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ORIGINAL PAPER

Quantitative Evaluation of Flood Control Measures and Educational Support to Reduce Disaster Vulnerability of the Poor Based on Household-level Savings Estimates

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Abstract
In developing countries, where budget constraints make it difficult to invest in disaster risk reduction, disasters worsen the poverty trap. To alleviate poverty by reducing the risk of disasters, not only the immediate direct impacts of disasters but also their long-term and indirect impacts should be considered. However, since the effects of individual policies are often evaluated based on the extent of damage reduction, the impact on the poor, who have few assets and thus small losses, is generally ignored. Here, we aimed to quantitatively evaluate the effects of flood control measures and educational support in terms of the flood vulnerability of the poor at the household level. We constructed a model to calculate the savings of individual households and used the flood damage-to-savings ratio to determine their flood vulnerability. Next, we estimated the extent to which the flood vulnerability is reduced by various policies. We found that educational support is suitable for reducing the flood vulnerability of the poor cost-effectively, especially when the budgets are small. Gini coefficient predictions confirmed that educational support is effective in reducing income inequality. The novelty of this study is that it quantitatively links flood damage, savings, and education, which are factors that affect the flood vulnerability of the poor, and it compares the effects of various flood control measures and educational support at the household level in terms of the flood vulnerability. While the model was developed using household survey data from Bago, Myanmar, the framework should be applicable to other regions as well.

Keywords Poverty · Flood vulnerability · Flood control · Educational support · Savings · Inequality

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Introduction

As poverty eradication is the first in the list of sustainable development goals (SDGs), improving the lives of the poor is necessary for sustainable development. However, the significant losses that the poor suffer from natural disasters are an obstacle to this goal (Guterres 2019). For example, it is estimated that, on average, more than 25 million people fall into extreme poverty each year owing to floods and droughts alone (Hallegatte et al. 2017). The poor are often severely affected because they live on lands and in houses that are vulnerable to disasters (Brouwer et al. 2007). Moreover, they often do not have significant savings, which can cause them to fall into debt and make it difficult to invest in their businesses and education (Collins et al. 2009; Linnerooth-Bayer and Hochrainer-Stigler 2015; Janzen and Carter 2013). As a result, it becomes extremely difficult for them to break the cycle of poverty (Hallegatte et al. 2020; Rentschler 2013; Carter et al. 2007; Shimomura 2020; Sen 2003; Dube et al. 2018; Banerjee and Duflo 2007).

Floods are particularly devastating, causing the largest cumulative global economic losses of any natural disaster since 1950 (Podlaha et al. 2020). Furthermore, it is estimated that global exposure to floods will more than triple by 2050, not only because climate change is expected to intensify floods but also because populations and economic assets in flood-prone areas are expanding (Jongman et al. 2012; McGranahan et al. 2007). Since climate change worsens the exposure of the poor in particular (Winsemius et al. 2018), there are concerns that future floods will lead to greater inequality.

However, since the effects of disaster risk reduction investments do not actualize over short periods and are difficult to evaluate quantitatively because of future uncertainties, disaster risk reduction measures are not prioritized as policies in developing countries with limited budgets (Watson et al. 2015; de Ruig et al. 2019). In addition, even when investments are made for disaster risk reduction, the effects of the individual policies are often evaluated in terms of benefits to the overall region (Ward et al. 2017), and the impact on the poor, whose assets and flood damages are small to begin with, is likely to be ignored (Masozera et al. 2007; Rao et al. 2017; Hallegatte and Rozenberg 2017). Moreover, although the poor fall into the trap of long-term poverty because of disasters, cost–benefit analyses of disaster risk reduction investments often focus only on the direct losses caused by disasters and do not consider the indirect effects on the long-term improvements in the livelihood of the poor (Kind et al. 2020; van Hattum et al. 2021). For these reasons, some policies may even increase the vulnerability of the poor and contribute to widening inequality (Pelling and Garschagen 2019). In addition, Thacker et al. (2019), who analyzed the impact of infrastructure on the SDGs, found that the indirect impact can be as high as three times the direct impact. Therefore, to quantitatively evaluate disaster risk reduction investments, it is necessary to determine their effectiveness in not only reducing the losses in the event of a disaster but also with respect to long-term poverty eradication.

Furthermore, in recent years, it has become clear that, in addition to flood control measures, educational support is effective in alleviating the poverty caused by floods (Masozera et al. 2007; Fang et al. 2016; Tahira and Kawasaki 2015; Kawamura and Kawasaki 2018). The poor often have low levels of education and are therefore forced to work in unstable, low-income jobs. This is one of the main reasons for the inequality. Therefore, if educational support were to be made equally available to the households that have not been able to afford education, the poor would have a better chance of finding stable jobs. This would make it easier for them to increase their savings and reduce their flood vulnerability. In addition, since the poor are often forced to drop out of school due to disasters (Maccini and

Yang 2009; Ferreira and Schady 2008; Baez et al. 2010; Cadag et al. 2017), educational support would be effective. However, no study has quantitatively confirmed this effect.

