MEASUREMENT OF COGNITIVE EFFECTS AGAINST DISASTER / ACCIDENT RISK FROM ACTUAL SOCIAL INVESTMENTS

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Abstract: In this paper, we proposed the consideration of decision-makers' cognitive effects on frequency and loss on investments for disaster / accident mitigation. At first, we showed the definition of cognitive effects. Secondly, how to measure these cognitive frequency and cognitive loss using actual disaster mitigation investment data is theoretically shown, including a definition of the original benefit calculated from disaster mitigation investments against risks of which both frequency and amount of loss continuously vary. Thirdly, we measured cognitive frequency and cognitive loss with three case studies: anti-accident traffic signal improvement investments on intersections, anti-flood reinforcement investments on river-embankments and anti-slope-failure investments on railway infrastructures. As a result, we obtained some important implications such as cognitive loss tend to larger than monetary loss especially on loss by humans' death, while cognitive frequency are often underestimated.

Key Words: Disaster / Accident Mitigation Investment, Cognitive Effects on Frequency and Loss, Traffic Signal Control, River Embankment, Slope Failure of Railroads

1. INTRODUCTION

The methodology for evaluating investments for disaster mitigation would normally be cost-benefit analysis (CBA). However, the optimal investment level calculated by CBA cannot often explain actual investment levels; that is, although a lot of investments have already been done in real world, the results of CBA cannot often show any special necessity for disaster mitigation investment because the frequency of catastrophic risks is very low leading to very low expected damage (the product of frequency and amount of loss) which is usually much smaller than the investment cost.

Why does this gap exist? Our thought is that it could be explained by introducing cognitive frequency and cognitive loss, basically founded on an assumption that decision-makers subjectively judge on frequency or/and loss of the risks because of their catastrophic, uncertain, and irreversible characteristics.

In this paper, we will first theoretically show how to measure cognitive probability and cognitive loss using actual disaster mitigation investment data, including a definition of the "original" (that means not through human cognitive process) benefit calculated from disaster mitigation investments against risks of which both frequency and amount of loss continuously vary. Secondly we will show some examples of the measurement of cognitive frequency and cognitive loss: anti-accident traffic signal improvement investments on intersections, anti-flood reinforcement investments on river-embankments and anti-slope-failure investments on railway infrastructures.

2. COGNITIVE EFFECTS ON FREQUENCY AND LOSS OF CATASTROPHIC RISK

We can often observe that expected damage acquired as simple product of frequency and loss is different from the damage that people actually recognize, for example, see Lichtenstein *et al.* (1978). Although various variables of risks have been tried to explain this kind of phenomena, basic elements are frequency and loss, therefore we focus on cognitive effects on these two elements.

2.1 Cognitive Effects on Frequency of Risk

It is expected that the difference between cognitive and actual frequency on the low frequency events will be larger than on high frequency events, because of the difficulty in assessing low frequency events. Now we introduce the Cognitive Frequency Function (CFF), $f(.)$, for expression of these cognitive effects on frequency of risk.

2.2 Cognitive Effects on Loss of Risk

Amount of loss affected from a disaster have some kind of uncertainty that means, even if the same disaster-scale level L, amount of loss that happen may be different. For example, even if same scale earthquakes happen, amount of loss will differ depending on the time or other random conditions, and it will be especially remarkable as bigger earthquake. Therefore, we assume the dispersion of L follow the normal distribution $N(D(L), \sigma^2(D(L)))$ and that variation $\sigma^2(D(L))$ is much bigger as $D(L)$ is bigger. That is,

$$\frac{d\sigma^2(D(L))}{dD(L)} > 0 \quad \text{, and} \quad \frac{d^2\sigma^2(D(L))}{d(D(L))^2} > 0. \tag{1}$$

Normally, as 'expected' monetary loss of the disaster-scale level L, decision-makers will consider average loss, $D(L)$, because it is easy to observe in most of cases. However, in case that catastrophic loss will be expected at the disaster-level even if it seldom happens, they may estimate loss much more than average loss for avoiding catastrophic situation. Therefore, $M(L)$, a loss that decision-makers actually take into account at the disaster-level L, will be expressed with average loss $D(L)$ and deviation $z \cdot \sigma(D(L))$ $(z > 0)$ from the average.

$$M(L) = D(L) + z \cdot \sigma(D(L)), \qquad (z > 0). \tag{2}$$

We call "cognitive loss" for $M(L)$. And the difference, Δ, between decision-makers' cognitive loss and average loss of disaster-scale level L is expressed as following,

$$\Delta = M(L) - D(L) = z \cdot \sigma(D(L)) > 0. \tag{3}$$

Differentiating Eq.(3) with respect to $D(L)$, and from Eq.(1),

$$\frac{d\Delta}{dD(L)} = z \cdot \frac{d\sigma(D(L))}{dD(L)} > 0 \text{ , and } \frac{d^2\Delta}{d(D(L))^2} = z \cdot \frac{d^2\sigma(D(L))}{d(D(L))^2} > 0 . \quad (4)$$

Therefore, Δ progressively increases as $D(L)$ increases (see Fig.1). This is the "progressive effect of loss". We introduce the Cognitive Loss Function (CLF), $g(.)$, for expression of this effect as following,

$$g\{D(L)\} = D(L) + z \cdot \sigma(D(L)). \quad (z > 0) \quad (5)$$

On the other hand, because investment for disaster mitigation has no uncertainty, this effect cannot be observed on investment cost.

