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Regional Climate Resilience as a Mediating Pathway Between Heavy Rainfall Adaptation Technologies and Flood Damage Reduction: Evidence from South Korean Municipalities

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Abstract

Climate change is increasing the frequency and intensity of heavy rainfall, creating growing challenges for regional flood risk management. Although adaptation technologies such as green roofs, permeable pavements, and rainwater retention tanks have been widely implemented, limited empirical evidence exists on the resilience mechanisms through which these technologies reduce flood damage and why their effectiveness varies across regions. This study develops a resilience-mediated analytical framework linking adaptation technologies to reductions in heavy rainfall damage through two dimensions of regional climate resilience: adaptive capacity and vulnerability reduction capacity. Using panel data for 229 municipalities in South Korea from 2016 to 2022, we first estimate how adaptation technologies strengthen each resilience dimension and then examine how these improvements reduce observed flood damage. The resulting damage reductions are translated into economic benefits using Benefit–Cost Ratio (BCR) and Cost-Effectiveness Threshold (CET) analyses.

The results show that adaptation technologies strengthen regional resilience through distinct pathways. Green roofs and rainwater retention tanks are primarily associated with adaptive capacity, whereas permeable pavements mainly improve vulnerability reduction capacity. Both resilience dimensions are associated with lower heavy rainfall damage, although their relative importance varies across municipalities. Economic evaluation further reveals substantial regional differences in the cost-effectiveness of adaptation technologies, indicating that region-specific technology portfolios provide more efficient adaptation than uniform investment strategies. By integrating resilience analysis with economic evaluation, this study provides an empirical framework for prioritizing regional adaptation investments under increasing climate risks.

Keywords: Heavy rainfall; Climate resilience; Adaptation technologies; Flood damage; Regional adaptation

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1. Introduction

Climate change has substantially increased the frequency and intensity of extreme precipitation events worldwide, resulting in escalating flood damages, infrastructure disruptions, and socioeconomic losses (IPCC 2014, 2022). Consequently, governments have invested heavily in adaptation measures designed to reduce flood risks and strengthen regional climate resilience to increasingly frequent hydrological extremes.

Heavy rainfall adaptation technologies such as green roofs, permeable pavements, and rainwater retention tanks have been widely adopted to reduce urban flood risks (Li et al. 2019; Azhar et al. 2025). Previous studies have demonstrated their hydrological performance, including runoff reduction, infiltration enhancement, and stormwater retention (Koo et al. 2013; Berndtsson 2010). However, technology performance often varies across regions because adaptation outcomes depend not only on engineering design but also on local rainfall, land-cover, catchment, and infrastructure conditions (Qin et al. 2013; Golden and Hoghooghi 2018).

Consequently, climate resilience has emerged as a central concept in adaptation research. Rather than viewing disaster losses solely as a function of hazard intensity, resilience emphasizes the capacity of communities and institutions to anticipate, absorb, adapt to, and recover from climate-related disturbances (IPCC 2012; Zevenbergen et al. 2020). At the regional level, resilience is shaped by place-based vulnerability and adaptive capacity (Cutter et al. 2008; Engle 2011). From this perspective, adaptation technologies may contribute to flood-damage reduction by strengthening regional resilience in addition to their direct engineering functions.

Despite growing research on flood damage prediction, resilience assessment, and engineering evaluation of adaptation technologies, three important limitations remain. First, previous studies largely estimate relationships between rainfall and damages without examining the mechanisms through which adaptation investments reduce losses (Adelodun et al. 2023; Song et al. 2025). Second, resilience is commonly measured using composite indices that compare regional conditions and spatial differences (Cutter et al. 2010; Yoon et al. 2016; Kim and Song 2018; Seo et al. 2022; Baik et al. 2024). However, such approaches often treat resilience as a static index rather than as an intermediate process linking adaptation measures to disaster outcomes (Carvalhoes et al. 2021; Laurien et al. 2022). Moreover, resilience indicators have rarely been empirically validated against observed disaster outcomes (Shiozaki et al. 2024). Third, economic evaluations often rely on engineering simulations rather than observed regional damage data, providing limited evidence on the real-world effectiveness of adaptation technologies across heterogeneous municipalities (Jee et al. 2023).

To address these gaps, this study develops a resilience-mediated analytical framework that links heavy rainfall adaptation technologies to flood damage reduction through two dimensions of regional climate resilience: adaptive capacity and vulnerability reduction capacity. Using panel data from 229 municipalities in South Korea during 2016–2022, we estimate how adaptation technologies strengthen these resilience dimensions, how resilience reduces observed flood damages, and how these effects translate into economic benefits using benefit–cost ratio (BCR) and cost-effectiveness threshold (CET) analyses.

This study makes three contributions. First, it demonstrates empirically that adaptation technologies reduce flood damage through distinct resilience pathways rather than a single direct mechanism. Second, it integrates technology deployment, multidimensional climate resilience, and observed flood damages within a unified empirical framework using nationwide municipal panel data. Third, it combines resilience analysis with economic evaluation to identify region-specific adaptation strategies that improve investment efficiency under increasing

climate risks.

2. Analytical Framework and Methodology

2.1 Conceptual and Empirical Framework

Climate adaptation technologies reduce heavy rainfall damage not only through their physical functions but also by strengthening the resilience of regional systems. Accordingly, this study conceptualizes regional climate resilience as the mechanism linking adaptation technologies to observed flood damage. Fig. 1 illustrates the analytical framework.

Fig. 1 Analytical framework of the two-stage economic evaluation

[Insert Fig. 1 here]

Heavy rainfall adaptation technologies—including green roofs, permeable pavements, and rainwater retention tanks—are assumed to influence two complementary dimensions of regional climate resilience: adaptive capacity and vulnerability reduction capacity. Adaptive capacity refers to the ability of municipalities to anticipate, respond to, and recover from heavy rainfall events through institutional, socioeconomic, and infrastructural resources. Vulnerability reduction capacity reflects improvements in physical and environmental conditions that reduce exposure and susceptibility to flood damage before hazards occur. Distinguishing these two dimensions enables the identification of technology-specific resilience pathways rather than treating resilience as a single composite construct.

To operationalize this framework, the empirical analysis follows a two-stage approach. In the first stage, adaptation technologies are linked to the physical components of adaptive capacity and vulnerability reduction capacity to estimate how different technologies strengthen distinct resilience dimensions. Because each technology addresses different aspects of flood risk management, they are expected to contribute to regional resilience through different mechanisms.

In the second stage, the predicted resilience measures obtained from the first-stage models are related to observed heavy rainfall damage. This approach reflects the assumption that adaptation technologies influence disaster losses indirectly by improving regional resilience rather than through a single direct effect. Estimating resilience separately from disaster outcomes also helps distinguish the contribution of adaptation investments from other environmental and socioeconomic factors affecting flood damage.

Finally, the estimated reductions in heavy rainfall damage are translated into monetary benefits and compared with annual technology costs using Benefit–Cost Ratio (BCR) and Cost-Effectiveness Threshold (CET) analyses. Within this framework, economic evaluation represents the final application of the resilience analysis, providing evidence for identifying region-specific adaptation strategies under heterogeneous climatic and socioeconomic conditions.

2.2. Empirical Models and Economic Evaluation

Following the conceptual framework described in Section 2.1, the empirical analysis consists of two sequential stages (Fig. 1). The first stage estimates how heavy rainfall adaptation technologies strengthen regional climate resilience, while the second stage examines how these resilience improvements reduce observed heavy rainfall damage. The resulting damage reductions are subsequently converted into monetary benefits for economic evaluation.

Stage 1. Effects of adaptation technologies on regional climate resilience

Regional climate resilience is represented by two complementary dimensions: adaptive capacity and vulnerability reduction capacity. Separate fixed-effects models are estimated for each resilience dimension as functions of adaptation technology adoption as following equations (1) and (2).

$$\ln(X1_{physical,it}) = \delta_0 + \delta_1 pmpv_{it} + \delta_2 grroof_{it} + \delta_3 retent_{it} + u_{it} + \varepsilon_i + \theta_t \quad (1)$$

$$\ln(X2_{physical,it}) = \gamma_0 + \gamma_1 pmpv_{it} + \gamma_2 grroof_{it} + \gamma_3 retent_{it} + u'_{it} + \varepsilon'_i + \theta'_t \quad (2)$$

where $X1_{physical,it}$ denotes physical component of adaptive capacities for municipality i in year t and $X2_{physical,it}$ denotes physical component of vulnerability reduction capacities for municipality i in year t . Explanatory variables include adoption quantities (units or area) of each of the three heavy rainfall adaptation technologies: permeable pavements ($pmpv_{it}$), green roofs ($grroof_{it}$), and rainwater retention tanks ($retent_{it}$). The terms ε_i and ε'_i represent municipality fixed effects, while θ_t and θ'_t represent year fixed effects. The error terms u_{it} and u'_{it} capture unobserved factors that are not explained by the technology variables or the fixed effects in equations (1) and (2), respectively. These error terms are assumed to have zero conditional means and constant conditional variances, such that $E(u_{it} | Tech_k) = 0$, $Var(u_{it} | Tech_k) = \sigma_u^2$ and $E(u'_{it} | Tech_k) = 0$, $Var(u'_{it} | Tech_k) = \sigma'^2_u$. All regressions use log-transformed dependent variables to reflect diminishing marginal effects of technology adoption on physical resilience components.