In this study, we quantitatively evaluated various policies for helping the poor decrease their flood vulnerability and compared the effects of flood control measures and educational support, which are considered effective strategies for reducing flood vulnerability. For this purpose, a model was constructed to calculate the savings related to the flood vulnerability of each household. The model estimated who would be affected by floods and to what degree by determining the changes in the household economy instead of changes in the economy of the entire region. In addition, instead of focusing on the damage caused by a single flood, we focused on the long-term changes in savings, considering the impact of frequent floods and the livelihood improvement for each household based on the savings. By combining the savings determined using this model with the results of inundation calculations based on various flood control measures, we could assess the extent by which the flood vulnerability of each household, as defined in this study, would be reduced. Furthermore, we also estimated the changes in income inequality owing to individual policies.

Borgomeo et al. (2017) had quantified the negative impact of floods on poverty. They analyzed the impact of floods on agricultural income as well as the resulting changes in household assets in the coastal areas of Bangladesh and found that floods exacerbate poverty. Based on this study, Barbour et al. (2022) estimated the long-term effects of infrastructural features such as embankments. However, these studies neither considered the changes in the living conditions as determined based on the assets of the individual households nor addressed inequality at the household level.

Hallegatte et al. (2017) also attempted to assess the losses experienced by the poor whose livelihoods were severely affected by disasters. They did this by defining the “well-being losses” based on the reduction in consumption during the recovery period after the disaster. Furthermore, case studies that used this index have shown that the magnitude of asset losses during disasters does not match that of the loss in well-being (Markhvida et al. 2019; Walsh and Hallegatte 2019). However, these studies did not attempt to estimate the effects of specific measures.

Poverty is a multifaceted problem that involves not only material poverty, represented by a lack of money, but also physical weakness, isolation, vulnerability, and powerlessness (Chambers 1983). This study aimed to approach poverty reduction from the aspects of both material poverty and disaster vulnerability.

Methodology

Target Areas for Case Study

In this study, four villages (Tar Wa Bu Tar, Kun Paung, Let Pan Win, and Htan Pin Chaung) in Bago District, Myanmar, were selected as the case study areas. Myanmar is classified as a least-developed country, where poverty is a major problem. It is also the country second-most affected by natural disasters in the 20-year period from 1999 to 2018 (Eckstein et al. 2019), and natural disasters are an obstacle to poverty eradication. Furthermore, climate change is expected to increase the flood risk in Myanmar, worsening both their intensity and frequency (Hirabayashi et al. 2013). All four villages are in the Bago River basin, an area that experiences floods almost every year because of the monsoon in the rainy season.

Yamagami (2020) demonstrated that some parts of the target areas experienced over 40 cm flooding every year from 1985 to 2015, with over 1 m flooding in 29 of the 31 years.

Development of Savings Estimation Model

To evaluate the flood vulnerability of individual households, a savings estimation model was developed, as shown in Fig. 1. The model estimates the following four socioeconomic factors annually for each household in the order shown: income, flood damage, savings, and educational investment.

Initially, we used the survey data for 416 households collected in 2019 by Shimomura (2020), the future GDP projections reported by Riahi et al. (2017) and Dellink et al. (2017), and the future population projections reported by KC and Lutz (2017) to determine the annual income of each household. Based on the GDP and population projections, the annual rate of change in the GDP per capita was calculated and multiplied by the income of each household in 2019. Although there are various possible patterns for the changes in the GDP and population, in this study, we used the results of the projections for the intermediate scenario, SSP2. Table 1 shows the descriptive statistics on the socio-economic factors of the sample used in the analysis.

Next, using the inundation calculations performed by Yamagami (2020) for the same area, we estimated the flood damage for each household based on its income as well as the house structure and materials used as reported in the household survey data. As shown in Eqs. (1a)–(1c), the damage functions developed by Win et al. (2018) were used to calculate each household's house, asset, and income losses, respectively. As for the precipitation, we assumed RCP4.5, which is the intermediate scenario for climate change. In the equation, HD is the amount of damage inflicted on the household's house (kyats), HV is the price of the house (kyats), FD is the flood depth (m), FH is the floor height from the ground (m),

