location j at time t, $\sum_{i=1}^{n} q_{ij}^t \leq 1$, π_{ij}^t is the premium of a company i in location j at time t, $c_{ij}^t(q_{ij}^t)$ are transaction costs or administrative, running or other costs. $L_j^t(\omega_t)$ is the loss (damage) in location j caused by a catastrophe ω_t at time t. Random catastrophic events $\omega = (\omega_0, \omega_1, ...)$ may affect a random number of different locations. In general, a catastrophic event at time t is modeled by a random subset of locations j and its magnitude in each j. The losses $L_j^t(\omega_t)$ depend on the event ω_t, mitigation measures (e.g., dikes against flooding), and vulnerability of property values in j.

Decision variables q_{ij}^t and π_{ij}^t allow to characterize the differences in risks at different locations. It is assumed that all agents may cover different fractions of catastrophic losses from the same location. In the case of a catastrophe, a location j faces losses (damages) $L_j^t(\omega_t)$. Individuals at this location receive compensation $L_j^t(\omega_t)q_{ij}^t$ from a company i when such a loss occurs, and pay insurance premiums π_{ij}^t. If W_j^0 is the initial wealth (property value), then the location's j wealth at time $t+1$ equals:

$$W_j^{t+1} = W_j^t + \sum_{i=1}^{n} (L_j^t(\omega_t)q_{ij}^t - \pi_{ij}^t) - L_j^t(\omega_t)\,,\ t = 0,1,\dots. \tag{2}$$

Let us note that random variables R_i^t and W_j^t implicitly depend on decision variables $x^k = (q^k, \pi^k)$, $q^k = \left\{q_{ij}^k,\ i = \overline{1:n},\ j = \overline{1:m}\right\}$, $\pi^k = \left\{\pi_{ij}^k,\ i = \overline{1:n},\ j = \overline{1:m}\right\}$, and random event ω_k, where $k = 0,1,...,t-1$. For the sake of simplicity we indicate in the following these path-dependencies of R_i^t and W_j^t as $R_i^t(x,\omega)$ and $W_j^t(x,\omega)$.

The robustness of insurance program depends on whether the accumulated risk reserve $R_i^t(x,\omega)$ at a random time $t=\tau(\omega)$ of a first catastrophic event avoids, in a probabilistic sense, the insolvency defined by events

$$E_1 = \{\omega : R_i^{\tau(\omega)}(x,\omega) < 0\}, \ \ i = \overline{1:n}. \tag{3}$$

Individuals (locations) are concerned with their wealth, which depends on whether the amount of premiums that they pay to the insurers does not exceed the compensation of losses at time $\tau(\omega)$, i.e., with events

$$E_2 = E_{21} \cup E_{22} \cup ... \cup E_{2m}, \tag{4}$$

where

$$E_{2j} = \{\omega : W_j^{\tau(\omega)}(x,\omega) < 0\} \text{ for } j = \overline{1:m},$$

and $L_j^t(\omega^t) = 0$, $t < \tau(\omega)$. Events (3)–(4) determine the stability (resilience) of the insurance program, in a sense, its systemic solvency. Therefore, a critical issue is to avoid these events as much as possible. For example, by minimizing the expected uncovered losses $E\sum_j (1-q_j)L_j^{\tau(\omega)}$ under a probabilistic constraint of the type

$$\Pr ob[E_1, E_2] \le \overline{p}, \tag{5}$$

where $\overline{p}$ is a critical probability threshold of the program's systemic insolvency (failure, default) that may occur, say, only once in 100 years. The notation $\Pr ob[E_1, E_2]$ is used to denote a probability of insolvency as a general function of E_1, E_2. An example of constraints (5) may be constraints $\Pr ob[E_1 \ or\ E_2] \le \overline{p}$ or equations (10), implicitly induced by optimal solutions of STO model (8) with specific risk (penalty) functions. Unfortunately, the straightforward use of probabilistic constraints (5) in the ICRM model is practically impossible due to their often discontinuous piece-wise constant and analytically intractable character owed to the discrete distributions of the random vector ω. Therefore, section 3.2.5 formulates the main ICRM model as a convex STO problem with specific non-smooth risk (penalty) functions enabling to derive optimal solutions implicitly inducing this type constraints (see (9), (10)). This problem is effectively solved by the linear programming methods (see eqs. (11)-(14)). Proposed in section 3 approach is central for large-scale integrated risk management problems (see e.g. [17]-[21]). Sections 4.2.1-4.2.3 demonstrate how it is possible to achieve the required level of $\overline{p}$.

3. CASE STUDY AND THE REGIONAL MODEL

3.1. Case study region

The case-study covers the outside dike rings areas in the RiD region including Rotterdam (Figure 1). Though many studies exist on how to enhance flood insurance system (1), (27), (28), (30), (32) in the Netherlands, they analyze primarily inside-dikes flood risks and consequent insurance premiums. This paper focuses on flood risks in the areas outside the main protections system and analyzes an example of a robust flood insurance program. We show how the robust location-specific premiums and coverages increase the stability and the attractiveness of a flood-loss sharing arrangement and, thus, insurability of risks, as compared with traditional AAL approach.

The RiD region is prone to both river and coastal flooding. The areas outside dike rings (Figure 2) differ from the areas inside the main protections system in terms of physical aspects of flood risk and responsibilities among stakeholders in a number of ways (Table I). Most important is that currently flood protection within the dike rings is fully the responsibility of the government, while for the outside dike ring areas there are no safety standards guaranteed by the government. New investments are at the risk of individuals, with no governmental compensation provided in the case of a hazard event. The Netherlands did not have insurance from river or coastal flooding until recently, which makes it difficult especially for the areas outside the main protections system to: (i) communicate risks, (ii) to take individual action to distribute losses in time, and (iii) to create stimuli for damage mitigation actions such as additional flood-proofing of houses.

Table I: Physical aspects of flood risks and responsibilities among stakeholders in the areas outside dike rings in comparison with the protected ones.

Areas outside the main protections system	**Protected areas within a dike-ring**
Flood and damage characteristics	
Government does not guarantee any safety standards. Actual return periods vary between 1:5, 1:10 years to 1:100, 1:1000 years or less frequent (e.g. 1:10000 for new harbor areas)	Safety standards assigned by law: 1:200 to 1:1250 years – river floods 1:2000 and 1:4000 for the estuary (tidal rivers) 1:4000- to 1:10000 years – coastal floods.
Probability of flood is location-specific and may be much higher than the official safety standard in the neighboring protected areas.	One homogeneous safety standard for the whole dike-ring.
Properties are elevated above sea level, i.e. on dunes, man-made high elevation grounds, etc.	Many developments inside dike rings are below sea level (up to -6 meters).
Flood water comes with low velocity and goes away quickly.	Flood water comes with high velocity and stays for a long period.
Flood protection and roles of different parties	
Developments are at the risk on individuals (households or firms). Municipalities may prohibit some socially-vital activities in these areas, e.g. hospitals.	Government is responsible to assure safety standards prescribed by law.
Individuals are responsible for their own protection and damage in the case of flooding.	Government refund any possible damage from a flood event.
Flood insurance does not exist but is argued to be financially feasible [44].	Until recently flood insurance did not exist. First contracts to insure flood risks became available in 2013 [3]. The issue is debatable since some consider it unfeasible [30], [32] while others think it is feasible under various reinsurance schemes [1].

Figure 1: Case-study region (this paper considers only the areas outside the primary embankments, see figure 2).