The estimated coefficients are used to derive the predicted adaptive capacity and vulnerability reduction capacity indices, which summarize the resilience improvements attributable to adaptation technologies. Based on the regression coefficients (δ_k , γ_k), we calculate the marginal effect of each technology k ($Tech_k$) on adaptation or vulnerability reduction as equations (3) and (4).

$$\frac{\partial X1_{physical,it}}{\partial Tech_k} = \delta_k \times X1_{physical,it}, \quad \text{where } k = 1,2,3 \quad (3)$$

$$\frac{\partial X2_{physical,it}}{\partial Tech_k} = \gamma_k \times X2_{physical,it}, \quad \text{where } k = 1,2,3 \quad (4)$$

Using these predicted values, we construct the predicted adaptive capacity index ($\widehat{X1}_{it}$) and the predicted vulnerability reduction capacity index ($\widehat{X2}_{it}$) by summing across all sub-sector indices including economic, social, physical, governance and human domains as equations (5) and (6). The detailed composition of each domain is presented in Tables 3 and 4.

$$\widehat{X1}_{it} = X1_{economy,it} + X1_{social,it} + \widehat{X1}_{physical,it} + X1_{governance,it} + X1_{human,it} \quad (5)$$

$$\widehat{X2}_{it} = X2_{economy,it} + X2_{social,it} + \widehat{X2}_{physical,it} + X2_{governance,it} + X2_{human,it} \quad (6)$$

Stage 2. Effects of resilience on heavy rainfall damage

The second stage evaluates how predicted improvements in regional climate resilience are associated with annual recorded heavy-rainfall damage costs. The dependent variable is defined as the sum of reported direct

damage and recovery expenditures for each municipality-year. Inspection of the administrative records revealed cases in which direct damage was recorded as zero despite positive recovery expenditures, indicating that individual components of economic loss may not always be fully captured in the direct-damage records. More generally, very small or unreported losses may be recorded at the lower reporting bound rather than at their underlying values. Accordingly, zero total-damage observations are treated as potentially left-censored at zero, and a panel Tobit model is employed.

Rather than using the observed resilience indices directly, the model incorporates the predicted adaptive-capacity and vulnerability-reduction-capacity indices obtained from the first-stage models, thereby focusing on the components of resilience systematically associated with adaptation-technology adoption.

This study considered a model where log-transformed heavy rainfall damage ($\ln(y_{it})$) is explained by the log-transformed predicted values of adaptive capacity ($\ln(\widehat{X1}_{it})$), predicted values of vulnerability reduction capacity ($\ln(\widehat{X2}_{it})$), and meteorological variables ($X3_{it}$, $X4_{it}$). Here, the meteorological variables $X3_{it}$ and $X4_{it}$ represent the heavy rainfall variables for period t and municipality i , respectively, denoting the total annual precipitation and the daily average precipitation on heavy rainfall days. The term α_i captures unobserved municipality-level heterogeneity that is not directly observed but may affect heavy rainfall damage costs. The error term e_{it} represents time-varying unobserved factors that are not explained by the resilience variables or meteorological controls. It is assumed to have a zero conditional mean and finite variance, and, under the standard Tobit maximum likelihood framework, is assumed to follow a normal distribution. The resulting heavy rainfall damage cost model is given by equation (7).

$$\ln y_{it}^* = \beta_0 + \beta_1 \ln(\widehat{X1}_{it}) + \beta_2 \ln(\widehat{X2}_{it}) + \beta_3 X3_{it} + \beta_4 X4_{it} + \alpha_i + e_{it}$$

$$y_{it} = \begin{cases} y_{it}^* & \text{if } y_{it}^* > 0 \\ 0 & \text{if } y_{it}^* \leq 0 \end{cases} \quad (7)$$

The estimated coefficients indicate the extent to which improvements in adaptive capacity and vulnerability reduction capacity are associated with reductions in observed heavy rainfall damage after controlling for meteorological conditions.

Economic evaluation

The estimated reductions in heavy rainfall damage are translated into monetary benefits by combining the first-stage technology effects with the second-stage resilience effects. Municipality-specific benefits are obtained by multiplying the estimated marginal damage reductions by observed damage costs.

The marginal economic benefit of each adaptation technology is calculated by combining the estimated effects from the first-stage resilience model with the resilience coefficients obtained from the second-stage damage model. The resulting marginal effect represents the expected reduction in economic damage associated with an additional unit of technology deployment while accounting for the resilience pathways identified in the empirical framework.

The marginal benefits of an additional unit of technology k in municipality i and year t are then derived by combining the marginal effects of technology on policy capacities (from Stage 1) with the marginal effects of those capacities on damage (from Stage 2).

$$\begin{aligned}
Benefit_{k,it} &= \frac{\partial \ln(\widehat{X1}_{it})}{\partial Tech_k} \times \frac{\partial y_{it}}{\partial \ln(\widehat{X1}_{it})} + \frac{\partial \ln(\widehat{X2}_{it})}{\partial Tech_k} \times \frac{\partial y_{it}}{\partial \ln(\widehat{X2}_{it})} \\
&= \delta_k \times \frac{\widehat{X1}_{physical,it}}{\widehat{X1}_{it}} \times \beta_1 \times y_{it} + \gamma_k \times \frac{\widehat{X2}_{physical,it}}{\widehat{X2}_{it}} \times \beta_2 \times y_{it} \quad (8)
\end{aligned}$$

The predicted reduction in heavy rainfall damage derived from this model constitutes the basis for the subsequent economic evaluation. Economic performance is then evaluated using two complementary indicators: the Benefit–Cost Ratio (BCR) and the Cost-Effectiveness Threshold (CET).

The BCR for adaptation technology j is calculated as $BCR_j = Total\ Benefit_j / Total\ Cost_j$, where $Total\ Benefit_j$ denotes the estimated annual economic benefit derived from resilience-mediated reductions in heavy rainfall damage, and $Total\ Cost_j$ represents the corresponding annualized implementation and maintenance cost. Although the BCR provides a useful measure of economic efficiency, it does not indicate the minimum level of damage reduction required for an adaptation technology to become economically viable, that is, the marginal effect. In this context, the CET indicates the expected benefits that can be achieved with limited resources, without assuming any additional stand-alone budget allocation (Thokala et al. 2018). The CET is calculated as $CET_j = \Delta Total\ Benefit_j / \Delta Total\ Cost_j$, where $\Delta Total\ Benefit_j$ and $\Delta Total\ Cost_j$ denotes the estimated marginal economic benefit and cost, respectively, generated by one additional unit of adaptation technology. Together, the resilience models and economic evaluation provide a unified framework for identifying region-specific adaptation strategies that combine resilience enhancement with economic efficiency.

3. Data

3.1. Data Structure

This study constructed a panel dataset of 229 cities, counties, and districts nationwide covering seven years from 2016 to 2022 (Table 1). The dependent variable, damage costs, was defined as total damage cost, calculated as summing the annual heavy rainfall and typhoon damage costs provided by the Ministry of the Interior and Safety's Natural Disaster Yearbook and Natural Disaster Situation Statistics, along with the corresponding region's recovery expenditure. This approach reflects the idea that heavy rain damage costs encompass not only the direct costs incurred at the time of occurrence but also the costs used to restore the affected areas afterward, thereby comprehensively reflecting the actual economic damage. Examining the total damage costs by region (Table 2), Chung-Buk, Jeju, Jeon-Nam, and Gyeong-Buk showed relatively high levels of heavy-rainfall damage, whereas Daegu, Incheon, Daejeon, and Sejong experienced comparatively low damage. The high-damage regions were largely province-level regions, which generally cover broader rural, agricultural areas, while the low-damage regions were mostly metropolitan cities with more compact urban territories. This pattern suggests that heavy-rainfall damage is not only related to rainfall intensity, but also to the spatial and land-use characteristics of each region.

[Insert Table 1 here]

[Insert Table 2 here]

The climate resilience index developed in this study was divided into two policy-relevant components: (i) Vulnerability Reduction Capacity, consisting of 13 indicators, and (ii) Adaptive Capacity, consisting of 36 indicators. Vulnerability Reduction Capacity refers to the ability of a region to reduce structural exposure and sensitivity before heavy rainfall causes severe damage, whereas Adaptive Capacity refers to the ability to absorb, respond to, and recover from the impacts after a heavy-rainfall event occurs. This distinction is important because heavy rainfall damage is not determined only by the magnitude of rainfall itself, but also by whether a region is structurally exposed to damage in advance and whether it has sufficient capacity to respond once damage occurs. This conceptual distinction builds on the resilience framework proposed by Hwang (2024) and extends it to the context of heavy rainfall and flooding in this study.