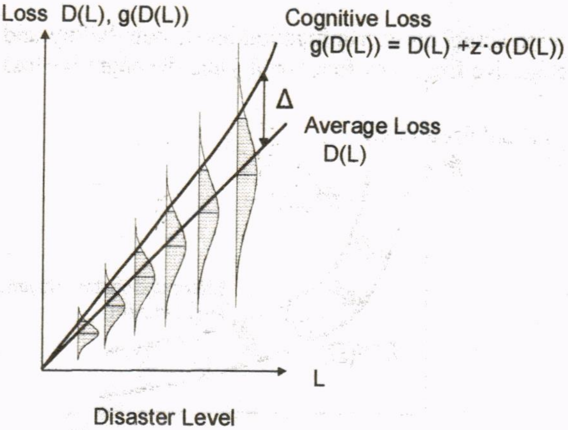

Figure 1. Progressive Effect of Loss

3. FORMULATION OF BENEFIT OF DISASTER MITIGATION INVESTMENT CONSIDERING COGNITIVE EFFECTS OF RISK

Suppose that a disaster-mitigation level, k, against a disaster / accident risk is given and that the amount of loss of a risk is inversely proportional to frequency of the risk. In Figure 2, this relation is shown as the loss-frequency function $fr^k(D)$, where D is amount of monetary loss. Now we assumed that a disaster mitigation investment brings an improvement of the disaster mitigation level from k to $k+l$. Therefore, the expected benefit by the improvement, ΔOB, is expressed the difference between expected damages (that is summation of the product of the amount of monetary loss and actual frequency on each disaster-scale level L) before and after the investment.

$$\Delta OB = \int_0^{\infty} D \cdot (fr^k(D) - fr^{k+l}(D))dD . \quad (6)$$

In the definition of ΔOB, it is not considered decision-makers' cognitive effects on frequency and loss against risks. In this sense, we call "Original Benefit" for this benefit. Based on the argument in Chapter 2, we introduce "Perceived Benefit", ΔPB, in Eq.(7), which is defined including the consideration of these cognitive effects (see Figure 3).

$$\Delta PB = \int_0^{\infty} g(D) \cdot \left[f\{fr^k(D)\} - f\{fr^{k+1}(D)\}\right] dD . \quad (7)$$

Decision-makers are assumed to decide incremental disaster mitigation level l to maximize "Perceived Net Present Value", *PNPV*, defined as Eq.(8).

$$\max_{l} PNPV$$

$$PNPV = \sum_{n=0}^{N-1} \frac{\Delta PB}{(1+i)^n} - \Delta C$$
$$= \sum_{n=0}^{N-1} \frac{\int_0^\infty g(D) \cdot \left[f\{fr^k(D)\} - f\{fr^{k+l}(D)\} \right] dD}{(1+i)^n} - \left(C^{k+l} - C^k \right), \quad (8)$$

where, N ; project life, i ; social discount rate (=0.04), C^k, C^{k+l}; construction cost of disaster mitigation facilities at the disaster-mitigation level k and $k+l$ respectively.

By solving Eq.(8) with actual disaster-mitigation levels both before and after the investment, we can obtain the cognitive frequency function $f(.)$ and the cognitive loss function $g(.)$.

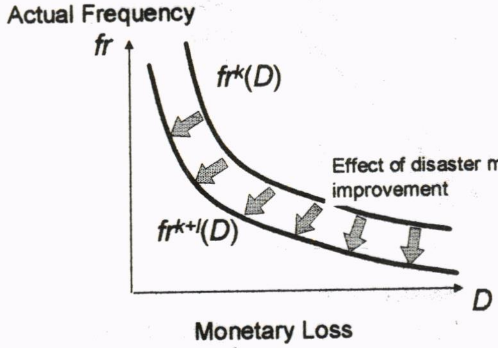

Figure 2. Loss-Frequency Function $fr^k(D)$ and Effect of Disaster Mitigation Investment

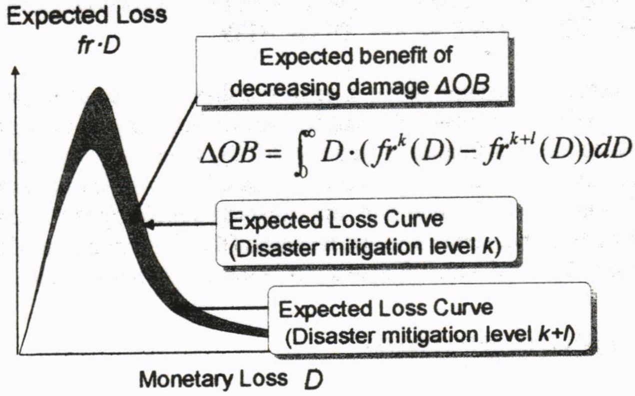

Figure 3. Expected Loss Curve and Expected Benefit of Disaster Mitigation Investment

4. MESUREMENT OF COGNITIVE EFFECTS ON ANTI-ACCIDENT TRAFFIC SIGNAL IMPROVEMENT INVESTMENTS ON INTERSECTIONS

4.1 Subject of Analysis and Decision-making Process

Main objective of traffic signal improvement investments is reducing traffic accident[1]. In a report of the Japan Traffic Management Technology Association (1998), several measures of traffic signal improvement showed in Table 1 were investigated in terms of cost-benefit analysis.

The effects on the reducing traffic accidents of each measure are different by each intersection due to its characteristics, such as its shape, traffic volume, and so on. In this study, decision-makers are assumed to invest for all 'effective' (i.e., $PNPV > 0$) intersections within project life of traffic signal (10 years). That is,

$$\min_{j} PNPV_{h,j} = 0, \forall h, \tag{9}$$

where, h : measure of traffic signal improvement, j : actually invested intersection.