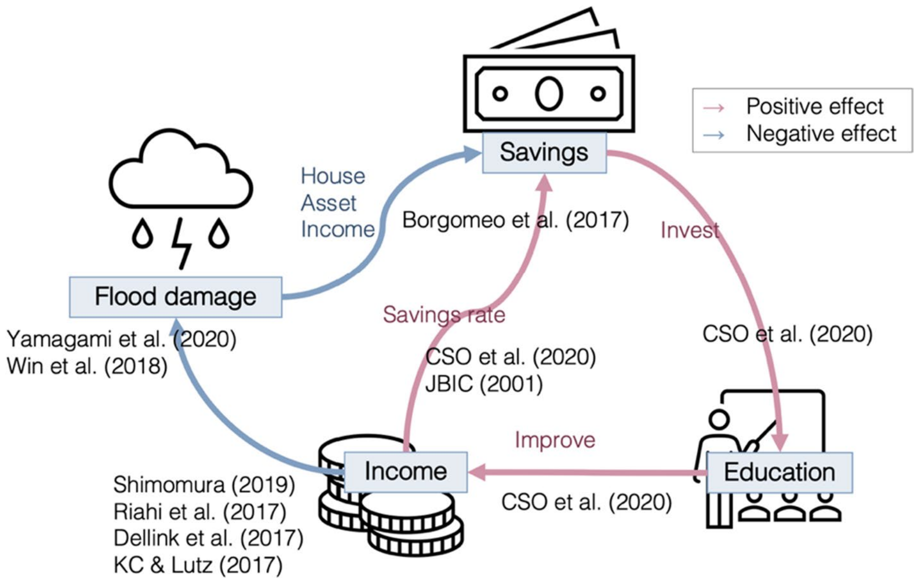

Fig. 1 Overview of developed savings estimation model

Table 1 Demographic information by economic level for the target area (%) (Recalculated based on Shimomura (2020)) (n=2095)

	Low-income (n = 744)	Middle-income (n = 952)	High-income (n = 365)
Gender			
Male	45.7	43.7	44.1
Female	54.3	56.3	55.9
Occupation			
Unemployed	30.8	24.5	25.2
Student	31.2	22.8	17.5
Government/factory employee/professional self-employed	8.9	15.3	15.6
Other self-employed	15.5	17.7	31.5
Daily laborer	11.4	19.0	6.8
Other	2.3	3.89	3.3
Education level			
Under middle	69.4	59.9	44.3
High	20.8	23.3	29.5
Specialty/University or higher	10.3	16.7	26.2

and x and y are dummy variables for the building materials (x_1: brick, x_2: wood, x_3: bamboo) and the presence/absence of soil erosion (y_1: no, y_2: yes). Furthermore, AD is the loss of each household's asset (kyats), AV is the price of the asset (kyats), and a is a dummy variable for the house structure (a_1: one story, a_2: two stories, a_3: stilt). In addition, IL is the loss of income of each household (kyats), HI is the annual income of the household (kyats), FDR is the number of days of inundation (days), and b is a dummy variable for the job category (b_1: daily/unstable job, b_2 full-time/stable job). The maximum annual inundation depth was used, regardless of the number of floods, because households tend not to repair or rebuild their houses during the monsoon season but wait until the end of the rainy season. With respect to the presence of soil erosion, we assumed that households within a 50-mile radius of the riverbank are affected by soil erosion, in keeping with Yamagami (2020). For the number of days of inundation, we used the number of days with inundation greater than 0.3 m, because we assumed that an inundation depth of more than 0.3 m would make it difficult to move safely (Kramer et al. 2016) and thus prevent commuting.

$$\mathrm{HD} = \mathrm{HV} \times \exp\left(1.930\mathrm{FD} - 0.320\mathrm{FH} + 0.0\mathrm{x}_1 + 0.887\mathrm{x}_2 + 0.965\mathrm{x}_3 + 0.0\mathrm{y}_1 + 0.264\mathrm{y}_2 - 5.565\right) \tag{1a}$$

$$\mathrm{AD} = \mathrm{AV} \times \exp\left(2.577(\mathrm{FD} - \mathrm{FH}) + 0.0\mathrm{a}_1 - 0.552\mathrm{a}_2 - 0.284\mathrm{a}_3 - 5.549\right) \tag{1b}$$

$$\mathrm{IL} = \mathrm{HI} \times \exp\left(0.862\log(1.012\mathrm{FDR} - 2.716) + 0.243\mathrm{b}_1 - 0.274\mathrm{b}_2 - 5.905\right) \tag{1c}$$

In addition to the income and flood damages thus obtained, the savings rate was used to determine the annual savings of each household. This calculation was performed as shown in Eq. (2) using the same framework as that employed for asset estimation by Borgomeo et al. (2017). Here, $S(t)$ is the household savings in year t (kyats), φ is the savings rate, $I(t)$ is the income in year t (kyats), and $L(t)$ is the flood damage in year t (kyats), i.e., the sum of the losses related to the house, assets, and income. Since there is a strong positive correlation between the savings rate and income (Dynan et al. 2004), it is necessary to define the savings rates based on the economic levels of the households. However, as there are no data available on the savings rates by income in the target area, the savings rates were calculated based on the average savings rate for Myanmar (CSO et al. 2020) and the distribution of the savings rates by income groups for Cambodia (JBIC 2001), a neighboring country with a similar economic level. Based on the savings rates of the 10 income groups in Cambodia and their average value, we determined a multiple of how much each group could save relative to the average. This multiple was then multiplied by the average savings rate in Myanmar to establish the savings rate for each of the 10 income groups.