Variables for each component were classified based on their functional attributes. Indicators representing vulnerability, such as the proportion of elderly population, the percentage of semi-basement or low-lying housing, and the impervious surface ratio, were normalized through sign reversal so that higher values indicate lower vulnerability and greater damage-reduction capacity. After normalization, the adaptive capacity and vulnerability-reduction capacity indices were constructed using the entropy weighting method. The entropy method assigns weights according to the degree of informational variation in each indicator, allowing indicators with greater variation across municipalities and years to contribute more to the composite index (Shannon 1948; Guo et al. 2021; Lee et al. 2020). This approach reduces the arbitrariness of equal weighting and allows the index to reflect the relative informational contribution of each indicator. The weighted indicators were then aggregated to construct the two composite indices used in the empirical analysis. The list of indicators included in each component and their detailed definitions are presented in Tables 3 and 4. This framework reflects the idea that heavy-rainfall damage is determined by the interaction between external shocks, such as rainfall intensity and frequency, and internal regional conditions, such as vulnerability, infrastructure, and adaptive capacity. Using this approach, this study examines whether locally implemented adaptation technologies reduce heavy-rainfall damage by strengthening specific components of climate resilience, namely vulnerability-reduction capacity and adaptive capacity.

[Insert Table 3 here]

[Insert Table 4 here]

3.2. Descriptive statistics of key variables

Table 5 reports the annual average values of heavy rainfall damage costs, climate resilience indices, and meteorological variables observed at the Si-Gun-Gu¹ level. Table 6 summarizes the average climate resilience index and precipitation characteristics by city/province.

¹ Si/Gun/Gu refers to South Korea's basic local administrative units, consisting of cities (Si), counties (Gun), and districts (Gu). This scale has been widely used as a community-level unit in Korean disaster resilience studies(Yoon et al. 2016).

[Insert Table 5 here]

[Insert Table 6 here]

4. Results

4.1. Effects of Adaptation Technologies on Resilience Pathways

4.1.1. First-stage estimates: Technology-specific effects on adaptive capacity and vulnerability reduction capacity

Table 7 presents the first-stage regression results estimating how the adoption of heavy rainfall adaptation technologies is associated with the physical components of regional climate resilience. The results show that green roofs and rainwater retention tanks have statistically significant positive associations with the physical component of adaptive capacity, whereas permeable pavements have a statistically significant positive association with the physical component of vulnerability-reduction capacity. These findings suggest that the observed effects of adaptation technologies are not uniform across resilience dimensions.

Technology-specific patterns can be interpreted in relation to the physical functions through which each measure supports heavy rainfall adaptation and regional climate resilience. Previous studies have shown that permeable pavements reduce surface runoff by increasing rainfall infiltration in impervious urban areas, thereby mitigating runoff concentration and flood risk (Koo et al. 2013). Green roofs have also been widely discussed as stormwater management measures because vegetation and substrate layers can retain rainfall, delay runoff, and reduce drainage pressure in urban areas (Berndtsson 2010). In addition, rainwater storage and drainage related measures are generally designed to temporarily store excess stormwater and reduce inundation risk, particularly in urban watersheds exposed to extreme rainfall (Choi et al. 2017; Jee et al. 2023).

Based on these functions, the estimated results suggest that each technology is associated with different components of regional climate resilience. Permeable pavements are closely linked to vulnerability-reduction capacity because they enhance infiltration and reduce runoff in urban areas where roads and paved surfaces account for a large share of the built environment. This function is consistent with the role of vulnerability reduction capacity, which captures improvements in physical and environmental conditions that reduce exposure and sensitivity before severe damage occurs. In contrast, rainwater retention tanks are more closely related to adaptive capacity because they expand the ability of regional systems to temporarily store and manage excess stormwater during heavy-rainfall events. Similarly, green roofs appear to contribute more strongly to adaptive capacity through urban green infrastructure functions, such as vegetation-based retention, localized stormwater buffering, and reduced pressure on drainage systems.

Overall, these results suggest that heavy rainfall adaptation technologies strengthen regional climate resilience through different pathways. This does not imply that the technologies are mutually exclusive or non-substitutable in all contexts. Rather, it indicates that their policy relevance should be evaluated according to the specific resilience dimension they are most likely to strengthen. Therefore, a tailored technology portfolio aligned with local resilience conditions may provide more useful policy guidance than a uniform dissemination strategy

based only on technology type.

[Insert Table 7 here]

4.1.2. Estimated Impacts of each capacity on heavy rainfall damage

Table 8 reports the results of the second-stage panel Tobit estimation, which examines the effects of climate resilience and meteorological conditions on heavy-rainfall damage costs. Since a substantial number of observations report zero damage, the dependent variable is transformed as $\ln(1 + \text{damage costs})$, and the model is estimated with zero as the left-censoring point. The predicted adaptive capacity and vulnerability-reduction capacity variables are log-transformed, while the meteorological variables include total precipitation and average precipitation on heavy-rainfall days.

The results show that both components of climate resilience are negatively associated with heavy-rainfall damage costs. Specifically, a 1% increase in adaptive capacity is associated with an approximately 2.8% decrease in damage costs, while a 1% increase in vulnerability-reduction capacity is associated with an approximately 10.2% decrease in damage costs. These estimates suggest that both resilience pathways contribute to damage reduction, but that the vulnerability-reduction pathway has a comparatively stronger association with observed heavy-rainfall damage.

The comparatively larger estimate for vulnerability reduction capacity is consistent with flood-risk frameworks that emphasize exposure and susceptibility as key determinants of heavy rainfall damage. Vulnerability reduction capacity captures pre-event physical and environmental conditions, such as impervious surfaces, low-lying or semi-basement housing, drainage channels, aged sewer infrastructure, and other exposure-related factors. Improvements in these conditions can reduce the likelihood that heavy rainfall is translated into severe economic damage by lowering the structural sensitivity of municipalities before damage occurs (Kreibich et al. 2005). Adaptive capacity represents a complementary resilience pathway. It reflects the ability of regional systems to anticipate, absorb, respond to, and recover from heavy-rainfall shocks through institutional, socioeconomic, and infrastructural resources. Its negative association with damage costs indicates that response, buffering, and recovery-related capacities also play a meaningful role in reducing heavy-rainfall damage. Therefore, the larger coefficient of vulnerability-reduction capacity should not be interpreted as evidence that adaptive capacity is unimportant. Rather, the results suggest that ex-ante reductions in exposure and susceptibility may be especially important in municipalities where physical and environmental conditions amplify rainfall impacts, while adaptive capacity remains necessary for managing residual risks that cannot be fully prevented.

The meteorological variables are positively associated with damage costs. A 1 mm increase in total annual precipitation is associated with an approximately 0.73% increase in damage costs, and a 1 mm increase in average precipitation on heavy-rainfall days is associated with an approximately 4.62% increase in damage costs. These results indicate that both the overall amount of rainfall and the intensity of heavy-rainfall events contribute to increasing economic damage.

Nevertheless, the magnitude of the resilience coefficients should be interpreted with caution. The resilience variables used in this study are composite indices constructed from multiple sub-domains rather than single physical indicators. Therefore, a 1% increase in these indices does not represent a change in one isolated factor,

but rather reflects simultaneous improvements across several underlying components. In addition, because the dependent variable is specified as $\ln(1 + \text{damage costs})$ in a censored panel Tobit framework, the coefficients should be interpreted as elasticity-type associations rather than precise engineering response parameters. Accordingly, the results are most useful for understanding the direction and relative importance of alternative resilience pathways in reducing heavy-rainfall damage.

[Insert Table 8 here]

4.2. Marginal Benefits of unit technologies

4.2.1. Distribution of marginal benefits of technologies

Table 9 reports the distribution of marginal benefits for each technology. All three technologies exhibited a minimum observed benefit of zero USD. This arises mechanically from the benefit calculation, because observations with zero damage costs yield zero benefits when multiplied by the estimated marginal effects. Permeable pavement provides an average benefit of approximately 4.785 USD per square meter, with benefits ranging from a minimum of zero USD to a maximum of 280.97 USD, and a median of 0.087 USD, indicating a relatively low level. Green roofs showed an average benefit of 11.706 USD per square meter, with a very wide distribution ranging from a minimum of zero USD to a maximum of 693.77 USD and a median of 0.179 USD. This wide range may reflect heterogeneity in installation contexts, vegetation types, building conditions, and regional exposure to heavy rainfall. Rainwater retention tanks generate an average estimated benefit of 5,027.54 USD per installed unit. Because the technologies are measured in different physical units, the absolute benefit estimates should not be directly compared across technologies. The estimated benefits of rainwater retention tanks also exhibit substantial variation, with benefits ranging from zero USD to a maximum of 299,401 USD and a median of 76.93 USD. This pattern is likely driven by large differences in installation scale across projects.

Taken together, the highly skewed distribution of marginal benefits suggests that the economic value of adaptation technologies is not determined by technology characteristics alone. Because marginal benefits are derived by translating resilience-mediated damage reduction into monetary terms, benefits become larger when three conditions coincide: the technology strengthens a relevant resilience pathway, the municipality is sufficiently exposed to heavy-rainfall damage, and the damage cost is large enough for resilience improvements to generate observable monetary benefits. Thus, the wide dispersion of marginal benefits provides additional evidence that adaptation effectiveness is jointly shaped by technology function, resilience pathway, and regional risk context.

[Insert Table 9 here]

Fig. 2 presents a scatter plot of the marginal benefits of three technologies. The X-axis represents climate resilience, defined as the sum of adaptive capacity and vulnerability reduction capacity. The Y-axis represents benefits for each technology.