Table 1. Measures of Traffic Signal Improvement

Measures, h	Total number of Invested intersections, n_h (/ 10 years)	Total number of reducing accident, ΔAcc_h (/ 1 year)	Average rate of decreasing accident pa_h	Cost, C_h (10,000 yen / 1 inter-section)	s_h	Frequency of traffic accident at a intersection where $PNPV_h$=0 (/ 1 year)
Semi-traffic-actuated Control	3,160	948	66.2%	300	43.1	0.25
Off-peak Pedestrian Push Button Signal	500	90	43.4%	40	291.9	0.14
Off-peak Semi-traffic-actuated Control	3,720	1,045	53.8%	140	29.0	0.58
High-speed Traffic-actuated Control	980	382	46.2%	340	41.5	1.36
Dilemma Traffic-actuated Control	780	337	45.9%	220	40.7	1.46
Right-turn Traffic-actuated Control	1,360	620	41.8%	120	18.9	1.53
Multi-phase Signal Control	6,700	3,310	53.8%	30	18.9	0.36
Handicapped-actuated Control	3,200	1,095	57.5%	60	28.8	0.76
Pedestrian-actuated Control	420	176	55.7%	160	133.8	1.18
Pedestrian Guid Facility with Sound	440	1,060	47.4%	20	290.6	0.35

4.2 Estimation of Input Data

a) The intersection that minimize $PNPV_{h,j}$

At first, we sort all intersections (around 160,000 intersections) in Japan in order of annual number of accidents. From the statistics of high frequency accident intersections (around 7,000 intersections), annual number of accidents, $Acc(x)$, at xth most accident-prone intersection is approximately expressed in Eq.(10).

[1] In some intersections, traffic signal improvement is made in order to reduce traffic congestion, however, it does not fit in all investments.

$$Acc(x) = \left(\frac{x}{25700}\right)^{-\frac{1}{1.38}}, \quad 1 \le x \le 7000$$
$$Acc(x) = 1.16 \times 10^{-5} \times (160000 - x), \quad 7000 \le x \le 160000 \tag{10}$$

Only the $(s_h \cdot x)$th ($x = 1,2,3,\ldots,n_h$; n_h is total number of invested intersections with a measure h) intersections are assumed to be effective by the improvement investment with the measure h. From the total reduced number of accidents, ΔAcc_h, and the average rate of reducing accident, Δpa_h, which can be both obtained from the report (the Japan Traffic Management Technology Association (1998), see Table 1), we can estimate s_h by each h from Eq.(11).

$$\Delta Acc_h = \int_1^{n_h} \Delta pa_h \cdot Acc(s_h \cdot x) dx . \tag{11}$$

Estimated s_h are also shown in Table 1. From the definition of s_h, it is clear that the intersection that minimize $PNPV_{h,j}$ is $(s_h \cdot n_h)$th most accident-prone intersection, and annual number of accidents at the intersection is $Acc(s_h \cdot n_h)$.

b) The loss-frequency function in the intersection that minimize $PNPV_{h,j}$

The population of the injured and dead by traffic accidents and amount of loss per person are shown in Table 2 by each injury / death status, based on the definition of the Abbreviate Injury Scale (AIS). All data in Table 2 are derived from automobile insurance statistics and a report from the Japan Research Center for Transport Policy (1994).

Table 2. Population and Loss per Person by Each Injury / Death Status

AIS	Status	Population		Medical Cost (million yen)	Job Compensation Cost (million yen)	Solatium Cost (million yen)	Loss of Death (million yen)	Total Loss (millon yen / person)
		Total number (persons / year)	Ratio					
1	Minor	771,496	76.4%	150,025	198,320	152,129		0.65
2	Moderate	152,164	15.1%	100,016	76,128	54,082		1.51
3	Serious	37,320	3.7%	43,007	25,397	17,005		2.29
4	Severe	11,942	1.2%	18,670	8,286	5,378		2.71
5	Critical	9,852	1.0%	15,669	7,048	4,481		2.76
6	Maximum (Unsurvivable)	498	0.0%	667	444	259		2.75
	Others	11,942	1.2%	5,334	1,841	2,524		0.81
	Death	14,685	1.5%	9,182	675	1,021	477,192	33.24
	Total	1,009,899	1	342,570	318,140	236,880		

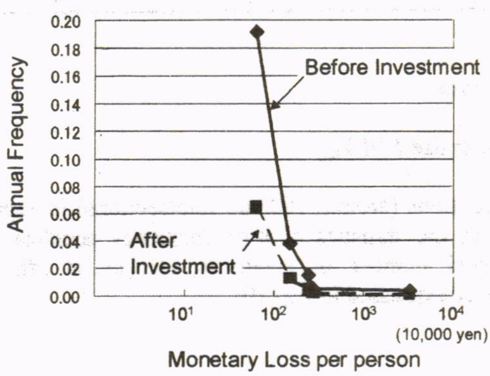

Figure 4. An Example of the Loss-Frequency Function (Semi-Traffic-Actuated Control)

The accident frequency of each injury / death status at the intersection is expressed as the product of the annual total number of accidents, $Acc(s_h \cdot n_h)$, and the population ratio of each status shown in Table 2. From the frequency and amount of loss of each status, we can describe the loss-frequency functions before and after investment by each measure. An example (Semi-Traffic-Actuated Control) is showed in Figure 4.