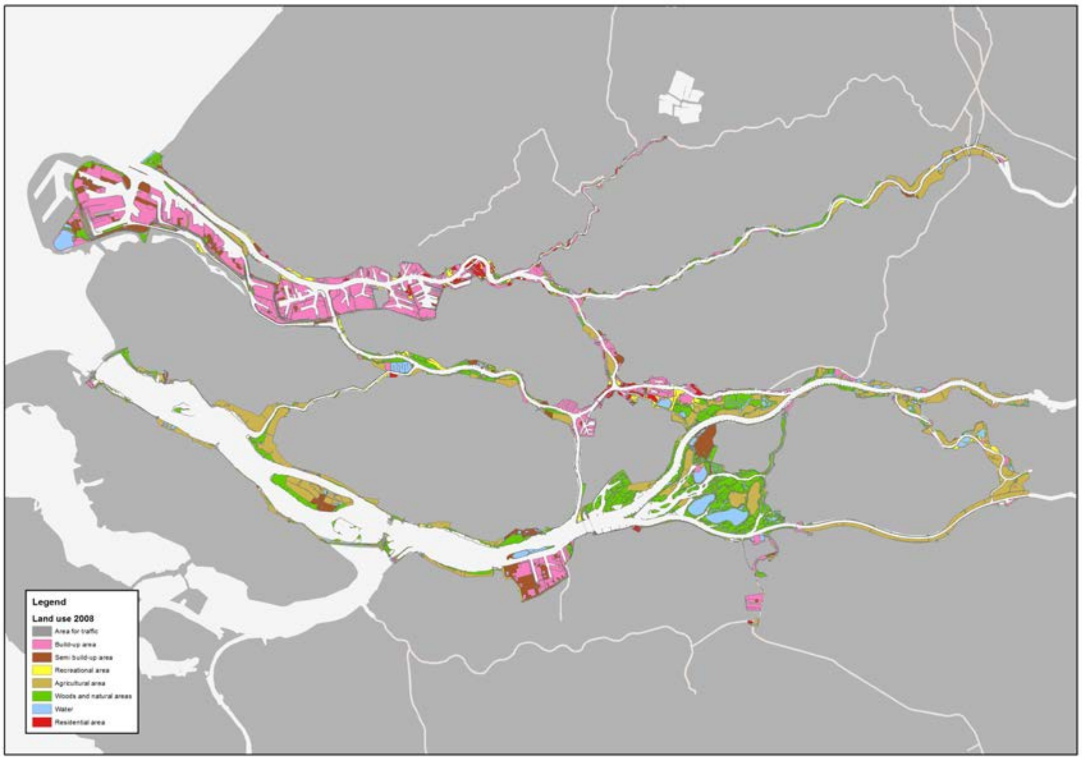


Figure 2: Land use in the Rijnmond-Drecthsteden region (the colored area is the area outside the main protection system). Source: [(11)].

3.2. Modules and data

This section describes main modules of the ICRM used for the analysis of optimal flood loss-sharing program in the case study area. In particular, the hazard, exposure and vulnerability modules (I, II and III, Figure 3) provide data inputs to estimate potential losses, i.e. damages in each location (Figure 3, IV). Based on the estimated damages, the ICRM model runs quantile-based stochastic optimization under a range of safety constrains across stakeholders (insurance companies, households and firms, government) to produce optimal risk-based location-specific insurance premiums and coverage (Figure 3, V). We describe each module separately when discussing the data inputs into the ICRM model.

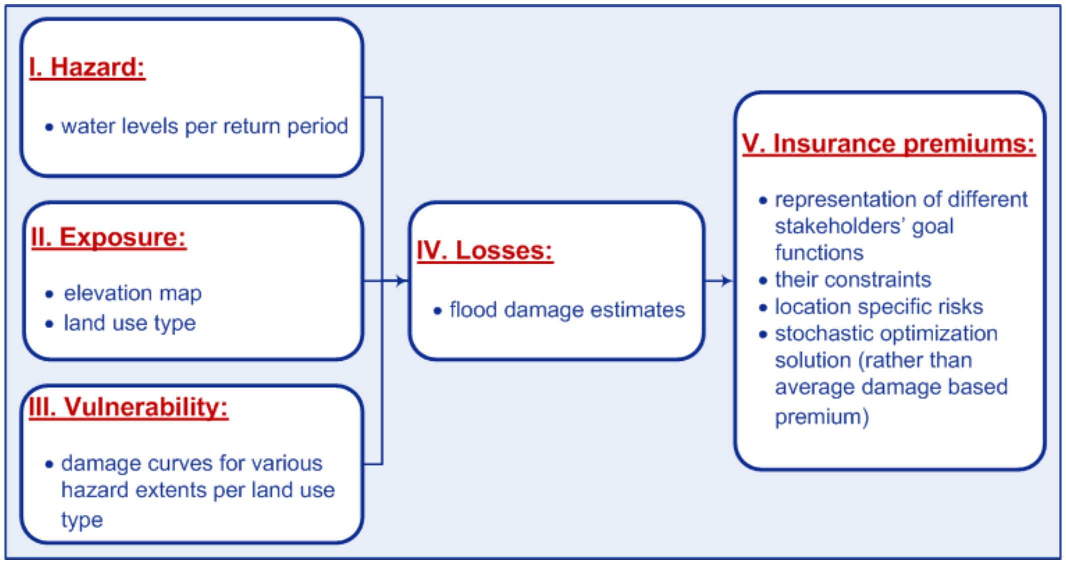


Figure 3: Scheme of modules and data flows.

3.2.1 Hazard module (I)

The geo-referenced estimates of water depth in the areas outside the main protection systems in RiD for various return periods floods were calculated. The LiDAR[2] elevation data on a 5mx5m cell was corrected to include local small embankments and structures [(11)]. The resulting 5mx5m water depths are used in the Deltaprogramme[3] and were reviewed by the Rotterdam Harbour Authority. In this paper we consider spatio-temporal damage patterns for "current climate" scenario and three flood scenarios (10-, 100-, and 1000- year floods).

3.2.2 Exposure data (II)

Exposure data (II) includes geographically explicit information on different land-uses in the case study region including geographically-referenced data on economy, transportation networks, buildings, population. For the case study region, these data have been compiled within HIS-SSM (Highwater Information System – Damage and Casualties Module [(31)]). HIS-SSM is often used to support FRM policy decisions for inside-dike areas in the Netherlands. Exposure data include assumptions about economic

[2]Light Detection and Ranging, a remote sensing method, e.g., http//oceanservice.noaa.gov/facts/lidar.html
[3]Dutch climate adaptation program, http://www.deltacommissaris.nl/english/topics/

growth and infrastructure expansion in the case study region. The data on land use, roads, railroads and houses has been updated compared to earlier HIS-SSM versions [31]. The new data on houses provides detailed information on the location of each individual building and its attributes (number of houses, elevation etc.) [11].

3.2.3 Vulnerability module (III)

Vulnerability curves reflecting damage for a particular land use at a particular water level and flood wave speed are the part of the HIS-SSM model. Originally designed for the inside-dikes areas, which are relatively homogeneous with respect to elevation, HIS-SSM operates at a scale of 100mx100m. Since buildings in the outside dikes areas are often elevated on an individual basis and vary greatly across locations, water-levels, and consequently damage, are highly location-specific. To be applicable to model damages in the outside-dikes areas the resolution of the HIS-SSM model has been reduced from 100m to 5m cell to capture all the obstructions, small levees and location-specific elevation in the water depth and vulnerability maps.

3.2.4 Loss estimates (IV)

Location specific damages (losses) for each of the 10-, 100-, 1000- year floods accounting for infrastructure developments in 2000, 2050, and 2100 years were estimated by HIS-SSM combining the data from the “Hazard”, “Exposure”, and “Vulnerability” modules. The damage estimation in HIS-SSM was adjusted to account for the features of the outside-dikes areas. Specifically, the damage functions and categories for residential buildings have been improved, categories and damage figures of agriculture, natural areas and the data on the presence of houses has been taken from another more detailed source and damage functions have been adapted [11]. To capture the situation in the areas outside main protection system, damage figures to agricultural and natural areas were set to zero. This was done since the high values for those categories are based on the presence of machinery, stables and high yield varieties, which is realistic only in areas with very low flood probabilities. The agricultural areas outside the primary defenses are situated along the rivers and are used for cattle breeding in summer. Cattle is removed in winter when peak flows occur, which makes damage negligible. The large natural areas outside the primary defenses become flooded deeply twice a day (every high tide) and their ecosystems benefit from those floodings.

These improvements in loss estimation resulted in a 60% damage reduction compared to the damage figures assessed in 2011 [(11)]. In 2013 further improvements were carried out mainly on damage figures, functions and data for companies and industries. Yet, these figures should be considered with care as several adjustments, especially to 10- year flood damage estimations, are likely to come in the next few years. Damage figures used in the current paper should be treated as illustrative to show the applicability of the ICRM model, its potential practical use, and new problems which can be addressed.