The three technologies exhibit broadly similar distributions in the plot, and all show a tendency for damage cost reduction to be larger at higher levels of climate resilience. In particular, the blue-marked point represents

Seogwipo City in Jeju, which records the largest damage cost reduction across all three technologies. This result may reflect Seogwipo City's distinctive climatic and geographical characteristics, under which additional adoption of heavy rainfall adaptation technologies generates particularly large marginal benefits. As part of Jeju Island, Seogwipo is exposed to island-specific climate risks, including relatively high total and average precipitation, frequent typhoon-related rainfall and wind events, and heavy rainfall influenced by coastal and mountainous topography. These conditions can lead to relatively high damage costs and therefore benefits from damage reduction are estimated to be larger when the technologies are applied.

Fig. 2 Distribution of estimated marginal benefits by technology and climate resilience: (a) Permeable Pavement, (b) Green Roofs, and (c) Rainwater Retention Tanks

[Insert Fig. 2 here]

4.2.2. Distribution of marginal benefits across municipalities

Table 10 summarizes the seven-year average distribution of marginal benefits and heavy-rainfall climate-resilience levels across 229 local governments, along with the marginal effects of each technology by region. As shown in Table 10, regions with high damage costs—such as Chung-Buk, Jeju, Jeon-Nam, and Gyeong-Buk—tend to exhibit higher marginal benefits. By contrast, regions with lower damage costs, such as Daegu, Incheon, Daejeon, and Sejong, show smaller marginal benefits. This pattern suggests that the monetary value of technology adoption is closely related to the underlying scale of heavy-rainfall damage. In other words, the same resilience-mediated improvement can generate larger estimated benefits in municipalities where potential avoided losses are greater.

However, damage exposure alone does not fully explain the regional distribution of marginal benefits. Although Jeju's average damage costs were lower than those of Chung-Buk, Jeon-Nam, and Gyeong-Buk, the marginal benefits from green roofs and rainwater retention tanks are higher. This may reflect Jeju's distinctive island characteristics, including high precipitation exposure, frequent rainfall, coastal topography, and mountainous terrain. These local climatic and geographical conditions can interact with technology-specific resilience pathways, making certain technologies more beneficial in Jeju than would be expected from damage costs alone. Therefore, adaptation benefits should be interpreted as region–technology-specific outcomes rather than as fixed technology-level effects. This reinforces the need to evaluate not only which technology is generally effective, but also where each technology is most likely to produce meaningful resilience-mediated damage reduction.

[Insert Table 10 here]

4.3. Cost-Effectiveness Thresholds among technologies

4.3.1. Annual costs of technologies

The annual total cost for each technology was calculated using data from Korea's open information portal, including installation costs, service life, and operational and maintenance expenses. Specifically, the installation cost was annualized by dividing it by the service life, and annual maintenance costs were then added to obtain the annual total cost per unit. The annual total cost was highest for rainwater retention tanks at approximately 6,826 USD, followed by green roofs and permeable pavement. Green roofs and rainwater retention tanks have relatively long service lives and require annual maintenance costs, whereas permeable pavement has a shorter service life and no separate management costs.

[Insert Table 11 here]

4.3.2. Cost-Effectiveness Thresholds and Benefit–Cost Ratios of technologies

Based on the estimated annual total costs and benefits, we conducted a benefit–cost ratio (BCR) analysis. First, the BCR analysis results (Table 12) show that the retention tank achieved an average BCR of 3.97 over the seven-year period. This implies that, on average, the technology reduced heavy rainfall damage costs by almost four times the amount invested during the same period. Permeable pavement achieved an average BCR of 1.70. Although the nationwide average BCR exceeds 1.0 indicating overall economic viability, there is substantial regional heterogeneity, with particularly high effectiveness observed in regions such as Gangwon and Gyeong-Buk. By contrast, green roofs show an average BCR of 0.58, indicating that this technology does not generate sufficient benefits to cover its costs even when evaluated over the full seven-year horizon. However, green roofs could potentially serve as an adaptation technology not only for heavy rainfall but also for other heavy weather events like heatwaves. Furthermore, they may become economically viable if integrated into green-building certification schemes such as LEED (Leadership in Energy and Environmental Design), where they can interact synergistically with other heavy rainfall adaptation technologies (Nordman et al. 2018). These considerations suggest that future research should further explore the broader economic value of green roofs beyond heavy rainfall damage reduction alone.

[Insert Table 12 here]

By contrast, the CET analysis (Table 13, Fig. 3) indicates that all three technologies exceed the cost threshold of 1.0, suggesting limited economic feasibility. However, the results need to be interpreted with caution because these are partly driven by the fact that current heavy rainfall damage costs do not include human casualties. In addition, as seen in Fig. 3, the CET are significantly higher in regions with low heavy rainfall damage due to local characteristics (e.g., areas with very little rainfall) or in regions with extensive damaged infrastructure (e.g., the metropolitan area). Adjusting these factors could improve the assessed CET of the technologies in future analysis. Taken together with the BCR results, these findings suggest that, at the unit-technology level, rainwater retention tanks and permeable pavements can be regarded as economically viable options.

[Insert Table 13 here]

Fig. 3 Cost-Effectiveness Thresholds (CETs) across 229 municipalities: (a) Permeable Pavement, (b) Green Roofs, and (c) Rainwater Retention Tanks

[Insert Fig. 3 here]

4.3.3. Policy priority classification based on economic evaluation indicators

To translate the BCR and CET results into policy implications, this study classifies each region–technology pair into four policy types, as shown in Fig. 4. The BCR and CET provide complementary information for classifying adaptation priorities. The BCR evaluates whether a technology generates sufficient cumulative benefits relative to its total costs over the analysis period, whereas the CET evaluates whether an additional unit of technology adoption is marginally cost-effective. Using these two criteria, each region–technology pair is classified into four policy types. Type I indicates cases in which total benefits exceed total costs and additional units are also marginally cost-effective, suggesting priority expansion. Type II indicates cases in which total benefits exceed total costs, but additional units require selective targeting. Type III indicates cases where additional units may be cost-effective, but total benefits do not yet exceed total costs, suggesting pilot-scale implementation. Type IV indicates cases where both total benefits and marginal cost-effectiveness are unfavorable, implying low priority.

This integrated classification shows that policy priorities differ not only across regions but also across technologies. For instance, capital-region municipalities such as Seoul and Gyeonggi may be classified as Type II when evaluated for rainwater retention tanks, but as Type IV when evaluated for green roofs. This indicates that the economic feasibility of adaptation technologies depends on the interaction between local conditions and technology-specific performance. Likewise, from the perspective of a single technology, the regions in which adoption should be prioritized may differ substantially. Therefore, the results should not be interpreted as supporting a uniform ranking of technologies across all municipalities. Rather, they suggest that local governments should design region-specific technology portfolios by considering both cumulative economic viability and marginal cost-effectiveness.

Fig. 4 Integrated Benefit–Cost Ratio (BCR) and Cost-Effectiveness Threshold (CET) policy matrix

[Insert Fig. 4 here]

5. Conclusion and Policy Implications

This study examined how heavy rainfall adaptation technologies reduce flood damage through regional climate resilience using panel data from 229 municipalities in South Korea between 2016 and 2022. Regional climate resilience was decomposed into two complementary dimensions—adaptive capacity and vulnerability reduction

capacity—to identify the pathways through which green roofs, permeable pavements, and rainwater retention tanks contribute to disaster risk reduction. The resilience-mediated damage reductions were subsequently translated into economic benefits using Benefit–Cost Ratio (BCR) and Cost-Effectiveness Threshold (CET) analyses.

The results provide three main findings. First, adaptation technologies strengthen different dimensions of regional climate resilience rather than operating through a common mechanism. Green roofs and rainwater retention tanks are more strongly associated with adaptive capacity, whereas permeable pavements primarily improve vulnerability reduction capacity. Second, improvements in both resilience dimensions are associated with lower heavy rainfall damage, although their relative importance varies across municipalities, highlighting substantial regional heterogeneity in adaptation effectiveness. Third, the economic performance of adaptation technologies differs considerably among municipalities, indicating that investment priorities should reflect local climatic, environmental, and socioeconomic conditions rather than relying on uniform technology deployment.

These findings suggest that adaptation planning should move beyond technology-centered approaches toward resilience-based regional strategies. Municipalities should identify whether their primary adaptation needs relate to strengthening adaptive capacity or reducing structural vulnerability and prioritize technology portfolios accordingly. The combined use of resilience analysis and economic evaluation provides a practical framework for supporting region-specific adaptation decisions under limited public resources.

This study also has several limitations. First, the analysis considers the effects of individual technologies but does not evaluate potential interactions or synergies among multiple adaptation measures. Second, the damage data capture only economic losses and therefore do not reflect broader social and environmental impacts, such as loss of life, health effects, or ecosystem services. Third, although the two-stage empirical framework clarifies the technology–resilience–damage relationship, endogeneity cannot be fully ruled out because municipalities with stronger institutional or fiscal capacity may both adopt more adaptation technologies and experience lower damages. Future research could address these issues by examining technology portfolios, incorporating broader measures of adaptation benefits, and applying causal identification strategies.

Overall, this study demonstrates that regional climate resilience is not only an outcome of adaptation but also an important mechanism linking adaptation technologies to disaster risk reduction. By integrating technology adoption, multidimensional resilience, observed flood damage, and economic evaluation within a unified empirical framework, the study provides evidence to support more effective and regionally differentiated climate adaptation policies under increasing heavy rainfall risks.