4.3 Measurement of Cognitive Functions

At First, the comparison of original benefit ΔOB and perceived benefit ΔPB at the intersection that minimize $PNPV_{h,j}$ is shown in Figure 5 by each measure h. Half of them, ΔPB is smaller than ΔOB. Two explanations are easier to understand this phenomenon; decision-makers are underestimating loss and/or frequency of the traffic accident risk, or all of the effective intersections cannot be invested due to budget constraint. The following argument is made under an assumption that the former explanation would be most dominant.

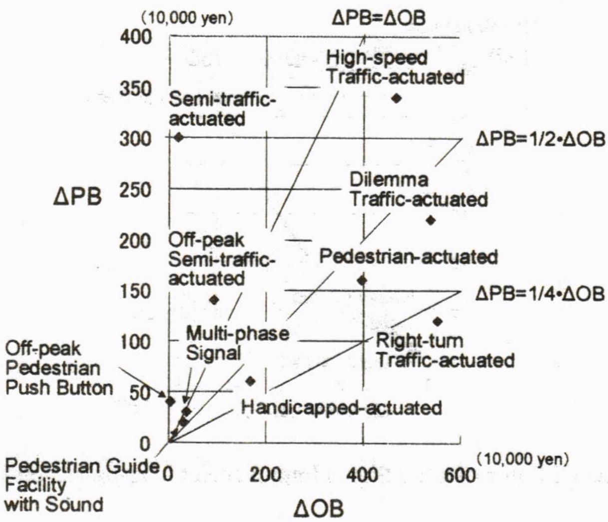

Figure 5. Original Benefit ΔOB and Perceived Benefit ΔPB of the Intersection that Minimize $PNPV_{h,j}$ by Each Measure h

Cognitive functions are assumed to be a power function as our past work (IEDA and SHIBASAKI, 2000),

$$g(D) = D + \alpha_1 \cdot D^{\alpha_2}$$
$$f(fr) = \alpha_3 \cdot fr^{\alpha_4} \quad , \qquad (12)$$

where, α_1, α_2, α_3, α_4; unknown parameter.

We can obtain unknown parameter vector $\boldsymbol{\alpha}(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$ in cognitive functions by solving Eq.(13) based on the OLS method.

$$\min_{\boldsymbol{\alpha}} \sum_h \left[\min_j \left\{ PNPV(\boldsymbol{\alpha})_{h,j} \right\} - 0 \right]^2 . \qquad (13)$$

Estimation results of cognitive functions are shown in Figure 6 and 7. It is confirmed by likelihood ratio test that these cognitive functions are significant comparing to the case without considering any cognitive functions.

Estimated cognitive loss function (CLF) $g(D)$ is shown in Figure 6. For the injured, amount of cognitive loss are nearly equal to amount of monetary loss, while for the dead, the cognitive loss (around 165 million yen per person) is 5 times the monetary loss.

Estimated cognitive frequency function (CFF) $f(fr)$ is shown in Figure 7. When actual frequency per annum is under 0.001, cognitive frequency is bigger than actual frequency. To the contrary, when actual frequency per annum is over 0.001, cognitive frequency is smaller than actual frequency. '0.001 per annum' corresponds to the frequency that people are killed or very heavily injured by traffic accident at low-frequent intersections. That is, decision-makers overestimate the frequency of fatal accidents, especially in low-frequent intersections, while underestimate the frequency of the accidents in high-frequent intersections or the light-injured accidents. The result may reflect decision-makers' way of thinking that put an important on equality among regions. That is, they also invest in low-frequent intersections, for example, in rural areas that the frequency of accidents is low due to traffic volume is small, not only in high-frequent urban intersections.

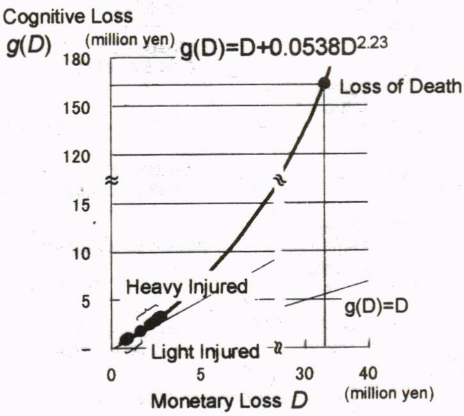

Figure 6. The CLF from Traffic Signal Improvement Investments on Intersection

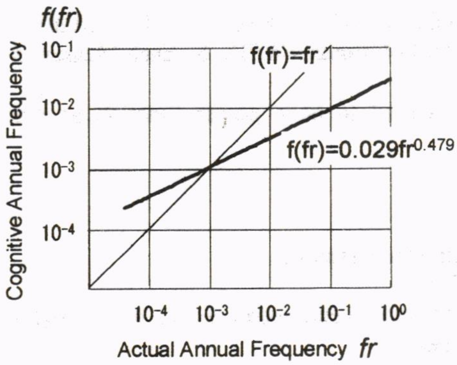

Figure 7. The CFF from Traffic Signal Improvement Investments on Intersection

5. MESUREMENT OF COGNITIVE EFFECTS ON ANTI-FLOOD INVESTMENTS ON RIVER-EMBANKMENTS

5.1 Subject of Analysis and Decision-making Process

Main objective of investment on river-embankments is the mitigation of damage due to floods. In this study, the Fuji River is dealt with as a case study of analysis, because of the availability of the simulation results of flooding; the River Bureau, Ministry of Land, Infrastructure and Transport open it. Temporary and future-planned disaster mitigation levels in this area are shown in Table 3. Calculated points (around 30 points) in this simulation are selected with following procedure. At first, peripheral area along the river are divided into 30 small local areas, by around 5 kilometers. Next, the place that could cause maximum damage in each local area`is selected as simulation point. Therefore, it means that the following analysis is made based on the maximum damage of each local area.