Damages for the areas outside the main protection system were calculated for the three return periods (Table II). These figures are current best estimates for all damage categories including direct and indirect damages across 27 land use types. Thus, the figures are much higher than for example in our previous study [(44)], which estimated damage to houses and house content only. The annual damage per residential house excluding any damage to firms and infrastructure in the areas outside the main protections system varies from 4-5 euro in Rotterdam and Dordrecht and up to 225-613 euro in Bergambacht and Nederlek for the current climate [(44)].

Table II: Losses from floods in the RiD area

	Damage, in 2012 Euro			Expected damage across 3 flood scenarios	
	Flood 1:10	Flood 1:100	Flood 1:1000	in 2012 Euro	in %
Infrastructure	45,195,972	62,531,184	96,080,670	5,117,549	35
Households	20,248,656	54,404,334	96,487,015	2,577,560	18
Businesses	51,452,184	154,445,118	309,459,919	6,752,502	47
Total damage (direct and indirect)	**116,896,812**	**271,380,636**	**502,027,604**	**14,447,611**	**100**
Number of affected citizens	**1,804**	**7,354**	**11,585**	**---**	**---**

Figures 4 and 5 display patterns of flood damages in the outside-dikes areas generated by adjusted HIS-SSM for the current climate.

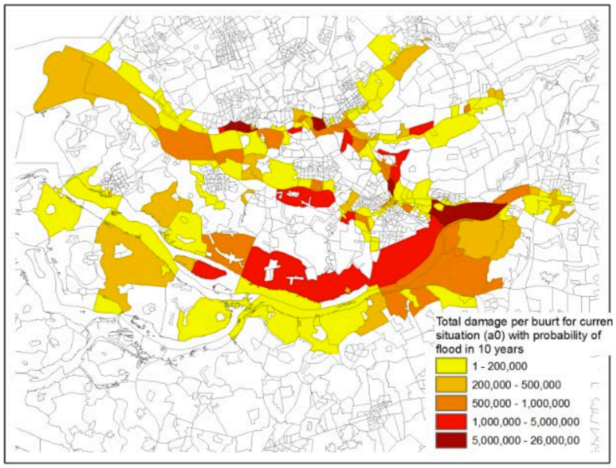


Figure 4: Losses, 10-yr. flood

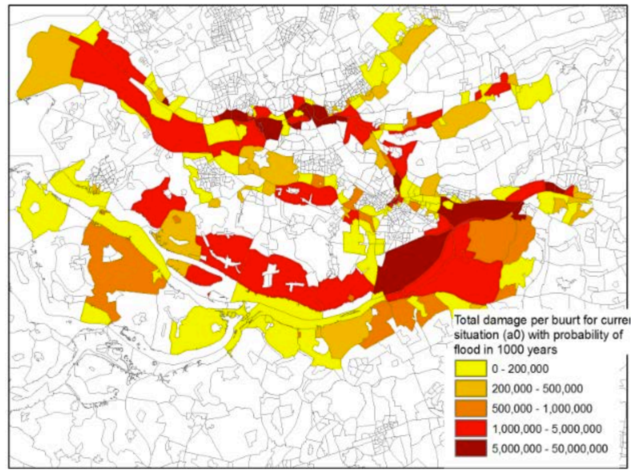


Figure 5: Losses, 1000-yr. flood

3.2.5 Regional Stochastic Integrated Catastrophe Risk Management Model (V)

For the case study, the general approach outlined in section 2 is specified to capture the specifics of available data, in particular, simulated by modules described in sections 3.2.1-3.2.4 scenarios of the flood and damages in the RiD region. The main goal of the case study is to compare impacts of location-specific premiums derived by using regional ICRM model vs traditional AAL premiums. In the case study we assume that only one “aggregate” insurer or a catastrophe fund operates in the region. We ignore costs $c_{ij}(q_j)$ and we also assume that $\pi_j^{\tau(\omega)} = \pi_j \tau(\omega)$, i.e., the accumulated premiums before the occurrence of a first flood are proportional to the arrival time $\tau(\omega)$.

The main concern regarding systemic insolvency of the flood insurance program is to avoid in a probabilistic sense events (6), (7) as much as possible:

$$E_1 = \{\omega : \sum_j (\pi_j \tau(\omega) - q_j L_j^{\tau(\omega)}(\omega)) < 0\}, \tag{6}$$

$$E_2 = E_{21} \cup E_{22} \cup ... \cup E_{2m}, \tag{7}$$

$E_{2j} = \left\{\omega : q_j L_j^{\tau(\omega)}(\omega) - \pi_j \tau(\omega) < 0\right\}$ for $j = \overline{1:m}$,

where q_j is insurance coverage to locations j, π_j is the level of premiums paid by locations, $L_j^{\tau(\omega)}(\omega)$ are stochastic losses to locations induced by arriving at $t = \tau(\omega)$ random floods ω, $\omega \in \Omega$. In this section, relying on general structure of our model outlined in section 2.2, we formulate its convex stochastic penalty function optimization version. The problem may be formulated as the minimization of function

$$F(x) = E\sum_j (1-q_j)L_j^{\tau(\omega)}(\omega) + \alpha E \max\{0, \sum_j (q_j L_j^{\tau(\omega)}(\omega) - \pi_j \tau(\omega))\}$$
$$+ \sum_j \beta_j E \max\{0, \pi_j \tau(\omega) - q_j L_j^{\tau(\omega)}(\omega)\}, \qquad (8)$$

which represents random events (6), (7) by expected imbalances defined by non-smooth convex risk functions $E\max\{0, \sum_j (q_j L_j^{\tau(\omega)}(\omega) - \pi_j \tau(\omega))\}$ and $E\max\{0, \pi_j \tau(\omega) - q_j L_j^{\tau(\omega)}(\omega)\}$, where vector x denotes all decision variables q_j, π_{ij}, and parameters $\alpha \ge 0$, $\beta_j \ge 0$, $j = \overline{1,m}$. Introducing constraints (6), (7) into the optimization model (8) via risk functions generates forces reducing discrepancies in inequalities (6), (7) towards 0 and even equal 0 (see e.g. section 4, Figure 10a). The first term in (8) stands for expected uncovered losses, the second is responsible for minimization of the expected shortfall (insolvency) of the insurance program whereas the third term represents expected overpayments by the insured. In this non-smooth stochastic model an aggregate insurance system or a catastrophe fund minimizes adjusted by the risk-functions total uncovered losses. However, this also implies more natural from the economic point of view profit maximization assumption. The lack of overpayments by insured and shortfalls of insurers increases demand for insurance, its coverages, hence, profits and compensations of insured, i.e., the welfare of all participating agents.

Formally, minimizing function $F(x)$ is equivalent to maximizing function $-F(x)$, i.e., the function

$$G(x) = E\sum_j q_j L_j^{\tau(\omega)}(\omega) - \alpha E \max\{0, \sum_j (q_j L_j^{\tau(\omega)}(\omega) - \pi_j \tau(\omega))\}$$
$$- \sum_j \beta_j E \max\{0, \pi_j \tau(\omega) - q_j L_j^{\tau(\omega)}(\omega)\},$$

because the term $E\sum_j L_j^{\tau(\omega)}(\omega)$ of the function $-F(x)$ does not depend on decision variables x. The first term of the function $G(x)$ forces to increase the profit of insurers, therefore maximizing $G(x)$ with respect to decision variables $x = (q, \pi)$ can be viewed as maximizing the risk-adjusted regional welfare by a paternalistic government designing a flood-loss sharing program.

Coefficients α and β_j regulate a tradeoff between the level of premiums and the total coverages. Coefficient α may also be defined as the price of a credit which the program (fund) will buy if his reserve drops below critical level. If one considers a multilayer insurance program, then the choice of α determines the governmental involvement in the PPP, i.e., the amount government would need to contribute in this PPP insurance scheme. Coefficient β_j ensures the desirable level of non-overpayments on the demand side of this insurance program.