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References

- Adelodun B, Odey G, Lee S, Choi KS (2023) Investigating the causal impacts relationship between economic flood damage and extreme precipitation indices based on ARDL-ECM framework: a case study of Chungcheong region in South Korea. *Sustain Cities Soc* 95:104606. doi: 10.1016/j.scs.2023.104606
- Azhar M, Kane B, Vahedifard F, AghaKouchak A (2025) Comprehensive portfolio of adaptation measures to safeguard against evolving flood risks in a changing climate. *Commun Earth Environ* 6:824. doi: 10.1038/s43247-025-02779-z
- Baik YS, Kim K, An D (2024) Spatial distribution analysis of climate resilience index in heavy rainfall: the case of Seoul. *Korea Spat Plan Rev* 122:119–138. doi: 10.15793/kspr.2024.122..007
- Berndtsson JC (2010) Green roof performance towards management of runoff water quantity and quality: a review. *Ecol Eng* 36:351–360. doi: 10.1016/j.ecoleng.2009.12.014
- Carvalhaes TM, Chester MV, Reddy AT, Allenby BR (2021) An overview and synthesis of disaster resilience indices from a complexity perspective. *Int J Disaster Risk Reduct* 57:102165. doi: 10.1016/j.ijdr.2021.102165
- Choi H, Lee EH, Joo JG, Kim JH (2017) Determining optimal locations for rainwater storage sites with the goal of reducing urban inundation damage costs. *KSCE J Civ Eng* 21:2488–2500. doi: 10.1007/s12205-016-0922-6
- Cutter SL, Barnes L, Berry M, Burton C, Evans E et al (2008) A place-based model for understanding community resilience to natural disasters. *Glob Environ Change* 18:598–606. doi: 10.1016/j.gloenvcha.2008.07.013
- Cutter SL, Burton CG, Emrich CT (2010) Disaster resilience indicators for benchmarking baseline conditions. *J Homel Secur Emerg Manag* 7:1–22. doi: 10.2202/1547-7355.1732
- Engle NL (2011) Adaptive capacity and its assessment. *Glob Environ Change* 21:647–656. doi: 10.1016/j.gloenvcha.2011.01.019
- Golden HE, Hoghooghi N (2018) Green infrastructure and its catchment-scale effects: an emerging science. *WIREs Water* 5:e1254. doi: 10.1002/wat2.1254
- Guo H, Chen J, Pan C (2021) Assessment on agricultural drought vulnerability and spatial heterogeneity study in China. *Int J Environ Res Public Health* 18:4449. doi: 10.3390/ijerph18094449
- Hwang J (2024) An economic evaluation of resilience to climate-related extreme events: evidence from extreme rainfall in South Korea. Master's thesis, Seoul National University, Seoul
- IPCC (2012) Managing the risks of extreme events and disasters to advance climate change adaptation. A special report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge
- IPCC (2014) Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate

542 Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi,
543 Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White
544 (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1132 pp.

545 IPCC (2022) *Climate Change 2022: Impacts, Adaptation, and Vulnerability*. Contribution of Working Group II to
546 the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M.
547 Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem,
548 B. Rama (eds.)]. Cambridge University Press. Cambridge University Press, Cambridge, UK and New York, NY,
549 USA, 3056 pp., doi:10.1017/9781009325844.

550 Jee HW, Kim H, Seo SB (2023) Analysis of runoff reduction effect of flood mitigation policies based on cost-
551 benefit perspective. *KSCE J Civ Environ Eng Res* 43:721–733. doi: 10.12652/Ksce.2023.43.6.0721

552 Kim D, Song SK (2018) Measuring changes in urban functional capacity for climate resilience: perspectives from
553 Korea. *Futures* 102:89–103. doi: 10.1016/j.futures.2018.05.001

554 Koo YM, Jo JA, Kim YD, Park JH (2013) A study on runoff analysis of urban watershed by hydrologic infiltration
555 experiment of permeable pavement. *KSCE J Civ Environ Eng Res* 33:559–571. doi:
556 10.12652/Ksce.2013.33.2.559

557 Kreibich H, Thielen AH, Petrow T, Müller M, Merz B (2005) Flood loss reduction of private households due to
558 building precautionary measures—lessons learned from the Elbe flood in August 2002. *Nat Hazards Earth Syst*
559 *Sci* 5:117–126. doi: 10.5194/nhess-5-117-2005

560 Laurien F, Martin JGC, Mehryar S (2022) Climate and disaster resilience measurement: persistent gaps in multiple
561 hazards, methods, and practicability. *Clim Risk Manag* 37:100443. doi: 10.1016/j.crm.2022.100443

562 Lee SM, Choi YJ, Yi JE (2020) Urban flood vulnerability assessment using the entropy weight method. *J Korean*
563 *Soc Hazard Mitig* 20:389–397. doi: 10.9798/KOSHAM.2020.20.6.389

564 Li C, Peng C, Chiang PC, Cai Y, Wang X et al (2019) Mechanisms and applications of green infrastructure
565 practices for stormwater control: a review. *J Hydrol* 568:626–637. doi: 10.1016/j.jhydrol.2018.10.074

566 Nordman EE, Isely E, Isely P, Denning R (2018) Benefit–cost analysis of stormwater green infrastructure practices
567 for Grand Rapids, Michigan, USA. *J Clean Prod* 200:501–510. doi: 10.1016/j.jclepro.2018.07.152

568 Qin H, Li Z, Fu G (2013) The effects of low impact development on urban flooding under different rainfall
569 characteristics. *J Environ Manage* 129:577–585. doi: 10.1016/j.jenvman.2013.08.026

570 Seo S, Jang S, Jung J (2022) Analysis of disaster resilience index using regional flood damage characteristics. *J*
571 *Korean Soc Hazard Mitig* 22:55–67. doi: 10.9798/KOSHAM.2022.22.6.55

572 Shannon CE (1948) A mathematical theory of communication. *Bell Syst Tech J* 27:379–423, 623–656. doi:
573 10.1002/j.1538-7305.1948.tb01338.x

574 Shiozaki Y, Nagamatsu S, Sato K, Bhattacharya Y (2024) A systematic literature review of empirical validation
575 of disaster resilience indicators. *Int J Disaster Risk Reduct* 111:104681. doi: 10.1016/j.ijdr.2024.104681

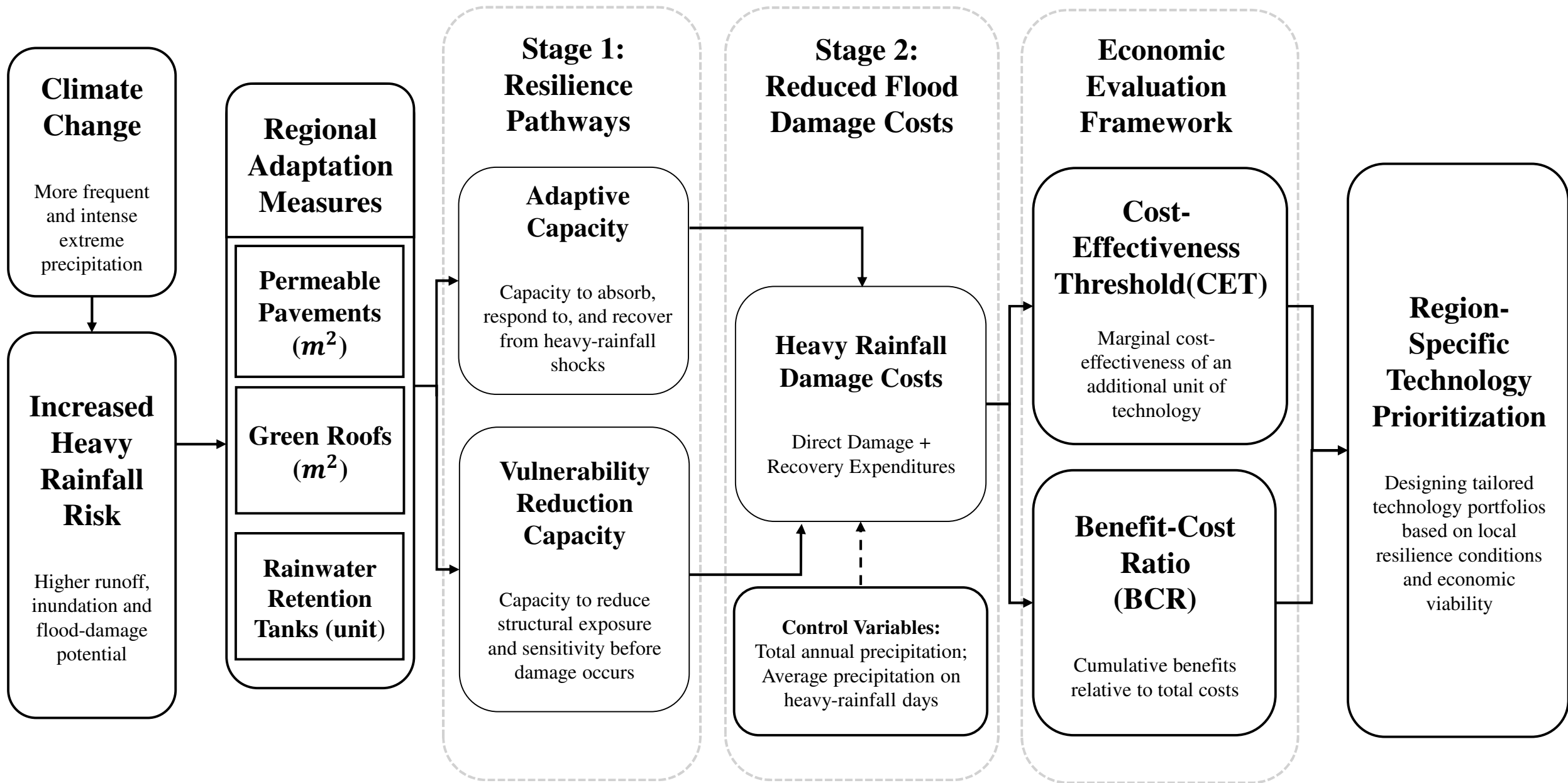
576 Song Y, Song YH, Park M, Kim SY (2025) Development of prediction model for damage costs of heavy rainfall
577 disasters using machine learning in the Republic of Korea. *Climate* 13:72. doi: 10.3390/cli13040072