$$S(t) = S(t-1) + \varphi I(t) - L(t) \tag{2}$$

Finally, we determined whether a household invests in education based on the amount of savings. We assumed that, among the households whose savings exceeded the cost of middle school, those with investment choice rates would invest in education. In Myanmar, secondary education is free, but the cost of uniforms, books, and stationery, as well as donations and extracurricular tuition, are a significant burden for the poor (JETRO 2016). On average, the annual expenditure per student is 123,200 kyat (CSO et al. 2020). The investment choice rate was defined as the percentage of households that currently give up education because of a lack of money and was calculated based on the income levels reported by CSO et al. (2020). This is because households without access to education due to non-financial reasons are not likely to invest in education even if they could save. Based on the same data, we assumed that the households that invested in education would see their average income increase by a factor of 1.26 after the completion of secondary education.

Policy Evaluation Methods for Identifying Vulnerabilities of the Poor

To evaluate the effects of various flood control measures on long-term poverty alleviation, in addition to damage reduction at the time of disasters, the flood vulnerability at the household level was also considered. In this study, the “damage rate,” which is the ratio of the loss in each household’s savings because of flood damage, was used an indicator of flood vulnerability. Appropriate flood control measures naturally mitigate flood damage and reduce the damage rate. Furthermore, since they also make it easy for households to save, the resulting savings can be used to buffer the impact of future floods. In particular, for those households that are unable to access education because of a lack of money, the damage rate can be significantly reduced because they can expect to increase their savings further when the flood damage is reduced, and these savings, in turn, can be invested in education. In the same manner, educational support can also reduce the damage rate by increasing savings. Thus, we compared the effects of various flood control measures and educational support from the same perspective, namely, that of flood vulnerability.

The five flood control measures evaluated in this study were embankment, retention area, dredging & widening, early warning, and building elevation. It was assumed that the embankments are raised by 3.0 m, 12 km on the right bank and 5 m on the left bank near the target area. As for the retention area, it was assumed that a 10-km^2 retention area was set up upstream. With respect to dredging & widening, it was assumed that the riverbed is dredged to a depth of 1.5 m over a length of 6.5 km, and the river width is widened by 5.0 m over a length of 1.0 km. These three structural measures would affect the flood depth and the number of days of inundation as determined through the inundation calculations. Early warnings can reduce asset damage by 4.6% (Pappenberger et al. 2015) while building elevation can reduce the damage to house and assets by raising the floor height of all the households by 50 cm. Although these two measures do not affect the flood depth or the number of days of inundation, they were considered in the calculations performed using Eqs. (1a) and (1b) to determine the amount of damage experienced by each household. The measures to be considered and where they should be introduced were the same as that in the study conducted by Yamagami (2020), which was designed after consulting the local planners, and in reference to flood risk management projects with similar sizes of beneficiaries in low- or middle- income countries.

For educational support, support for secondary education was considered. Although many students in Myanmar are enrolled in primary education, the enrollment rates drop sharply for secondary education. Therefore, for households where children are unable to attend middle school for financial reasons, we considered providing all the expenses necessary to attend middle school for four years.

In this study, we assumed that these policies would be introduced in 2040 and calculated their impact until 2070. An overview of this methodology is shown in Fig. 2.