Minimization of function (8) allows achieving a robust probabilistic supply-demand insurance equilibrium characterized by quantile-based systemic insolvency constraints of type (5). Let us illustrate this critically important fact assuming that a convex function $F(x)$ in (8) has continuous derivatives (say, underlying probability distribution has a continuous density function), what allows to avoid otherwise complicated non-smooth analysis. The optimality test ($\mathrm{grad}F(x)=0$) with respect to positive components of risk premiums $\pi_j(q)$ solving the stochastic model (8) for a given vector of coverages $q=\{q_j\}$ have (assuming $\tau(\omega)>0$) the following form(16) of systemic risk equilibrium:

$$F_{\pi_j} = -\alpha \Pr ob[\sum_j (q_j L_j^{\tau(\omega)}(\omega) - \pi_j \tau(\omega)) \geq 0\}] + \beta_j \Pr ob[\pi_j \tau(\omega) - q_j L_j^{\tau(\omega)}(\omega) \geq 0] = 0 . \quad (9)$$

The following example clarifies the role of parameters α and β_j.

Example (aggregate region). Let us simplify the model assuming that there is only one region, i.e., decision variables q and π are independent of j, $E_1 = \{\omega : \pi\tau(\omega) - qL_j^{\tau(\omega)}(\omega) < 0\}$ and $E_2 = \{\omega : qL_j^{\tau(\omega)}(\omega) - \pi\tau(\omega) < 0\}$. It is clear that $\Pr ob(E_1 \; or \; E_2) = 1$, i.e. the constraint $\Pr ob(E_1 \; or \; E_2) \leq \overline{p}$ is not applicable because it is satisfied only in the trivial case $\overline{p} = 1$. As reviewer of the manuscript pointed out, the same holds also for events (6) and (7).

Equations (9) define equilibrium prices $\pi(q)$ for a given coverage q. Because $\Pr ob\{qL^{\tau(\omega)}(\omega) - \pi\tau(\omega) \geq 0\} = 1 - \Pr ob\{\pi\tau(\omega) - qL^{\tau(\omega)}(\omega) \geq 0\}$, then from eqs. (9) the following insolvency equations are derived:

$$\Pr ob\{\pi\tau(\omega) \leq qL^{\tau(\omega)}(\omega)\} = \frac{\beta_j}{\alpha + \beta_j} . \quad (10)$$

We can see that parameters α, β_j, and coverages q affect this probability. Deeper analytical analysis of these interdependencies for general model (8) is beyond the scope of this paper. In the following we investigate the role of α, β_j, reformulating the unconstrained STO model (8) with non-smooth risk (penalty) functions into the constrained linear programming model (11)-(14) in a larger space of decision variables $(\pi_j, q_j, \varsigma_j^s, \varepsilon^s)$. New decision variables ς_j^s and ε^s represent ex-post decisions, e.g., credits, governmental assistance, which are made after observation of stochastic losses $L_j^{\tau(\omega_s)}$. These variables allow to eliminate underpayments and overpayments of insurer and insured in order to secure systemic solvency of the flood program.

In numerical calculations we assume that catastrophes, i.e., floods, are represented by scenarios $s=\overline{1:S}$, which induce random scenarios of losses $L_j^s = L_j^t(\omega_s)$ for $t=\tau(\omega^s)$ in locations $j=\overline{1:m}$, with probabilities p_s, $s=\overline{1:S}$, $\sum_s p_s = 1$. Using S scenarios, the model defined by equation (8) is equivalently replaced by the model: minimize

$$F(x) = \sum_{s=1}^{S} p_s \sum_j (1-q_j) L_j^s + \alpha \sum_{s=1}^{S} p_s \sum_j \zeta_j^s + \beta \sum_{s=1}^{S} p_s \varepsilon^s \tag{11}$$

under constraints

$$\zeta_j^s \geq 0,\ \varepsilon^s \geq 0,\ s=\overline{1:S} \tag{12}$$

$$\sum_j (q_j L_j^s - \pi_j \tau^s) \geq \varepsilon^s\ , \tag{13}$$

$$\pi_j \tau^s - q_j L_j^s \geq \zeta_j^s . \tag{14}$$

The model (11)-(14) includes new ex-post adaptive decision variables ζ_j^s and ε^s to adjust strategic decisions $x=(q,\pi)$ for all scenarios of flood events $s=\overline{1:S}$ in all locations j, $j=\overline{1:m}$. This approach converts non-smooth stochastic optimization model (8) into a linear optimization problem (11)-(14) that is solved very fast by the linear programming methods.

4. NUMERICAL RESULTS

4.1 Spatial patterns of the robust model-derived premiums

The main purpose of these experiments is to compare two alternative ways of calculating insurance premiums: the traditional annualization (AAL) approach and the robust derived with the regional ICRM model. Therefore, in the following we assume that $\tau(\omega)=1$, i.e., catastrophic floods may occur within a one year time interval with probabilities 1/10, 1/100, and 1/1000 corresponding to 10-, 100-, 1000- year floods, respectively. This is, in a sense, a worst-case situation for the robust premiums because the accumulation of premiums is not accounted for. Yet, losses occur as "spikes" in the region, and premiums have to be calculated properly based on location-specific risk exposures. In the RiD case study region, the robust quantile-based premiums derived according to (11)-(14) are computed at the resolution of 100mx100m, which approximately corresponds to a block of 16- 25 residential houses. The resolution may be refined to represent specifics of some areas, e.g., a residential house, a shopping mall, concentrated infrastructure, intensive transportation node. Figure 6 shows spatial distribution of premiums aggregated to a neighborhood (local community) level and Figure 7 displays premiums as percent of the 100-year flood losses.

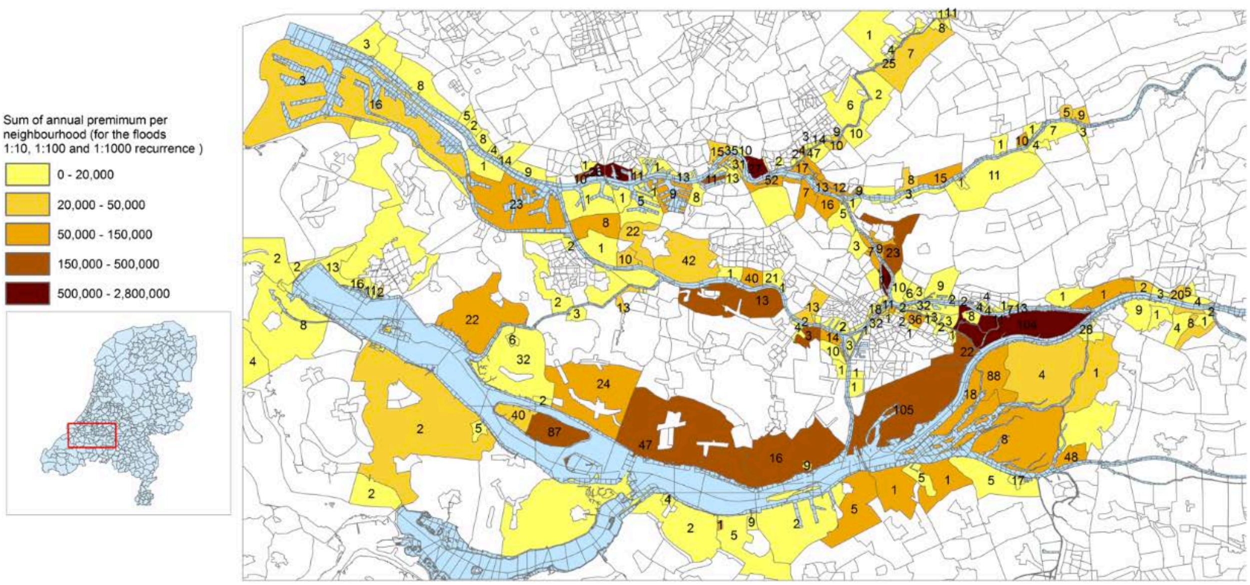


Figure 6: Robust annual premiums at neighborhood level.