578 Thokala P, Ochalek J, Leech AA, Tong T (2018) Cost-effectiveness thresholds: the past, the present and the future.
579 *Pharmacoeconomics* 36:509–522. doi: 10.1007/s40273-017-0606-1

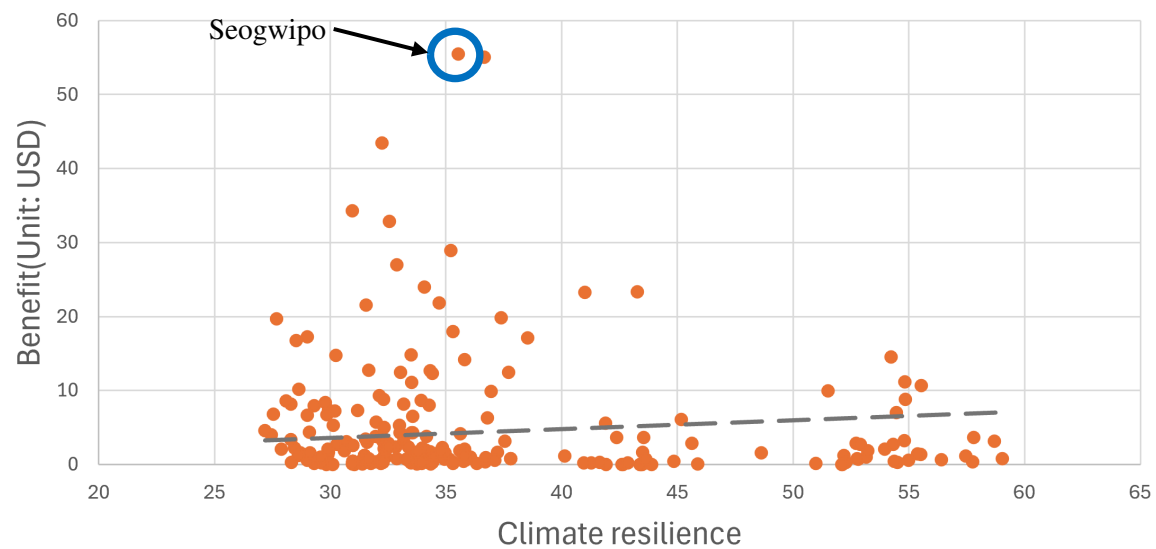
580 Yoon DK, Kang JE, Brody SD (2016) A measurement of community disaster resilience in Korea. *J Environ Plan*
581 *Manag* 59:436–460. doi: 10.1080/09640568.2015.1016142

582 Zevenbergen C, Gersonius B, Radhakrishnan M (2020) Flood resilience. *Philos Trans A Math Phys Eng Sci*
583 378:20190212. doi: 10.1098/rsta.2019.0212

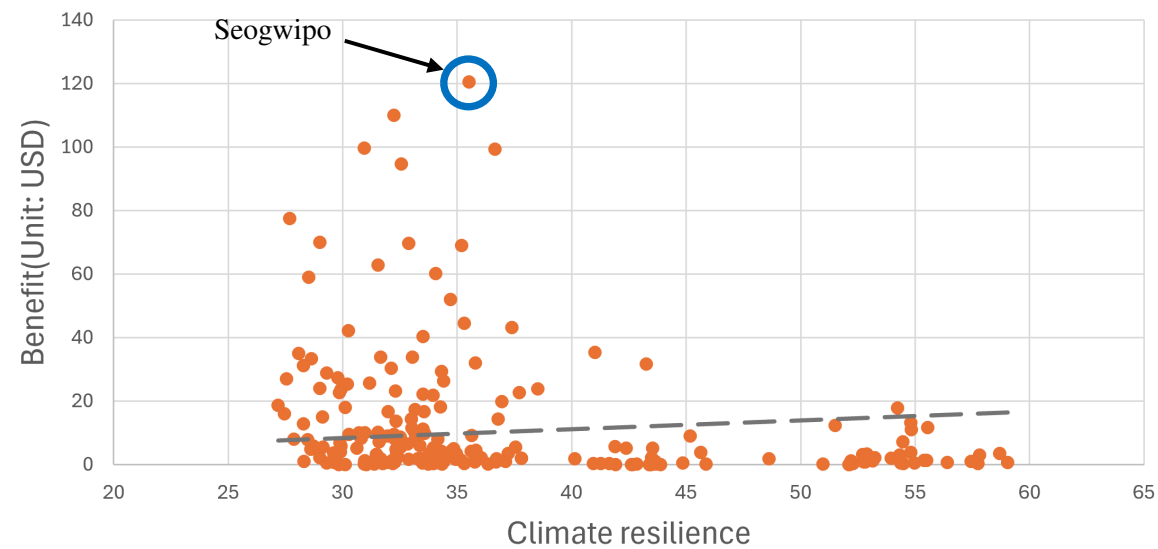
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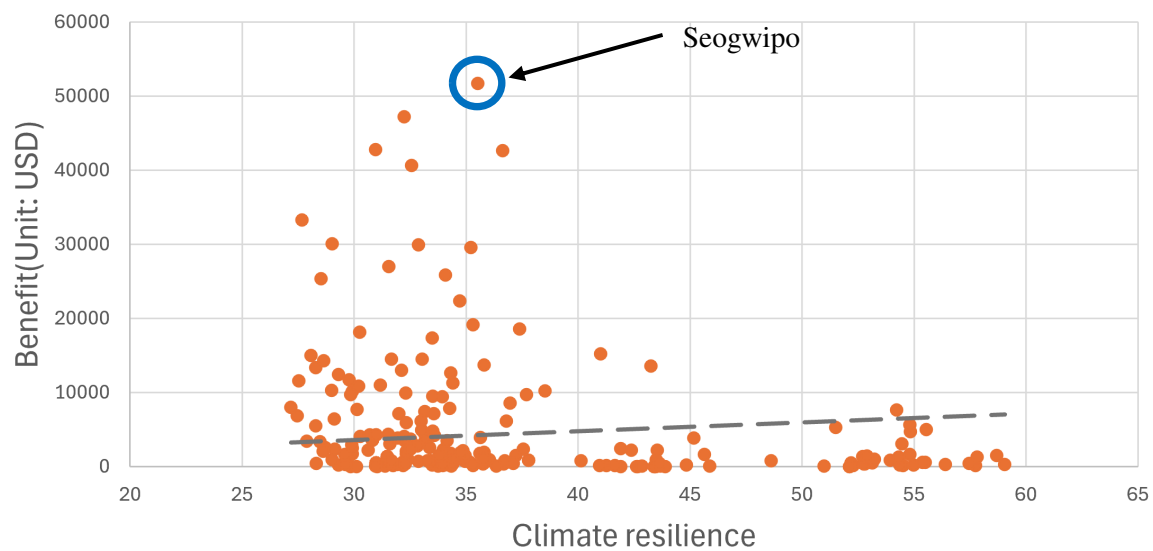
(a) Permeable Pavement