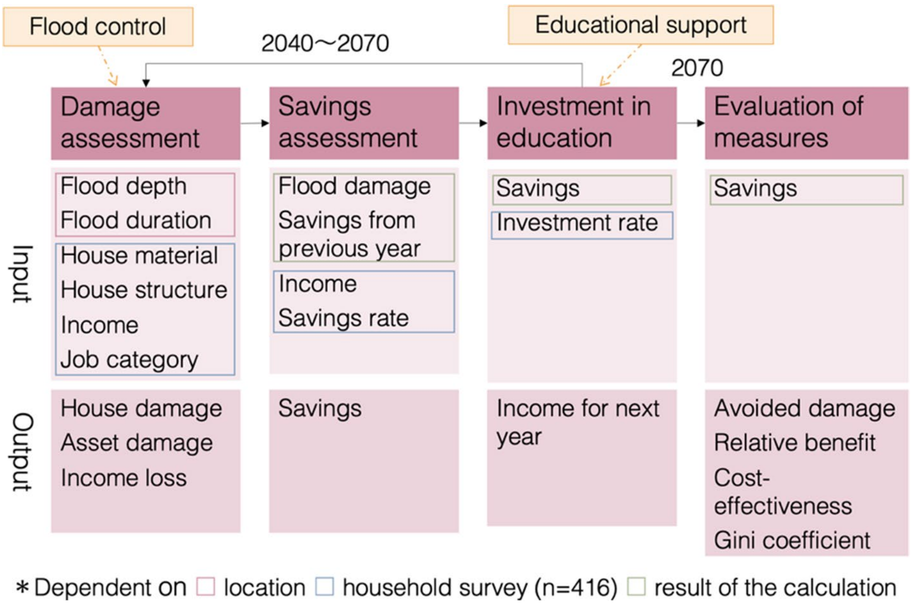

Fig. 2 Overview of methodology used in this study

Results

Flood Damage for Each Household in Absence of Policies

Figure 3 shows the total amount of damage caused by floods over 31 years for each household while Fig. 4 shows the damage rate, which was calculated by dividing the total damage by the amount of savings. The horizontal axes of the two figures show the rank of each household, sorted by income in ascending order. In other words, the households on the right of the figure have higher incomes. Figure 3 shows that the amount of flood damage tends to be smaller for households with lower income. This can be attributed to the fact that the poor have less to lose in the event of a flood because they have smaller incomes and fewer assets and live in cheaper houses. On the other hand, as can be seen from Fig. 4, the damage rate is expected to be higher for poor households with smaller savings, which quantitatively indicates the high flood vulnerability of the poor. Specifically, for households with an income in the bottom 10%, many households have damage rates as high as 40–80. Thus, to save 40–80 times as much as they should, they would need to reduce their daily expenditures significantly, which would be a severe burden.

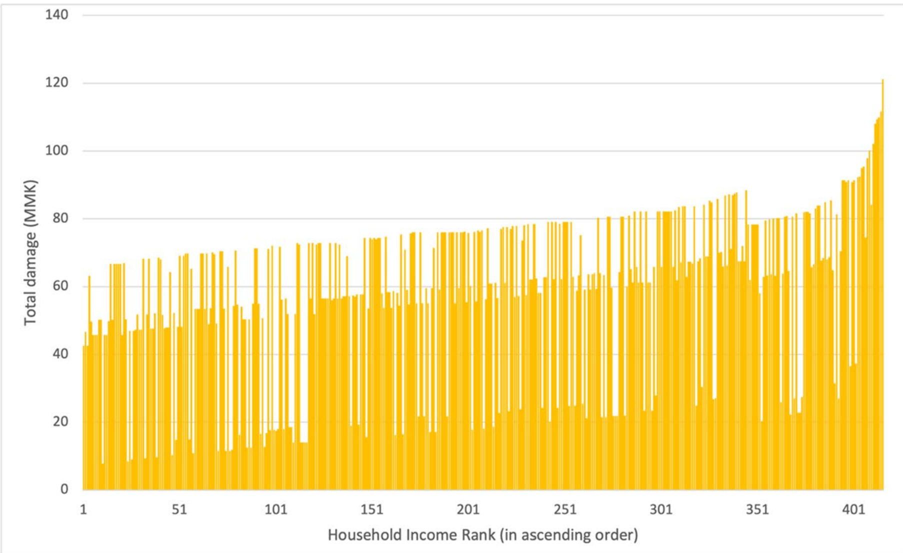

Fig. 3 Total flood damage over 31 years for individual households, sorted by household income

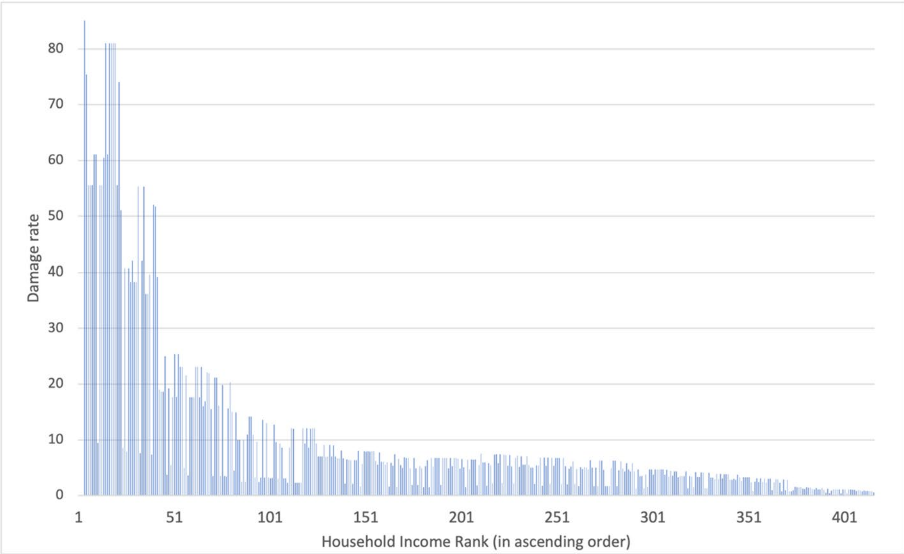

Fig. 4 Damage rate for individual households, sorted by household income

Comparison of Effects of Individual Policies

To begin with, the cost–benefit ratio for each policy is shown in Table 2. Here, the benefit is the sum of the reduction in the flood damage and the amount of increased income based on improvements in the education level. All six policies have a cost–benefit ratio of more than 1. In particular, the cost–benefit ratio of dredging & widening is the highest. In the case of educational support, the cost–benefit ratio is moderately high, because the benefit itself is small. However, its cost is extremely small too.