We assume that the amount of investment on embankment of each area is decided to maximize the *PNPV* in Eq.(8). Note that until the embankments broken there are caused almost no damage, however, that once the embankments broken, damage will be catastrophic, independently with the disaster mitigation level. Therefore, the loss-frequency function curve is discontinuous at maximum allowable flow rate Q^k of the embankment at the disaster-mitigation level k (see Figure 8). Then Eq.(8) is rewritten as Eq.(14).

$$\max_l PNPV \Leftrightarrow \frac{d}{dl} PNPV(l) = 0$$
$$\Leftrightarrow \sum_{n=0}^{N-1} \frac{\frac{d}{dl}\int_{Q^k}^{Q^{k+l}} g\{D(Q)\}\cdot f\{fr(Q)\}\cdot dQ}{(1+i)^n} - \frac{d}{dl}\{C(Q^{k+l}) - C(Q^k)\} = 0. \quad (14)$$
$$\Leftrightarrow \sum_{n=0}^{N-1} \frac{g\{D(Q^{k+l})\}\cdot f\{fr(Q^{k+l})\}}{(1+i)^n} = \frac{d}{dl} C(Q^{k+l})$$

That is, at the future-planned disaster mitigation level $k+l$ (after investment), the marginal perceived benefit *MPB* $(= \sum_{n=0}^{N-1} \frac{g\{D(Q^{k+l})\}\cdot f\{fr(Q^{k+l})\}}{(1+i)^n})$ is equal to the marginal cost *MC* $(= \frac{d}{dl} C(Q^{k+l}))$.

Table 3. Temporary and Future-Planned Disaster Mitigation Level on the Fuji River

Area	Temporary	Future Plan
Upper Area (Kofu Basin)	Durable of flow occured once per 20 years ···50%	Durable of flow occured once per 100 years
Middle Area (Minobu District)	Durable of flow occured once per 50 years ···50%	Durable of flow occured once per 150 years
Lower Area (Fuji City etc.)		Durable of flow occured once per 150 years

5.2 Estimation of Input Data

We approximate a relation between flow rate Q (m^3/s) and its frequency per annum, $fr(Q)$, as Eq.(15) from an interview survey of a local office of MLIT.

$$fr(Q) = 3.30\times10^{9}\cdot Q^{-3.805} \quad (Upper\ Area)$$
$$fr(Q) = 4.24\times10^{16}\cdot Q^{-5.294} \quad (Middle\,/\,Lower\ Area) \quad (15)$$

And from the simulation results, we can know the amount of loss, $Ddest^k_j$ (billion yen), with the embankments at the temporary disaster-mitigation level k in each local area j. We assume a linear relationship between flow rate Q (m^3/s) and the amount of loss, $D(Q)$ (billion yen), as Eq.(16).

$$D(Q)=\frac{Ddest^k_j}{Q^k}\cdot Q, \qquad (Q \geq Q^k), \qquad (16)$$
$$D(Q)=0, \qquad (Q<Q^k)$$

where, Q^k (m^3/s) : the maximum allowable flow rate at the temporary disaster-mitigation level k.

An example of the loss-frequency function is shown in Figure 8. We also approximate a relation between the flow rate Q^k (m^3/s) at the disaster-mitigation level k and the construction cost of each area j, $C_j(Q^k)$ (billion yen / km), as Eq.(17), based on an interview survey.

$$C_j(Q^k)=l_j\cdot 0.274\cdot\exp(1.50\times10^{-4}\cdot Q^k) \quad (Upper\ Area)$$
$$C_j(Q^k)=l_j\cdot 0.169\cdot\exp(1.16\times10^{-4}\cdot Q^k) \quad (Middle/Lower\ Area), \qquad (17)$$

where, l_j : length of embankment at area j (km).

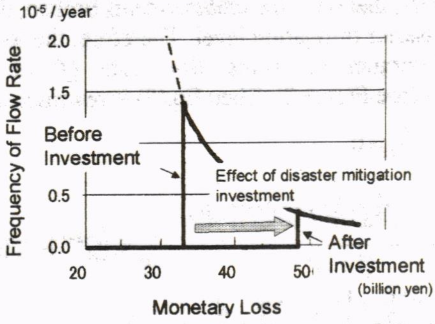

Figure 8. An Example of the Loss-Frequency Function
(A Local Point in the Upper Area of the Fuji River)

5.3 Measurement of the Cognitive Functions

At first, a comparison of marginal original benefit *MOB* and marginal perceived benefit *MPB* at the future-planned disaster-mitigation level is shown in Figure 9 by each local area i. Actually, in around 70% area, *MPB* is smaller than *MOB*, especially it is strong tendency in the area where *MOB* is bigger.