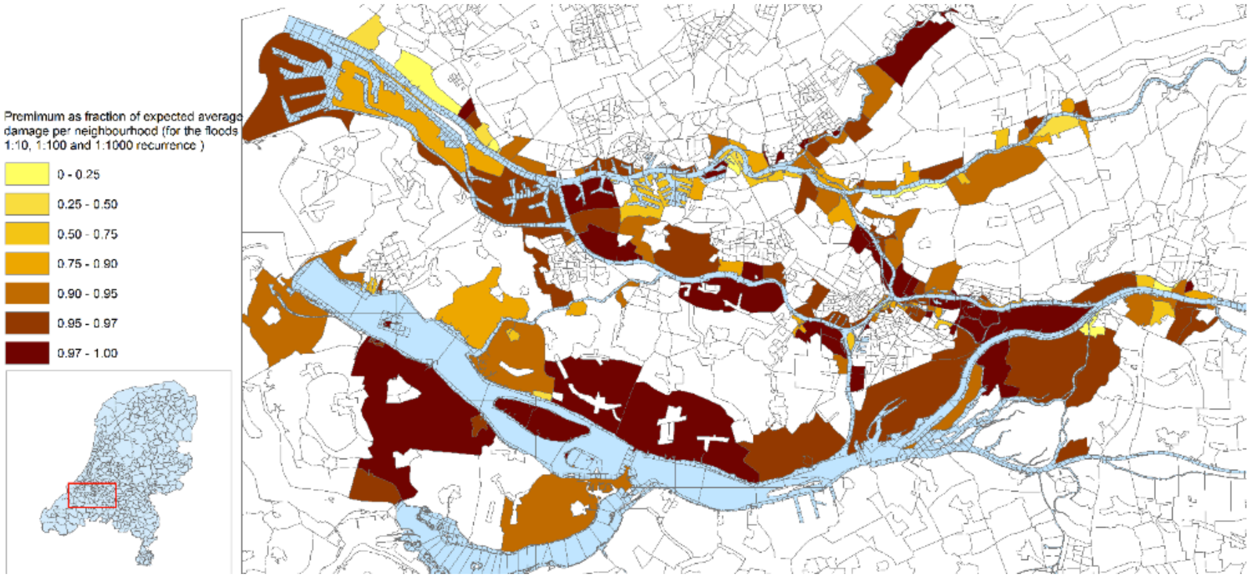
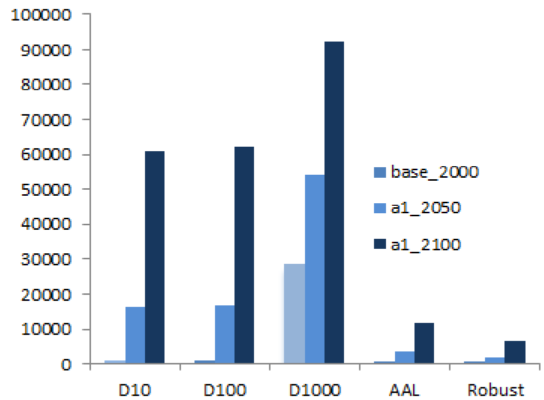


Figure 7: Premiums as percent of the 100-year flood damages at neighborhood level.

While the area is relatively small, robust premiums show big spatial variability reflecting heterogeneity of location-specific risk exposures. The spatial heterogeneity of the robust premiums guarantees the stability of the insurance program. It also highlights the importance of spatially resolved policies. In the majority of neighborhoods, annual insurance premiums do not exceed 5000 euro for infrastructure, businesses and households. Few neighborhoods, where insurance premiums reach 50000-100000 euro per location and year, are characterized by high concentration of infrastructure and businesses. Businesses may suffer much larger damages compared to households since in addition to the direct property damage they also incur indirect damage from business interruption.

In the following we discuss in detail the advantages of robust premiums, compared to the AAL, for the design of flood-loss sharing program.



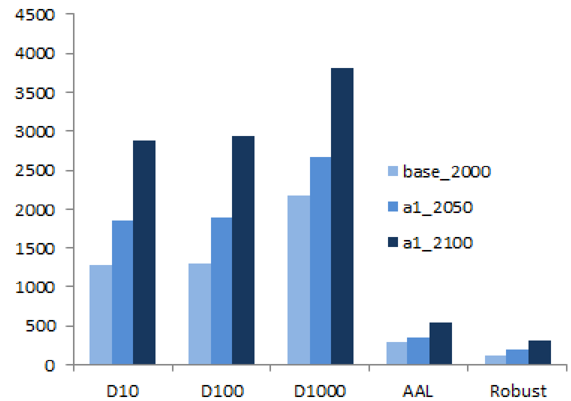


Figure 8.a: **Figure 8.b**:
Total flood damages for 3 return periods: D10, D100, D1000 correspond to 10-, 100-, and 1000- year floods, respectively, in 2000, 2050, 2100 years; and total AAL and Robust premiums (per year).

In Figures 8.a and 8.b on the horizontal axis D10, D100, and D100 correspond to total flood damages for 10-, 100-, 1000- year floods, and total robust and AAL premiums, in 2000, 2050, 2100 years corresponding to different infrastructure developments in the region. Figures indicate that total robust premiums are lower than AAL premiums. Thus, besides guaranteeing a financial stability of the flood loss-sharing program, the robust premiums reduce insurance prices. In turn, this increases attractiveness of the program for economic agents, which may increase demand for insurance and its take up rates.

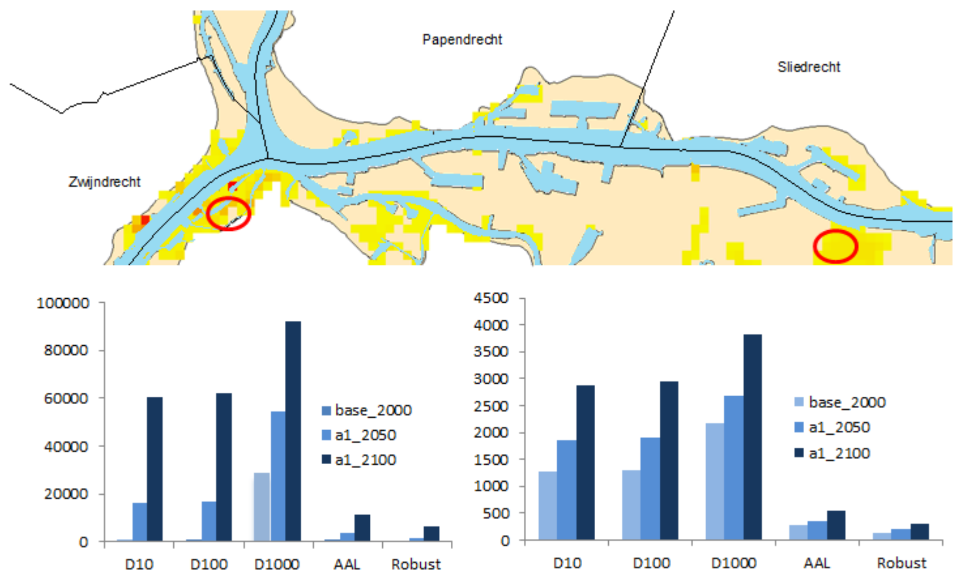


Figure 9: Spatial differences between two representative locations within the same neighborhood in the case study region: D10, D100, D1000 - flood damages for 10, 100, 1000-year floods, respectively, in 2000, 2050, 2100 years; AAL and Robust premiums.

Figure 9 shows that there may be a large differentiation of risks and premiums between locations (100mx100m grids) within the same neighborhood. The location to the right exhibits a gradual increase in damages and insurance premiums, while the location to the left is characterized by abrupt jumps in damages and corresponding premiums, both robust and AAL, in 2000, 2050, 2100 years. In the right location, AAL is closer to the robust premium than in the left.

4.2 Analysis of optimal insurance program per stakeholder

4.2.1 Analysis of the insurance program financial stability on the side of the insurer

By varying coefficients α and β in (11) it is possible to derive robust premiums ensuring required solvency for the insurer and desired level of non-overpayments for individuals. Figures 10.a and 10.b present histograms of an indicator $I^1_{j,s} = p_s(\pi_j - q_j L^s_j)$ estimating the balance between premiums paid into and compensations paid out of the insurance fund, for robust and AAL premiums, respectively. Negative values on the horizontal axis identify when compensations exceed premiums, and the vertical axis shows the number of locations. In AAL case (Figure 10.b), compensations are higher than premiums in many locations. In Figure 10.a, for robust premiums, the balance is achieved in about 3500 locations (0 on the horizontal axis), while for AAL in Figure 10.b, only about 2000 locations are in balance.