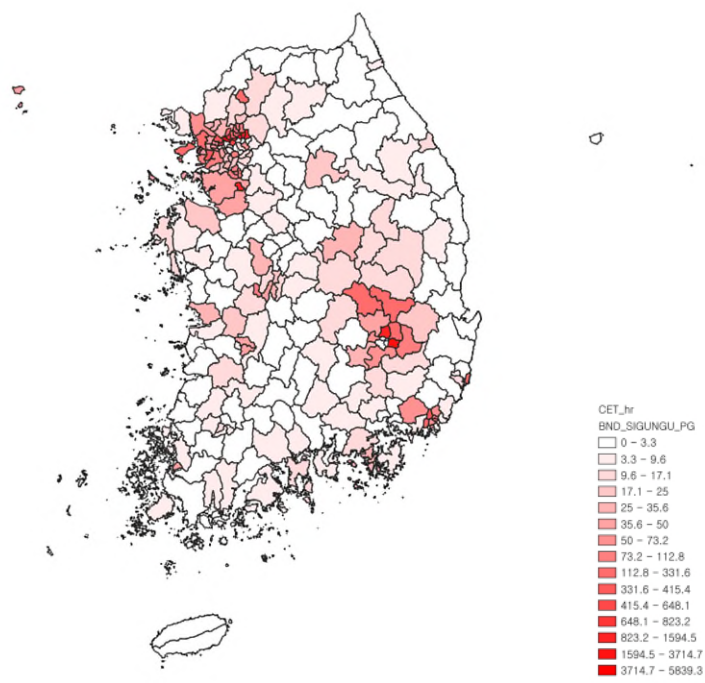


(b) Green Roofs

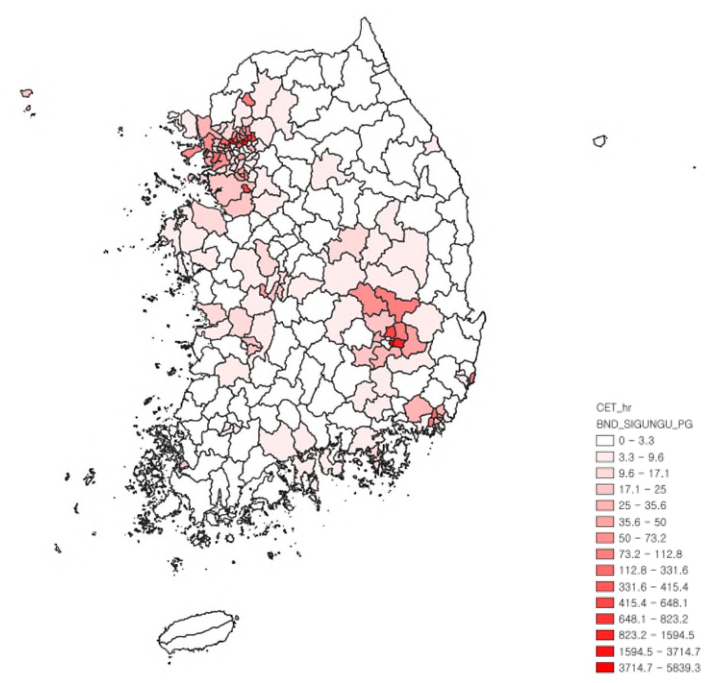


(c) Rainwater Retention Tank

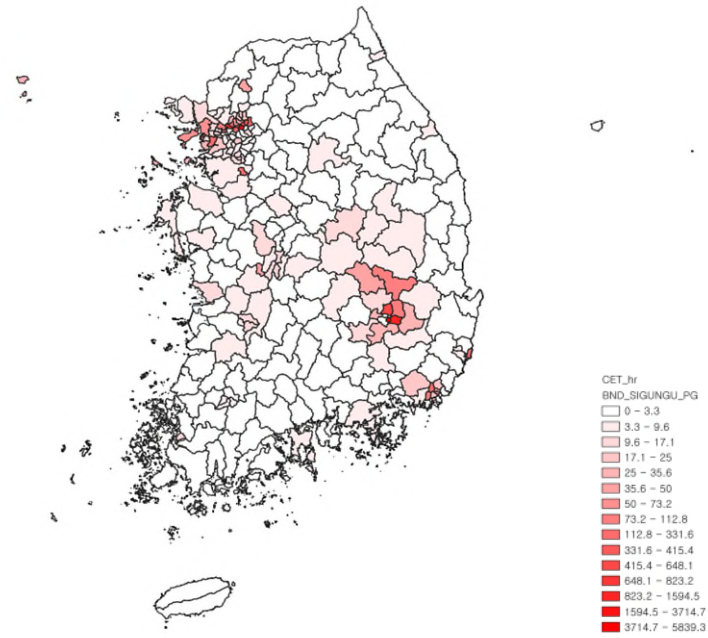




(a) Permeable Pavement



(b) Green Roofs



(c) Rainwater Retention Tank

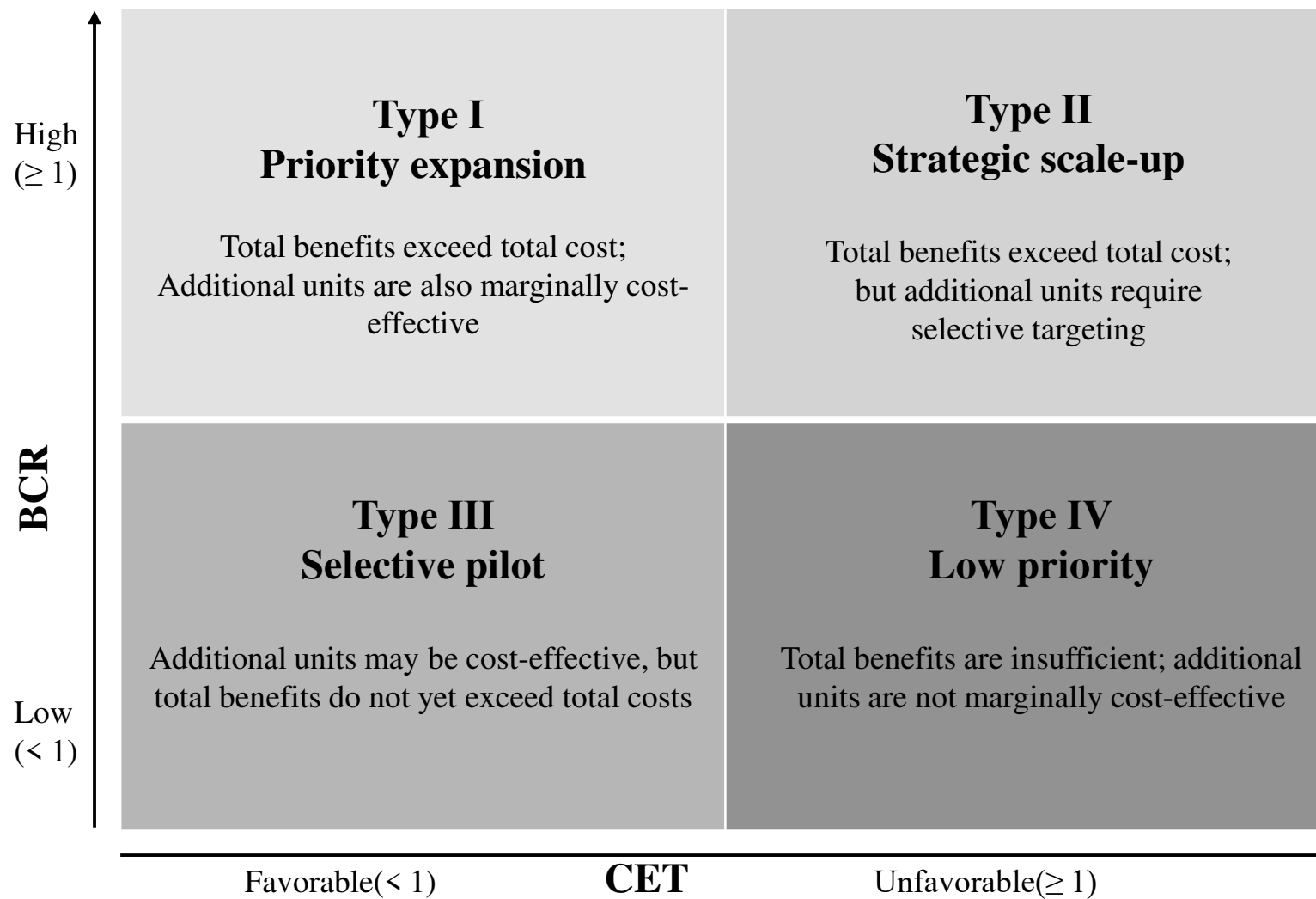


Table 1. Input data lists and sources

Data	Items	Source
Flood and storm damage costs (Dependent variable)	Total annual damage costs by municipality, including property damages, damages to public and private facilities, and total recovery expenditures	Ministry of the Interior and Safety (MOIS), <i>Natural Disaster Yearbook</i> (MOIS Natural Disaster Yearbook)
Heavy rainfall variables	Annual total precipitation and average rainfall on heavy rainfall occurrence days	Korea Meteorological Administration (KMA), <i>Open MET Data Portal</i> (ASOS & AWS observations)
Heavy rainfall adaptation technology installations	Annual data on the adoption of rainfall adaptation technologies	Open information portal of Korea

Note: All collection periods range from 2016 to 2022

Table 2. Average Damage Costs by Region

Region	Average Heavy Rainfall Damage	Region	Average Heavy Rainfall Damage
Seoul	1,710,611	Gangwon	6,415,250
Busan	1,428,235	Chung-Buk	10,774,730
Daegu	28,933	Chung-Nam	7,007,328
Incheon	308,057	Jeon-Buk	4,438,629
Gwangju	2,014,571	Jeon-Nam	9,517,522
Daejeon	595,034	Gyeong-Buk	9,531,980
Ulsan	4,990,581	Gyeong-Nam	4,467,442
Sejong	330,605	Jeju	9,045,154
Gyeong-Gi	3,142,187	Average	4,455,331

Note. Values are expressed in USD. Damage costs include reported heavy-rainfall and typhoon damage costs and recovery expenditures.