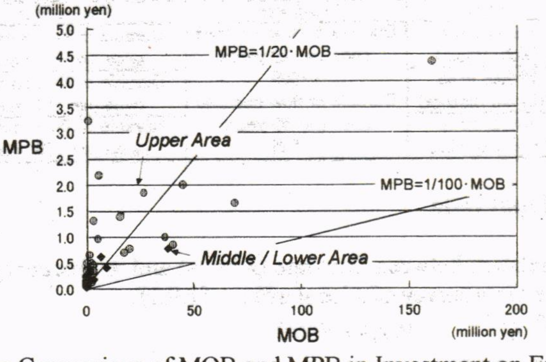

Figure 9. The Comparison of MOB and MPB in Investment on Embankment

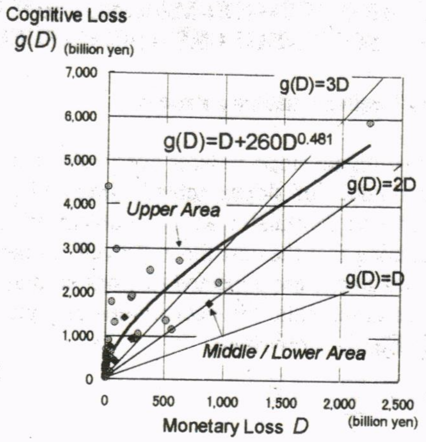

Figure 10. The CLF from Investment on River-Embankments

We assume the CLF is a power function in the same way as chapter 4. However, for the CFF, we can know only two frequencies fr^{k+l} (fr^{k+l} = $3.22\cdot10^{-6}$ in the Upper area and fr^{k+l} = $1.93\cdot10^{-6}$ in the Middle/Lower area), because the maximum allowable flow rate is same within the Upper area and also within in the Middle/Lower area of the Fuji River. Therefore, we assume simpler function for the CFF, shown in Eq.(18).

$$g(D) = D + \beta_1 \cdot D^{\beta_2}$$
$$f(fr) = \beta_3 \cdot fr \qquad (18)$$

where, β_1, β_2, β_3 ; unknown parameter.

Therefore, we can obtain unknown parameter vector $\boldsymbol{\beta}(\beta_1, \beta_2, \beta_3)$ in cognitive functions, by solving Eq.(19).

$$\min_{\alpha} \sum_{j} \left[\frac{d}{dl} PNPV_j(l, \boldsymbol{\beta}) \right]^2 . \qquad (19)$$

We also confirm by likelihood ratio test that these cognitive functions are significant comparing to the case without considering any cognitive functions.

Estimated CLF is shown in Figure 10. Cognitive loss is at least double as monetary loss, although a gradient of the CLF gradually decreases as monetary loss increases. The following description is reasonable to explain that. In river-embankment investments, embankments are needed to keep the same disaster-mitigation level in any area. Otherwise, it is very unfair because embankments will be always broken at the same point. Therefore, they would decide the disaster-mitigation level so that catastrophic loss can be avoided even if the worst case (i.e., the case that embankments is broken at the point where maximum loss is affected). As a result of these investments, in other areas cognitive loss seemed to be more than double.

The CFF is estimated as Eq.(20).

$$f(fr) = 0.0103 \cdot fr . \qquad (20)$$

That is, cognitive frequency is only around 1/100 of actual frequency. And if unknown parameters in Eq.(18) are estimated respectively in the Upper area and the Middle / Lower area, it will be 0.0117 and 0.0091. From these results, we deduce the frequency of flood is much underestimated in low frequencies.

6. COGNITIVE EFFECTS AND DECISION-MAKING PROCESS ON INVESTMENT FOR RAILWAYS AGAINST SLOPE-FAILURE RISK CASUED BY RAINFALL

6.1 Subject of Analysis and Decision-making Process

Railway companies invest to mitigate slope-failures every year. However, because the number of slopes is numerous, the number of slopes actually invested per annum is very limited. Therefore, this problem has to be formulated as the problem of choosing investment points with budget constraint. Assuming that the cost for improvement per 100m of slope is equal at any place and that all invested slopes are expected to work similarly against rainfall depth Q (mm / 24 hour). From above arguments, the decision-making process of investment that is maximizing $PNPV$ shown in Eq.(8) is rewritten;

$$\max_{z_1, z_2, \cdots, z_J} \sum_j^J PNPV_j, \qquad s.t.\ c \cdot \sum_j^J z_j \le C$$

$$PNPV_j = \sum_{n=0}^{N-1} \frac{\Delta PB_j}{(1+i)^n} - c \cdot z_j, \tag{21}$$

where, J : total number of railway lines, j : each railway line, z_j : a length (km) of invested slopes per annum of each railway line j, c : improvement cost per 1km-slope, C : yearly budget for investment for improving slope, m : items of damage (m=1 to 3; details are explained in next section), and suffix ^{o} : no investment, ^{w} : with investment.

Because the improvement cost is constant, the amount of $PNPV_j$ depends on the amount of perceived benefit ΔPB.

6.2 Estimation of Input Data

We approximate a relation between rainfall depth Q (mm / 24 hour) and its annual frequency $fr(Q)$ from daily rainfall depth data provided by the Meteorological Agency of each area as Eq.(22).

$$fr(Q) = a_j \cdot Q^{-b_j} \tag{22}$$

where, a_j, b_j : parameter decided by each line j.

We have slope investment data and slope-failure data of a railway company (JR East) for three years (1997-99) divided into 170 lines. With comparing the daily rainfall depth data, relations between the probability of disaster happening and rainfall depth are estimated respectively without and with investment.

$$\begin{aligned} P^o(Q) &= 1.6 \cdot 10^{-3} \cdot Q \\ P^w(Q) &= 5.4 \cdot 10^{-6} \cdot Q^2 + 6.3 \cdot 10^{-4} \cdot Q \end{aligned}, \qquad (30 \le Q \le 400) \tag{23}$$

where, $P^o(Q)$: probability of failure at not invested slope (per 1 km) when rainfall depth is Q, $P^w(Q)$': probability of failure at invested slope when rainfall depth is Q.