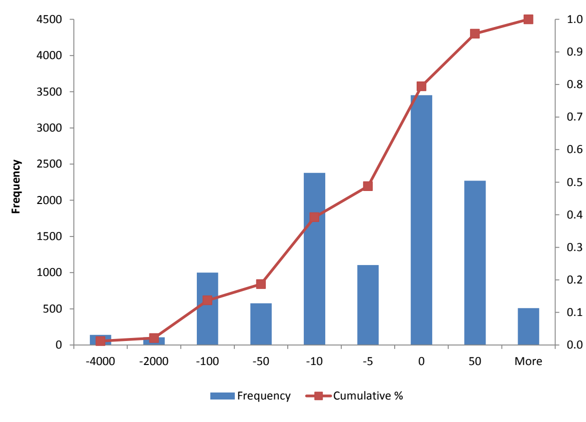


Figure 10.a: Non-overcompensations by insurance companies under Robust premiums $\alpha = 1$, $\beta = 1$.

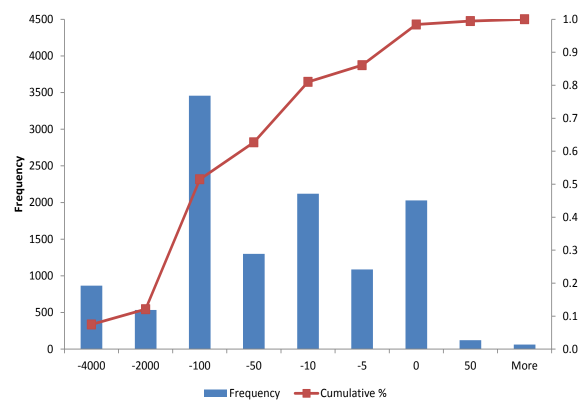


Figure 10.b: Non- overcompensations by insurance companies under AAL premiums.

By increasing coefficient α from $\alpha = 1$ in Figure 10.a to $\alpha = 10$ in Figure 10.c, and $\alpha = 100$ in Figure 10.d, it is possible to improve the business of insurer completely eliminating the insolvency by increasing premiums. In this case Figures 10.c and 10.d indicate that higher premiums result in overpayments by individuals, i.e., positive values on the horizontal axis. Adjusting coefficient β in (11), the distribution of overpayments can be reshaped as it is discussed in section 4.2.2.

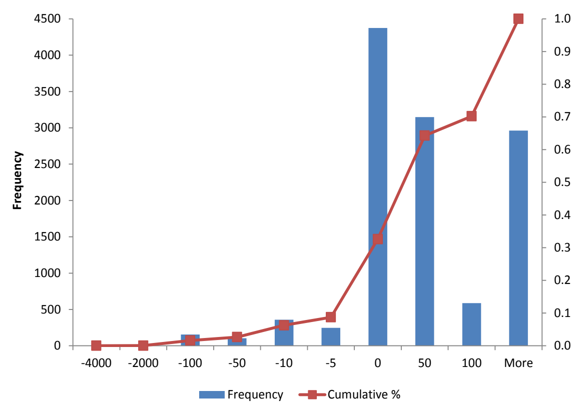


Figure 10.c: Non-overcompensations by insurance companies under Robust premiums
$\alpha = 10$, $\beta = 1$

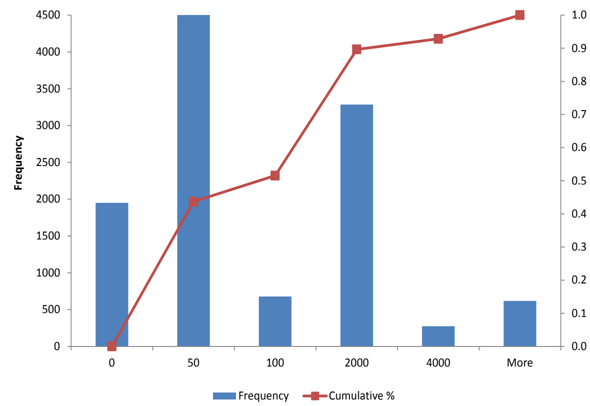


Figure 10.d: Non-overcompensations by insurance companies under Robust premiums
$\alpha = 100$, $\beta = 1$

Overcompensations increase financial risk to the insurer. Figure 11.a displays a histogram of an indicator $I_s^2 = p_s \sum_j (\pi_j \tau^s - q_j L_j^s)$, estimating the total insurer's balance between paid in premiums and paid out coverages, with $\alpha = 1$ and $\beta = 1$, for scenarios $s = 1,2,3$ (i.e., 10-, 100-, and 1000-year floods), respectively. Positive values on the vertical axis mean shortage of capital. With robust premiums, the insurer has no problems compensating 10- and 100- year flood damages, and he experiences only small expected capital deficit in the case of 1000-year flood, the expected imbalance between premiums and coverages is about 0.4 mln euro. In contrast, the AAL premiums bring the financial stability of the insurance under question. As demonstrated in Figure 11, the expected deficit with AAL premiums is the biggest for 10-year event. For 100-year event, the capital deficit of the insurer is around 2.8 mln, and the insurer's expected shortfall is equal to 0.5 mln in the case of 1000- year flood scenario.

In model (11)-(14), premiums underpayments may be avoided by adjusting the insurer's risk coefficient α. For example, Figure 11.b shows the financial situation of the insurer if α is changed from 1 to 10. With robust premiums in the case of 10-year flood, the insurer's expected capital surplus of about 2 mln euro indicated by the negative value in Figure 11.b (marked with "10-yr" on the horizontal axis). The insurer's reserve is still positive in the case of 100-year event, and only 1000- year flood causes about 0.1 mln euro capital deficit.

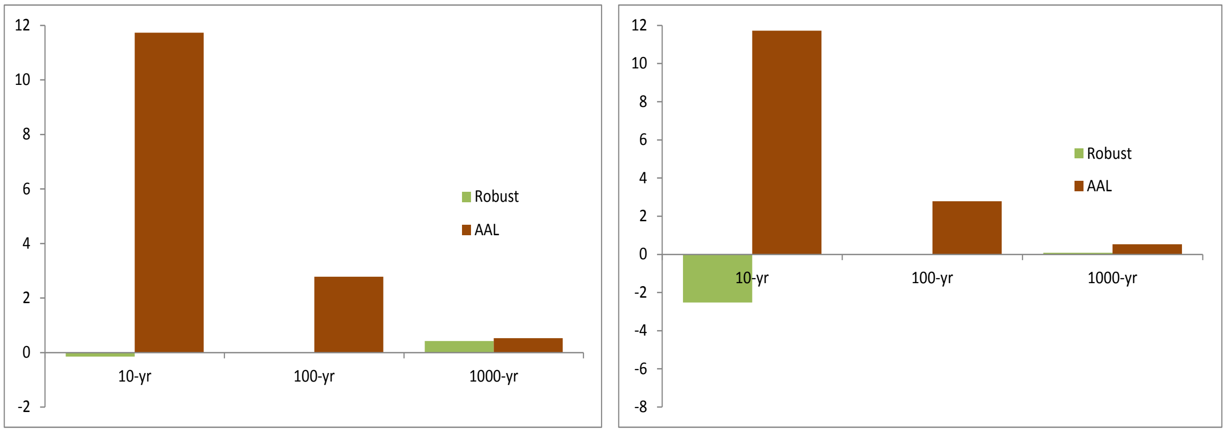


Figure 11: Insurer's balance between premiums and coverages: for Robust and AAL premiums,

11.a: $\alpha = 1$, $\beta = 1$ 11.b: $\alpha = 10$, $\beta = 1$

4.2.2 Analysis of the insurance program financial stability on the side of a households and firms

Changing α from 1 to 100 increases premiums and reshapes the profile of the indicator $I^{1}_{j,s}$ as it is shown in Figures 10.a, 10.c, and 10.d. In particular, increasing robust premiums by setting $\alpha = 10$ (Figure 10.c) improves the insurer's business, but also leads to overpayments by individuals. Further increase of α ensures complete safety of the insurer (Figure 10.d), i.e., no capital deficit, however this is for much higher premiums which may reduce insurance demand.