Table 3. Indicator configuration variables for Vulnerability Reduction capacities

Sector	Sub sector	Variables	Source
Economy	Industry development	Unemployment rate	Economically Active Population Survey from KOSIS
Human	Vulnerable populations	Population under 5years of age/ population of over 65years of age/ number of the disabled	Population Based on Resident registration of KOSIS
		Basic livelihood security recipients/ People who ungraduated from elementary school	Korean Urban Statistics
Physical Infra	Vulnerable facilities	Number of Houses over 30 years old, Semi-basements/ Roads area/ Railways area/ River area/ Drainage channel area	Geospatial Information Platform
	Green infrastructure	Ratio of aged sewer pipes	Korean Urban Statistics

Note: Indicator classification and data source selection were adapted from Hwang (2024).

Table 4. Indicator configuration variables for Adaptive capacities

Sectors	Sub sectors	Variables	Sources
Economy	Economic Power	Amount of local tax per capita/ financial independence rate/ GRDP	Korean Statistical Information Service (Referred to as KOSIS) Regional Income
	Industry development	R&D expenditures per capita, number of researchers	Survey of R&D in Korea
Social	Medical response capability	Number of ambulances	Emergency Medical Services Statistics
		Number of hospitals, health centers, medical personnel, emergency medical centers/ Unmet healthcare ratio	Korean Urban Statistics
		Number of hospital beds per 1,000 people	e-Regional Indicators of KOSIS
	Social infrastructure	Number of welfare facilities for the aged, the homeless, the disabled, the female and children/ Number of registered volunteers	Korean Urban Statistics
Physical Infra	Green infrastructure	Park area/ green area/ forest area	Korean Urban Statistics
		Dikes/ Installed length of sewer pipes/ Detention basin/ Water retention area	Water Resources Management Statistical Yearbook
Governance	Budget	Amount of welfare budget	Local Finance Integrated Open System
		Natural disasters management fund, Natural disasters aid fund	KOSIS
	Disaster readiness	Population per 1 fire-fighting officer/ number of Municipal officials, Province officials, fire-fighters	Korean Urban Statistics
		Wind and flood insurance subscriptions, Temporary housings for refugees, Relief supplies reserves	Ministry of the Interior and Safety
human	KOSIS	Population density	KOSIS

Note: Indicator classification and data source selection were adapted from Hwang (2024).

Table 5. Annual Averages of Key Variables

Year	Heavy Rainfall Damages (USD)	Adaptive Capacity Index	Vulnerability Reduction Index	Total Annual Precipitation (mm)	Average Precipitation On Heavy Rainfall Days
2016	3,634,605	26.69	14.59	1,240.64	114.44
2017	1,219,008	16.75	14.87	961.03	82.42
2018	1,519,474	32.78	14.67	1,401.08	117.24
2019	4,467,838	19.59	16.07	1,152.36	84.32
2020	16,316,347	16.88	16.18	1,630.91	112.69
2021	1,028,370	18.66	15.98	1,220.02	68.37
2022	6,444,844	18.35	15.43	1,198.30	94.69
Average	4,947,119	21.39	15.40	1,257.76	96.31

Table 6. Regional Averages of Key Variables

Region	Adaptive Capacity Index	Vulnerability Reduction Index	Total Annual Precipitation (mm)	Average Precipitation On Heavy Rainfall Days
Seoul	22.28	15.68	1,244.26	95.47
Busan	21.99	15.74	1,551.81	118.71
Daegu	21.33	15.73	1,005.71	70.90
Incheon	20.74	15.51	1,071.70	95.53
Gwangju	18.44	15.63	1,267.23	103.55
Daejeon	20.32	14.86	1,248.55	86.25
Ulsan	22.27	14.83	1,447.96	123.52
Sejong	22.42	14.82	1,274.00	90.92
Gyeong-Gi	21.82	15.27	1,224.06	94.87
Gangwon	21.61	15.31	1,327.74	106.12
Chung-Buk	22.58	15.34	1,159.50	88.30
Chung-Nam	22.64	14.71	1,102.51	82.79
Jeon-Buk	22.56	15.05	1,247.54	82.80
Jeon-Nam	20.73	15.66	1,283.04	101.65
Gyeong-Buk	20.44	15.42	1,115.49	79.04
Gyeong-Nam	19.44	15.57	1,427.28	112.92
Jeju	18.81	15.82	2,029.86	139.36
Average	21.20	15.35	1,295.78	98.39

Table 7. Stage 1 regression Results: Effects of Unit Technologies on Physical dimensions of each capacity

	Dependent Variable: $\ln(X1_{physical,it})$		Dependent Variable: $\ln(X2_{physical,it})$	
	Parameters	Coeff. Estimates (Standard Errors)	Parameters	Coeff. Estimates (Standard Errors)
Intercept	δ_0	0.33032*** (0.007552)	γ_0	2.04488*** (0.0022319)
Permeable Pavement (per m^2)	δ_1	-4.44e-07 (2.74e-07)	γ_1	1.90e-07** (8.66e-08)
Green Roofs (per m^2)	δ_2	0.0000107* (6.29e-06)	γ_2	-2.55e-06 (1.68e-06)
Rainwater Retention Tank (per unit)	δ_3	0.004578* (0.00224256)	γ_3	-0.0008734 (0.000774)

Note: Robust standard errors in parentheses.

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Stage 2 panel Tobit results: Estimated impact on heavy rainfall damage

		Dependent Variable: <i>ln(Heavy Rainfall Damage + 1)</i>	
	Parameters	Coeff. Estimates	Standard Errors
Intercept	β_0	36.79489**	17.2152
$\log(\widehat{X1}_{it})$	β_1	-2.799147**	1.326548
$\log(\widehat{X2}_{it})$	β_2	-10.23913*	5.457848
$X3_{it}$	β_3	0.0073118***	0.0007964
$X4_{it}$	β_4	0.0451242***	0.0055381

Note: The dependent variable is $\ln(1 + \text{heavy rainfall damage costs})$. A panel Tobit model is estimated with zero as the left-censoring point. Robust standard errors are reported in the final column.

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Descriptive statistics of marginal benefits of technologies

	Minimum	2 nd Quartile	Median	3 rd Quartile	Maximum	Mean
Permeable Pavement (USD/ m^2)	0	0.0013	0.0866	1.1319	280.9661	4.7785
Green Roofs (USD/ m^2)	0	0.0031	0.1791	2.4620	693.7766	11.7060
Rainwater Retention Tank (USD/ unit)	0	1.3492	76.9308	1,057.3839	299,401.19	5,027.536

Note: Summary statistics are calculated across all municipality-year observations.

Table 10. Regional averages of marginal benefits of technologies

Region	Permeable Pavement (USD/per m^2)	Green Roofs (USD/per m^2)	Rainwater Retention Tank (USD/per unit)
Seoul	1.82	2.50	1,074.53
Busan	1.43	3.26	1,401.62
Daegu	0.03	0.08	36.41
Incheon	0.32	0.82	350.81
Gwangju	2.11	5.07	2,264.23
Daejeon	0.60	1.48	636.43
Ulsan	4.76	14.62	6,280.66
Sejong	0.31	1.08	465.07
Gyeong-Gi	3.08	3.49	1,501.52
Gangwon	6.09	21.59	9,273.77
Chung-Buk	10.26	29.88	12,835.32
Chung-Nam	6.81	14.48	6,218.88
Jeon-Buk	4.10	12.87	5,528.54
Jeon-Nam	8.62	21.96	9,432.66
Gyeong-Buk	9.53	22.32	9,587.71
Gyeong-Nam	4.53	9.28	3,984.77
Jeju	8.50	31.15	13,379.17
Average	4.29	11.54	4,956.63

Note: Regional values represent seven-year averages. The final row reports the unweighted arithmetic mean across the 17 first-level administrative regions.

Table 11. Estimated annual total cost of technologies

	Green Roofs (USD/ m^2)	Permeable Pavement (USD/ m^2)	Rainwater Retention Tank (USD/ unit)
Installation cost	198.82	26.61	102,662.49
Service life (years)	40	5	20
Annual maintaining cost	24.96	0	1,693.37
Annual total cost	29.94	5.32	6,826.49

Table 12. Benefit-Cost Ratio of technologies across municipalities

Region	Green Roofs (per m^2)	Permeable Pavement (per m^2)	Rainwater Retention Tank (per unit)
Seoul	0.68	0.19	1.28
Busan	0.31	0.39	2.09
Daegu	0.01	0.09	0.17
Incheon	0.20	0.13	0.07
Gwangju	0.01	1.48	2.12
Daejeon	0	0.39	0.64
Ulsan	1.33	0	1.67
Sejong	0	0	0
Gyeong-Gi	0.31	2.88	1.81
Gangwon	1.28	7.68	5.78
Chung-Buk	0.05	0.05	5.99
Chung-Nam	1.41	5.01	5.37
Jeon-Buk	0.10	0.56	1.87
Jeon-Nam	0.02	1.40	4.17
Gyeong-Buk	3.13	7.87	15.37
Gyeong-Nam	0.16	0.87	7.35
Jeju	0.91	0	11.77
Average	0.58	1.70	3.97

Note: Values reported as zero indicate regions where the corresponding technology was not installed during the study period.

Table 13. Cost-Effectiveness Thresholds by technology

	Marginal Benefit	Annual Total Cost	CET
Permeable Pavement (USD/ m^2)	4.29	5.32	1.24
Green Roofs (USD/ m^2)	11.54	29.94	2.59
Rainwater Retention Tank (USD/ unit)	4,956.63	6,826.49	1.38