Losses by slope-failure are considered as following three items;

i) Cost for removing collapsed soil and restoring the status-quo, D_1. These are defined respectively without / with investment. And we cannot find any relationship between this cost and rainfall depth, that is, once slope-failure happens, cost for removing and restoring is same independently with rainfall depth.

$$\begin{aligned} D_1^o &= 0.85 \\ D_1^w &= 0.38 \end{aligned} \quad \text{(million yen / 1km-slope).} \tag{24}$$

And occurrence probability of slope-failure is $P^o(Q)$ and $P^w(Q)$ respectively.

ii) Loss of fare income due to suspension of trains, D_2. If slope-failure occurs, all trains in the region (assumingly within 10km from the failed slope) are suspended. That is,

$$D_{2,j} = Finc_j \cdot Sday\,, \tag{25}$$

where, $Finc_j$: fare income (per 10 km) of line j, $Sday$: suspended period (assumed 1 day constantly).

And the probability of suspension, $Psus_j$, is expressed as Eq.(26), considering all trains int the region will be suspended when slope-failure occurs even if at only one point.

$$Psus_j = \left\{1-\left(1-P^o(Q)\right)^{l_j^o} \cdot \left(1-P^w(Q)\right)^{l_j^w}\right\}, \tag{26}$$

where, l_j^o, l_j^w : length (km) of slopes without / with investment of line j. Then the amount of change of the probability, $\Delta Psus_j$, by z_j km-investment of slope is expressed as,

$$\Delta Psus_j = \left(1-P^o(Q)\right)^{l_j^o} \cdot \left(1-P^w(Q)\right)^{l_j^w} - \left(1-P^o(Q)\right)^{l_j^o - z_j} \cdot \left(1-P^w(Q)\right)^{l_j^w + z_j}. \tag{27}$$

iii) Loss of dead, injured passengers and train body due to collision with failed slope, D_3.

$$\begin{aligned} D_{3t} &= 100 \text{ (million yen) (Train Body)} \\ D_{3d} &= 33.2 \text{ (million yen) (Dead Passengers)} \\ D_{3inj} &= 0.88 \text{ (million yen) (Injured Passengers)} \end{aligned} \tag{28}$$

The probability of collision, $Pcol_j$, is approximated to the probability that train is running there just at the time when the slope-failure occurs. Therefore[2],

$$Pcol_j = \frac{Ntrain_j \cdot Ptime}{24} \cdot P(Q), \tag{29}$$

where, $Ntrain_j$: the number of trains per day in the line j, $Ptime$: passing time through 1km-slope (assumed 0.02 hours). Then the probabilities of death, Pd_j, and injured, $Pinj_j$, are

$$\begin{aligned} Pd_j &= Drate \cdot \frac{Pflow_j}{Ntrain_j} \cdot Pcol_j \\ Pinj_j &= (1-Drate) \cdot \frac{Pflow_j}{Ntrain_j} \cdot Pcol_j \end{aligned} \tag{30}$$

where, $Drate$: the rate of death out of passengers, we assumed to be 0.072 from historical data, $Pflow_j$: passengers flow per day of line j.

From above arguments, the perceived benefit ΔPB_j in Eq.(21) is expressed as,

$$\Delta PB_j = \int_{30}^{400} \begin{bmatrix} \left\{g(D_1^o) \cdot f(P^o(Q)) - g(D_1^w) \cdot f(P^w(Q))\right\} \cdot z_j \\ + g(D_2) \cdot \Delta Psus_j + g(D_{3t}) \cdot \left\{f(Pcol_j^o(Q)) - f(Pcol_j^w(Q))\right\} \cdot z_j \\ + g(D_{3d}) \cdot \left\{f(Pd_j^o(Q)) - f(Pd_j^w(Q))\right\} \cdot z_j \\ + g(D_{3inj}) \cdot \left\{f(Pinj_j^o(Q)) - f(Pinj_j^w(Q))\right\} \cdot z_j \end{bmatrix} dQ \cdot \tag{31}$$

6.3 Effect of Considering Cognitive Functions

First, results that we calculate ΔOB_j by each line j are shown in Figure 11. In this figure, each line is sorted in descending orders of ΔOB_j, and actually invested lines for three years are

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2 We assume the railway company is not suspended the train in advance before slope-failure.

marked in a circle. All lines are divided into 2 groups according to its gradient in the figure. Of the first group with large gradient, in almost all lines several lengths of slopes are invested, although it is not all of slopes in the line. The fact that even in the line that ΔOB_j is very large not all of slopes are invested implied that our hypothesis that decision-makers will maximize *PNPV* has to be modified. Of the second group with small gradient, invested lines seem to be randomly selected because benefits from investment are not so different.

Comparing these two groups with lengths of invested slopes, average length of the first group is 80m per 10km while that of the second group is 31m. Also in the first group, the length of invested slopes of each line is shown in Figure 12. The length of invested slopes of each line *j* during three years seems to be proportional to ΔOB_j, so decision-makers assumed to consider the benefit of each line at least in the group with large gradient because they can recognize the difference of benefits by lines. On the other hand, in the second group there is no particular relation between ΔOB_j and length of invested slopes. One of possible explanations is that they equally allocate the budget to their branch offices. Actually, strong relationship between the amount of investment of branch offices and their total lengths of railroads can be observed.