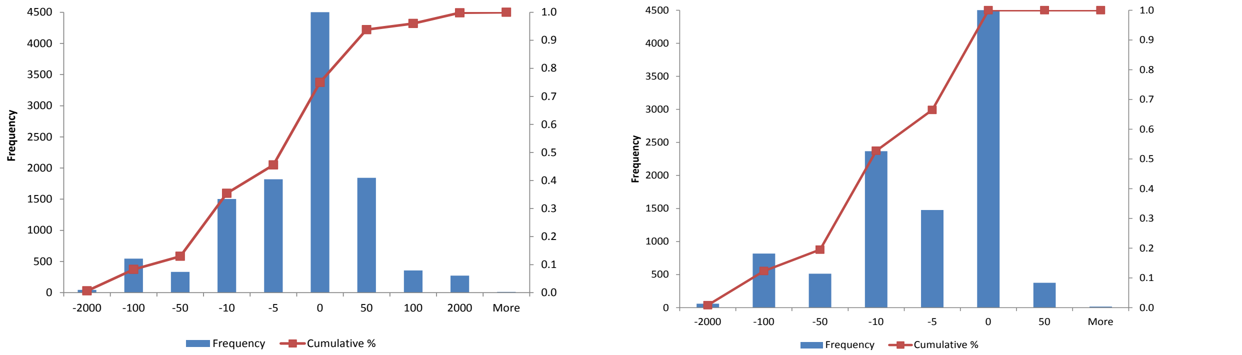


Figure 12: Non-overpayments by economic agents (firms and households)

12.a: robust premiums, $\alpha = 10$, $\beta = 10$. **12.b**: robust premiums, $\alpha = 10$, $\beta = 100$.

Overpayment can be reshaped by altering coefficient β. For example, compared to Figure 10.c, changing from $\beta = 1$ to $\beta = 10$ results in almost symmetrical distribution in Figure 12.a. Figure 12.b shows that $\beta = 100$ further reduces the overpayments. When reshaping the distributions in Figures 10 and 12, the first term in formula (8) plays an essential role. The minimization of this term ensures insurer's presence in the region. Otherwise, altering coefficients α and β, in particular, increasing β may result in reducing or even quitting insurance activities in some locations.

4.2.3 Insurer's demand for financial instruments

The analysis of imbalances between premiums and claims characterized by variables ζ_j^s and ε^s enables to derive a conclusion about adequate initial capital reserve required by the insurer, as well as his demand for reinsurance or financial instruments, e.g. contingent credit, to maintain desirable solvency. As discussed in sections 4.2.1 and 4.2.2, premiums derived with $\alpha = 10$ and $\beta = 10$ are "fair" in the sense of indicator $I_{j,s}^1 = p_s(\pi_j - q_j L_j^s)$, i.e., balancing out premiums and claims on the side of the insurer and insured. Further increase of α in (11) may derive premiums that would completely avoid capital deficit for the insurer, however the premiums may no longer be attractive for the insured regarding "nonoverpayments" indicator. In this situation, the distribution of indicator $I_s^2 = p_s \sum_j (\pi_j - q_j L_j^s)$ allows to tune the insurer's decision as to what layer of the risk defined by I_s^2 he will cover by reinsurance or/and transfer to the capital market.

5. Concluding remarks

This paper analyses the importance of properly designed integrated spatially explicit financial arrangements for sharing flood losses by comparing insurance premiums estimated based on average annual damage vs quantile-based premiums. We present an illustrative example of a robust insurance program for a case study region around Rotterdam in the Netherlands. The discussed loss-sharing program is based on pooling flood risks through private flood insurance, and a contingent credit to the insurance for "buffering" the risk. The success of this program depends on the mutual stability of the involved stakeholders. For the analysis of the stability, we use the ICRM model allowing to derive robust insurance policies, e.g., premiums and coverage of the insurer, involvement of individuals, accounting for complex interplay between multivariate spatially and temporally explicit probability distribution of flood losses and risk exposures of the stakeholders. Robust policies satisfy two goals: (i) to fulfill goals and constraints of the involved stakeholders, and (ii) to guarantee program's solvency under potential flood scenarios rather than one average event in the case study region. The ICRM is comprised of the geographically-detailed updated HIS-SSM model and of spatially-explicit quantile-based multi-agent multi-criteria stochastic optimization procedure integrated as follows: 1) water depth levels are processed in HIS-SSM to calculate flood damages for 10-, 100-, and 1000- year floods; 2) stochastic optimization estimates robust policies fulfilling the spatially explicit interdependent safety requirements of the program.

Numerical experiments compare two alternative ways of calculating insurance premiums: the robust derived with ICRM and the AAL approaches. In the case of catastrophic flood losses, which occur as "spikes" in time and space, the AAL approach does not guarantee a proper balance between premiums and claims, and the insurer may experience a deficit in capital to cover all losses. Robust premiums calculated according to (11)-(14) make the insurer better-off. As known, in the Netherlands, most of the flood losses in "inside-dike" areas are covered by the government, private flood insurance is very limited. In "outside-dike" areas, neither private nor public insurance is available. Therefore, the aim of the numerical experiments in sections 4.2.1, 4.2.2 was to demonstrate the approach which improves attractiveness and stability of private insurance and therefore may increase insurability of flood risks in flood-exposed areas. Robust policies of the private insurance can be integrated with governmental support. The government may provide only limited compensation. The level of compensation substantially depends on the governmental budget, opinions of various stakeholders, involvement of private insurance. Determining optimal share of governmental compensation requires modification of the model (11)-(14) and is a topic of the next paper.

We argue that because of significant interdependencies among catastrophic losses across different locations, the demand for a particular financial instrument cannot be separated from the demand for other risk transfer and risk reduction measures. In particular, our numerical experiments show that robust premiums of insurance decrease the demand for contingent credit, as discussed in section 4.2.3. Sections 4.2.1 and 4.2.2 explain how ICRM allows tuning robust premiums towards the required trade-off between the level of insurer's solvency and the overpayments by the individuals, thus increasing demand for the insurance and its take up rates. One of the future directions for the ICRM approach would be to consider a coupled choice of financial loss sharing measures among stakeholders and structural flood mitigation measures, such as zoning of certain land use functions, elevation of an area or particular buildings, and wet and dry flood-proofing [(12)]. We plan to better address the outlined stopping time concept and the spatio-temporal interdependencies among losses and robust policies.

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REFERENCES

1. Aerts J, Botzen W. Climate change impacts on pricing long-term flood insurance: A comprehensive study for the Netherlands. Global Environmental Change-Human and Policy Dimensions. 2011; 21:1045-60.
2. Amendola A, Ermolieva T, Linnerooth-Bayer J, and Mechler R. Integrated catastrophe risk modeling: Supporting policy processes. Dordrecht/ New York/London: Springer Verlag; 2013. 287 p.
3. AON. Voldoende dekking overstromingsrisico dichter Bij Dan Ooit. Available online; http://www.aon.com/netherlands/persberichten/2012/10-09-12_Voldoende_dekking_overstromingsrisico_dichter_bij_dan_ooit.jsp (in Dutch). 2012.
4. Bagstad K, Stapleton K, and D'Agostino J. Taxes, subsidies, and insurance as drivers of United States coastal development. Ecological Economics. 2007; 63:285-98.
5. Banks E. Catastrophic risk: Analysis and management. London: Wiley; 2005. 193 p.
6. Barnhizer D. Givings recapture: Funding public acquisition of private property interests on the coasts. Harvard Environmental Law Review. 2003; 27:295-375.
7. Bin O and Landry C. Changes in implicit flood risk premiums: Empirical evidence from the housing market. Journal of environmental economics and management (forthcoming).
8. Botzen W, van den Bergh J, and Bouwer L. Climate change and increased risk for the insurance sector: A Global perspective and an assessment for the Netherlands. Natural Hazards. 2010; 52:577-98.
9. Brown D, Page S, Riolo R, Zellner M, and Rand W. Path dependence and the validation of agent-based spatial models of land use. International Journal of Geographical Information Science. 2005; 19:153-74.
10. Daykin C, Pentikainen T, and Pesonen M. Practical risk theory for actuaries. Monographs on Statistics and Applied Probability. London: Chapman and Hall Ltd.; 1994.
11. De Bruijn K, Kind J, Slager K, Van Buren R, and Van der Doef M. Verbetering van de gevolgenbepaling van overstromingen buitendijks in de regio Rijnmond-Drechtsteden. Project 1206053-000 report. Deltares, Delft, The Netherlands (In Dutch). 2012.