Next, the percentage reduction in the damage rate for the individual households was calculated for each policy. Table 3 shows the average percentage reduction in the damage rate for all 416 households and the average percentage reduction in the damage rate for the 41 households with income levels in the bottom 10% (hereafter referred to as the poor). In addition, to compare the cost-effectiveness of the policies, the percentage reduction divided by the cost is also shown. The percentage reduction in the damage rate was also the greatest for embankment, which had the largest benefit. On the other hand, educational support, whose benefit itself was the smallest among the six policies, was found to be moderately effective in reducing vulnerability. In addition, embankment significantly reduces the vulnerability of the nonpoor instead of the poor, since the percentage reduction in the damage rate for all households

Table 2 Cost-effectiveness of each policy calculated based on costs and benefits

	Embankment	Retention area	Dredging & widening	Early warning	Building elevation	Educational support
Benefit (MMK)	29,900	4330	17,100	790	16,800	621
Cost (MMK)	7500	3000	2300	600	4400	182
Cost-benefit ratio	4.0	1.4	7.4	1.3	3.8	3.4

Table 3 Percentage reduction in damage rate (indicator of flood vulnerability) for all households and for the poor by each policy

	Embankment	Retention area	Dredging & widening	Early warning	Building elevation	Educational support
Average for all households (%)	26.9	3.2	13.9	0.3	14.0	4.7
Average for the poor (%)	23.8	3.9	16.4	0.2	15.5	7.8
Average for all households/cost (%/BMK)	3.6	1.1	6.1	0.5	3.2	26.0
Average for the poor/cost (%/BMK)	3.2	1.3	7.1	0.3	3.5	42.8

was higher. On the other hand, the quantitative results also show that educational support contributes significantly to reducing the vulnerability of the poor. The results of the cost–benefit analysis show that educational support is highly effective. In fact, educational support is 13.5 times more cost effective than embankment and 6.0 times more cost effective than dredging & widening.

Discussion

Verification of Results Through Comparison with those of Previous Studies

To begin with, the results for flood damage are consistent with those of previous studies such as that by Hallegatte et al. (2017). Although the amount of damage caused to the poor by flooding itself is small, owing to their low assets and income, the negative impact of floods on their livelihoods is larger because of their low income and savings. These results also suggest that the negative impact of disasters on the poor is not readily reflected in macroeconomic analyses that focus on the extent of damage experienced by the region in general, while in fact they are the most severely affected. Therefore, to identify the policies suitable for mitigating the impact of floods on the poor, it is essential to not only focus on the damage reduction rate but also on flood vulnerability, as was done in this study.

Next, the results on the cost–benefit ratio calculations are compared with those of Yamagami (2020), who used the same inundation calculation results. The cost–benefit ratios calculated in this study were smaller than those reported by Yamagami (2020). This is because the benefits of improved income, which are accounted for as indirect benefits, were considered by Yamagami (2020). The following two factors explain the differences in the ratios. The first is that, in the above-mentioned study, the average income was used in the calculations instead of the income of each household, and the second is that it was assumed that living in an area that is less prone to floods improves the income regardless of one's financial situation. In contrast, in this study, the income of the group with the highest investment choice rate with respect to education was set very low based on the household survey data, and the poorest group was assumed to have no ability to invest in education even in the absence of flood damage. Therefore, it was difficult to improve the livelihoods through investments in education in general. Furthermore, even when the livelihoods were improved, the improvement in income was small and not reflected in the overall benefits to the community. We believe that there is room for further study on the effects of investment choice rates and the corresponding rate of income growth.

For the same reason, the relationships among the cost–benefit ratios of the various flood control measures were also different. In the previous study, the indirect benefits of all the policies were large, and the total benefits did not differ significantly. Thus, the cost–benefit ratio was generally larger for those policies with lower costs. On the other hand, in this study, the cost–benefit ratio tended to be larger for those policies that significantly reduced flood damage because the indirect benefits were not so large.

Finally, a cost–benefit ratio of 3.4 for educational support is generally consistent with those (2.2–3.7) proposed by Psacharopoulos (2014) for secondary education in Asia.

Effectiveness of Policy in Reducing Inequality

Using the savings estimation model developed in this study, we examined how economic inequality within a region changes as the income increases because of improvements in the education levels, as determined based on the Gini coefficient. Using the 416-households survey data, the current (2019) Gini coefficient was calculated to be 37.9%, which is 92nd in the World Bank's ranking of 167 countries, indicating greater inequality than the global average. In addition, according to the World Bank, Myanmar's national Gini coefficient was 30.7% as of 2017, ranking 28th in the world. This means that the inequality in Bago, Myanmar, is particularly severe. It was estimated that the Gini coefficient would change to 37.3% if embankments, which can reduce the vulnerability of the poor the most, were to be built and to 36.9% if educational support were to be provided. In addition, it was found that educational support reduced the Gini coefficient by 1.0%, placing it 85th in the world ranking of inequality.