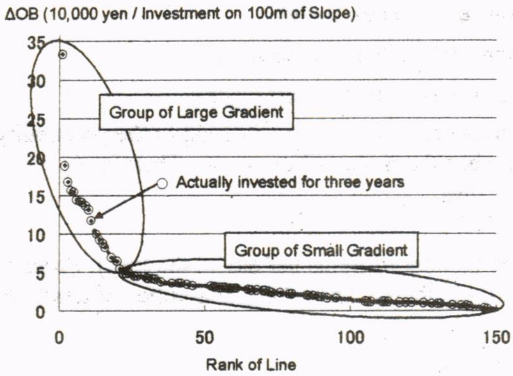

Figure 11. ΔOB_j of Each Line *j*

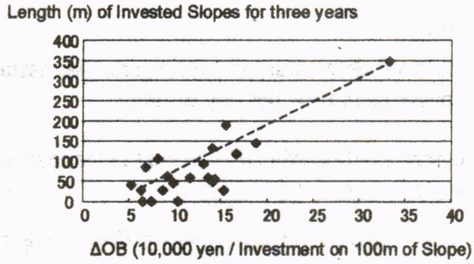

Figure 12. ΔOB and Lengths of Invested Slopes in the First Group

Because Eq.(31) is too complicated to estimate cognitive functions, in following section, a kind of sensitivity analysis is shown. Three hypothetical cognitive functions are assumed from our past study (2000) and result of previous chapters.

i) Recognition on frequency of rainfall doesn't depend on locality. That is, in Eq.(22), $a_j \equiv 79.7, b_j \equiv 2.36$ (the rainfall data of Tokyo area) in all lines. Any other cognitive functions are not considered.

ii) Only loss of death is overestimated as ten times. That is, in Eq.(31), $g(D_{3d}) = 10 \cdot D_{3d}$ and any other cognitive functions are not considered.
iii) Consideration of the progressive effect of loss. That is, in Eq.(31), $g(D) = D + D^2$(yen) in all cognitive loss functions, and cognitive frequency function is not considered.

On above three hypotheses, the summations of ΔPB_j are calculated. Because the amounts of benefits are different by each hypothesis, we compare the rate of ΔPB_j out of total benefits on the assumption that all slopes are invested. If the rate of a hypothesis is higher than that of an original case (it is summation of ΔOB_j), the hypothesis is more explainable to actual investments than without any consideration of cognitive functions. From results shown in Figure 13, the first hypothesis (cognitive frequency is equal among all regions) is rejected while the last two hypotheses (both is common in that cognitive loss is larger than monetary loss) are adopted.

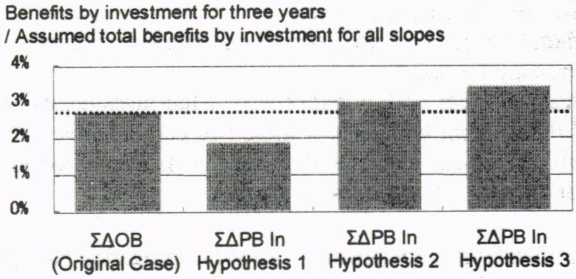

Figure 13. Comparison of the Rate of Benefits by Investment for Three Years out of Assumed Total Benefits by Investment for All Slopes

7. CONCLUSION

In this paper, we discussed decision-makers' cognitive effects on frequency and loss against disaster / accident risk in mitigation investments.

At first, we showed the definition of cognitive effects and how to measure cognitive frequency and cognitive loss using actual disaster mitigation investment data is theoretically shown. Secondly, we actually measured cognitive frequency and cognitive loss with three case studies: anti-accident traffic signal improvement investments on intersections, anti-flood reinforcement investments on river-embankments and anti-slope-failure investments on railway infrastructures. As a result, we obtained following implications by each case study.

i) from anti-traffic-accident investments;
- For the injured, amount of cognitive loss are nearly equal to amount of monetary loss, while for the dead, the cognitive loss is 5 times the monetary loss.
- When actual frequency per annum is under 0.001, cognitive frequency is bigger than actual frequency, and in other cases cognitive frequency is smaller than actual frequency. Because this criterion corresponds to the frequency that people are killed or very heavily injured at low-frequent intersections, decision-makers seem to put an important on equality among regions regardless of the frequency of accidents.

ii) from anti-flood investments;
- Cognitive loss is at least double as monetary loss, although a gradient of the CLF gradually decreases as monetary loss increases. Because embankments are needed to keep the same disaster-mitigation level in all areas, they would decide the disaster-mitigation

level so that catastrophic loss can be avoided even if the worst case happens.
- Cognitive frequency is only around 1/100 of actual frequency. We deduce the frequency of flood is much underestimated in low frequencies, around 10^{-6} per annum.

iii) from anti-slope-failure investments;
- As like as results from above two case studies, considering cognitive effects on loss of slope-failure is more likely to explain actual anti-slope-failure investment than without any consideration of cognitive effects.
- Consideration of the locality of each area is more likely to explain actual anti-slope-failure investment than without any consideration of locality.

From these results, common implications through three case studies are as following;

A) Progressively cognitive effect on loss of disaster / accident risks can exist. At least, actual results of decision-making can be explained more strongly.
B) Especially, the cognitive loss by the death very larger than the monetary loss due to its catastrophic and irreversible characteristics.
C) In the case that frequency is very low, cognitive frequency of disaster / accident risks is much smaller than actual frequency.
D) Decision-maker may consider both effectiveness of the investments and fairness among local areas. Equilibrium point to balancing these two contradictive viewpoints will differ by each case. One of critical elements may be the difference of loss between where disaster happens and where disaster does not happen.

In many cases, actual investments for disaster / accident mitigation are pragmatically made, based on accumulated experiences. However, as we have discussed in this paper, several unconscious but common cognitions about fundamental characteristics of risks may exist across various disaster / accident risks. By accumulating these discussions, we can obtain some implications when we have to take some brand-new or less-experienced measures against disaster / accident risks, which have never acquired from decision-makers' experience itself.

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