12. De Moel H, Van Vliet M, and Aerts J. Evaluating the effect of flood damage-reducing measures: A case study of theunembanked area of Rotterdam, the Netherlands. Regional Environmental Change. 2013 Feb.

13. Defra. Government response to the conclusions and recommendations of the environmental audit committee: Adapting to climate change. Sixth Report of Session 2009-10. London: The Stationery Office Limited on behalf of the Controller of Her Majesty's Stationery Office; 2010. p. 20.

14. Di Mauro M and de Bruijn K. Application and validation of mortality functions to assess the consequences of flooding to people. Journal of Flood Risk Management. 2012; 5:92–110.

15. Directive 2007/60/EC Of the European Parliament and of the Council of 23 October 2007 on the Assessment and Management of Food Risks. Official Journal of the European Union; 2007. p. 27–34.

16. Ermoliev Y, and Norkin V. On nonsmooth and discontinuous problems of stochastic systems optimization. European Journal of Operations Research. 1997; 101:230-244.

17. Ermoliev Y, Ermolieva T, MacDonald G, and Norkin V. Insurability of catastrophic risks: The stochastic optimization model. Optimization Journal. 2000; 47:251–65.

18. Ermoliev Y, Ermolieva T, MacDonald G, and Norkin V. Stochastic optimization of insurance portfolios for managing exposure to catastrophic risks. Annals of Operations Research. 2000; 99:207-25.

19. Ermolieva T, and Ermoliev Y. Modeling catastrophe risk for designing insurance systems. In: Amendola A, Ermolieva T, Linnerooth-Bayer J, and Mechler R, editors. Integrated Catastrophe Risk Modeling: Supporting Policy Processes. Dordrecht/ New York/London: Springer Verlag; 2013. p. 29-53.

20. Ermolieva T, Ermoliev Y, Fischer G, and Galambos I. The role of financial instruments in integrated catastrophic flood management. Multinational Finance Journal. 2003; 7:207-30.

21. Ermolieva T, Ermoliev Y, and Norkin V. Spatial stochastic model for optimization capacity of insurance networks under dependent catastrophic risks: Numerical experiments. Interim Report IR-97-028. Int. Inst. For Applied Systems Analysis (IIASA), Laxenburg, Austria; 1997.

22. Filatova T, Mulder J, and van der Veen A. Coastal risk management: How to motivate individual economic decisions to lower flood risk?. Ocean & Coastal Management. 2011; 54:164-72.

23. Fulcher G, Archer-Lock P, Caton R, Davies D, Fick T, James G, Kam H, Kershaw P, Masi L, Postlewhite S, Skinner J, and Wong D. Catastrophe modelling working party. In: General Insurance Convention, UK. Available online: http://www.actuaries.org.uk/research-and-resources/documents/report-catastrophe-modelling-working-party; 2006. p.61.

24. Grandell J. Aspects of risk theory. Springer series on statistics: Probability and iIts applications. New York/Berlin/Heidelberg: Springer Verlag; 1991.

25. Grossi P, Kunreuther H, and Windeler D. An introduction to catastrophe models and insurance. In: Grossi P, and Kunreuther H, editors. Catastrophe modeling: A new approach to managing risk. Dordrecht/ New York/London: Springer Verlag; 2005. p.23-42.

26. IPCC. Managing the risks of extreme events and disasters to advance climate change adaptation. Field CB, Barros V, Stocker TF, Qin D, Dokken DJ, Ebi KL, Mastrandrea MD, Mach KJ, Plattner G-K, Allen SK, Tignor M, and Midgley PM. Cambridge, England: Cambridge University Press; 2012. p. 582.

27. Jongejan R and Barrieu P. Insuring large-scale floods in the Netherlands. Geneva Papers on Risk and Insurance-Issues and Practice. 2008; 33:250-68.

28. Jonkman SN, Kok M, and Vrijling JK. Economic optimization as a basis for choice of flood protection strategies in the Netherlands. In: International association for XXX IAHR Congress, August, 2003. Auth, Thessalon, Greece. Available online: http://www.hkv.nl/documenten/EconomicOptimizationasabasisfortheChoiceoffloodprotectionstrategiesintheNetherlands_MK.pdf; 2003.

29. Klijn F, de Bruijn K, Knoop J, and Kwadijk J. Assessment of the Netherlands' flood risk management policy under global change. Ambio. 2012; 41:180–92, doi:10.1007/s13280-011-0193-x.

30. Kok M, Vrijling JK, van Gelder PH, and Vogelsang P. Risk of flooding and insurance in the Netherlands. In: Wu B, Wang Z-Y, Wang G, Huang G, Fang H,and Huang J, editors. Flood Defence. New York: Science Press; 2002. p. 146 - 54.

31. Kok M, Huizinga HJ, Vrouwenvelder AC, and Van den Braak WE. Standaardmethode 2005. Report Pr999.10, Hkv Consultants and Tno Bouw, Lelystad; 2005.

32. Matthijs Kok, Een waterverzekering in Nederland: Mogelijk en wenselijk?. In: Opdrachtgever: Adviescommissie WaterHKV: LIJN IN WATER; 2005. p. 1-33.

33. Kunreuther H, and Pauly M. Rules rather than discretion: Lessons from hurricane Katrina. Journal of Risk and Uncertainty. 2006; 33:101-16.

34. Kuzak D, and Larsen T. Use of catastrophe models in insurance rate making. In: Grossi P, and Kunreuther H, editors. Catastrophe modeling: A new approach to managing risk. Dordrecht/ New York/London: Springer Verlag; 2005. p. 97-118.

35. Lalonde D. Risk financing. In: Grossi P, and Kunreuther H, editors. Catastrophe modeling: A new approach to managing risk. Dordrecht/ New York/London: Springer Verlag; 2005. p.135-164.

36. Lave T, and Lave L. Public perception of the risks of floods: Implications for communication. Risk Analysis. 1991; 11: 255-67.

37. Lescrauwaet AK, Vandepitte L, Van den Berghe E, and Mees J. Europese duurzaamheidsindicatoren voor kustgebieden in Nederland: Een eerste inventarisatie. In: *VLIZ* Special Publication, 31. Ostende, Belgium: Vlaams Instituut voor de Zee; 2006. p. 128.

38. Michel-Kerjan E, and Kunreuther H. Redesigning flood insurance. Science. 2011; 333:408-09.

39. Mukhopadhyay A, Dasgupta R, Hazra S, and Mitra D. Coastal hazards and vulnerability: A review. International Journal of Geology, Earth and Environmental Sciences. 2012; 2:57-69.

40. Munich Re. 2012 Natural catastrophe year in review. Munich: Munich Re; 2013.

41. Nowak P, and Romaniuk M. Pricing and simulations of catastrophe bonds. Insurance: Mathematics and Economics. 2013; 52:18–28.

42. Rockafellar T, and Uryasev S. Optimization of conditional Value-at-Risk. Journal of Risk. 2000; 2:21-41.

43. Schwarze R, and Wagner R. The political economy of natural disaster insurance: Lessons from the failure of a proposed compulsory insurance scheme in Germany. European Environment. 2007; 17:403–15.

44. Veerbeek W, Zevenbergen C, and Gersonius B. Flood risk in unembanked areas. Part C, vulnerability assessment based on direct flood damages. Utrecht: Dutch National Research Programme Knowledge for Climate; 2011.

45. Walker G. Current developments in catastrophe modelling. In: Britton NR, and Oliver J, editors. Financial risks management for natural catastrophes. Brisbane, Griffith University, Australia; 1997. p. 17-35.

46. Wiener J. Research opportunities in search of federal flood policy. Policy Sciences. 1996; 29:321-44.

47. Yang H. An integrated risk management method: Var approach. A Multinational Finance Journal. 2000; 4:201-19.