As an additional analysis, we also calculated the change in the Gini coefficient while assuming that all the households received secondary education and support for higher education, instead of only those who wished to receive it, as was done in the initial part of this study. The results are shown in Fig. 5. Education contributes greatly to the reduction in inequality in the region. However, many households do not have access to education owing to reasons other than a lack of money, and very few households have

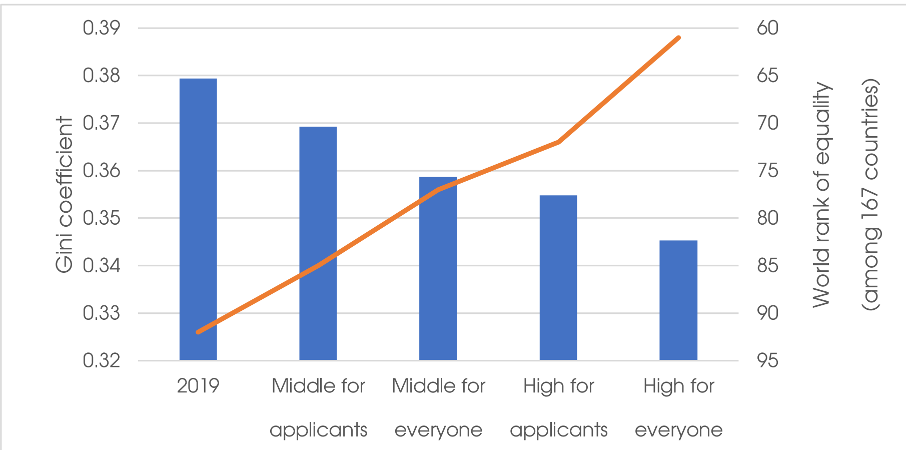

Fig. 5 Changes in Gini coefficient in region after educational support of different levels

access to higher education. Therefore, policies that encourage education in ways other than monetary subsidies are essential.

Sensitivity Analysis

Finally, to investigate the uncertainty of the model, a sensitivity analysis was performed. Of the various model parameters, we targeted the savings rate and conducted the same analysis by doubling and quintupling the savings rate, as it is an important parameter, even though it is not directly based on the household survey data collected from the target area. Figure 6 shows the cost–benefit ratio for each policy shown in Table 2 as recalculated using different savings rates while Fig. 7 shows the average percentage reduction in the damage rate for the poor corresponding to each policy shown in Table 3 as recalculated using different savings rates.

Figure 6 shows that the cost–benefit ratio increases as the savings rate increases. This is because when the savings rate is high, more households can invest in education, which is expected to increase their income. Therefore, the cost–benefit ratio increases in the case of the measures that are more effective in increasing the income of the poor as they also improve their education level, instead of those that reduce the damage itself. This result also suggests that encouraging people to save more will have some effect.

On the other hand, Fig. 7 shows that the percentage reduction in the vulnerability of the poor is almost independent of the savings rate. This indicates that the effects of additional flood control measures and educational support are not particularly large, because increasing the savings alone reduces the flood vulnerability. This suggests that the rate of reduction of the flood vulnerability as defined in this study is independent of the savings rate and has a high degree of certainty.

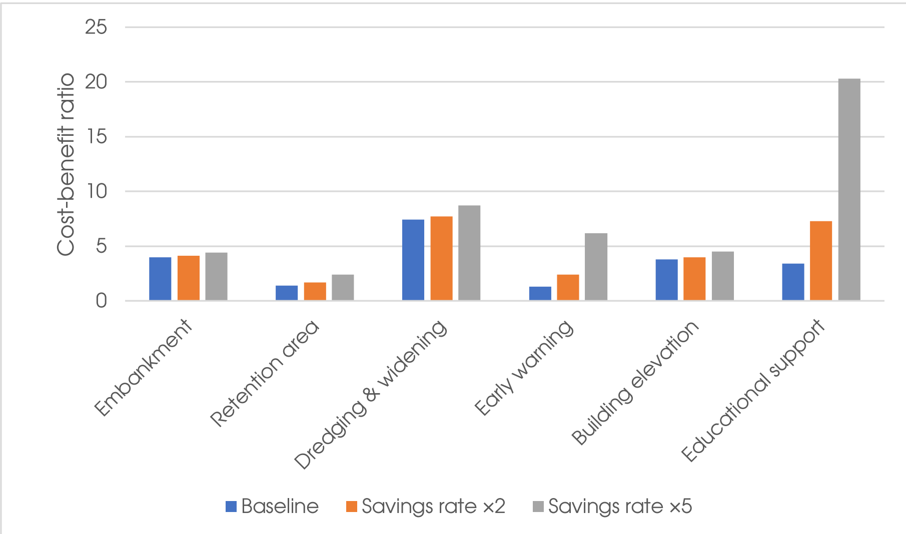

Fig. 6 Results of sensitivity analysis of cost-effectiveness of each policy

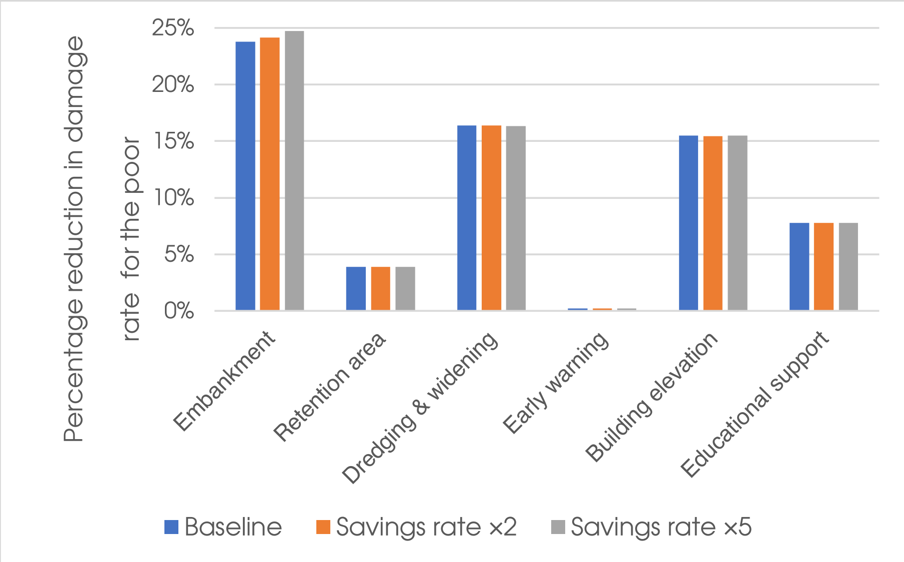

Fig. 7 Results of sensitivity analysis of average percentage reduction in damage rate for the poor

Policy Implications

Next, we discuss the appropriate policies under the conditions investigated in this study, given the results described above. Embankments have the greatest monetary benefit and lead to the greatest reduction in the vulnerability of the poor as well as that of the entire region (Table 3). However, the cost of embankments is enormous. Therefore, dredging & widening, which has the largest cost–benefit ratio (7.4), is the most appropriate method for ensuring cost-effectiveness (Table 2). Dredging & widening is also expected to reduce the vulnerability of the poor by 16.4% (Table 2).

On the other hand, in developing countries where budget constraints are particularly severe, educational support may be a good option. The cost–benefit ratio of educational support is 3.4, which is lower than those of dredging & widening, embankment, and building elevation (Table 2). However, for the entire region, the benefits exceed the cost. Educational support is a policy specifically designed to reduce the vulnerability of the poor who had previously given up on education. Not only does it reduce flood vulnerability, but it also contributes significantly to reducing income inequality within the region. Therefore, even though its absolute benefits may not be large, educational support may be effective in some areas because it can efficiently reduce the vulnerability of the poor with a small budget while also providing overall benefits.

Conclusions

Although natural disasters can cause serious damage and result in economic losses, especially to the poor, evaluations have rarely focused on the poor, whose losses may be small. Therefore, in this study, we aimed to quantitatively evaluate various disaster prevention policies in terms of the vulnerability of the poor and compare the effects of both flood control measures and educational support, which are effective in reducing flood vulnerability, at the household level. This comparison was possible only after quantitatively linking floods, savings, and education, which are factors that affect the flood vulnerability of the poor and quantifying the flood vulnerability based on the amount of savings.

The results suggest that educational support is also effective in reducing the flood vulnerability of the poor and is particularly economical owing to its low cost. This is a conclusion one could not have arrived at through cost–benefit analyses, which are usually used for policy evaluation. In other words, even if we do not have the budget for large-scale flood control measures, we should proactively reduce the vulnerability of the poor by supporting education.

In this study, owing to a lack of household survey data, some of the settings of the developed model were simplified or assigned values based on assumptions. Therefore, collecting more detailed household survey data would allow us to estimate the effects of disaster prevention policies more accurately. Furthermore, while the model employed in this study was developed using household survey data for Bago, Myanmar, the model framework and the method used for identifying the flood vulnerability should be applicable to other regions as well. Therefore, the next step would be to develop a more general assessment method using a larger household survey dataset and inundation calculation results for other regions.

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Data Availability The datasets generated and analyzed during the current study are not publicly available due to protection the privacy of the respondent but are available from the corresponding author on reasonable request.

Declarations

Competing Interests The authors have no relevant financial or non-financial interests to disclose.

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