

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

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ABSTRACT

The attribution of climate change to various natural disasters, including flood events, has continued to receive a considerable attention as it impacts the socioeconomic sustainability of society. However, the existing knowledge on the influential role of extreme precipitation on flood events and subsequent economic damage is limited. Thus, this study investigates the causal relationship between flood damage cost, flooded area, and extreme precipitation indices in the Chungcheong region of South Korea using the autoregressive distributed lag-error correction model (ARDL-ECM) framework and pairwise Granger causality analysis. Four extreme precipitation indices: consecutive wet days (CWD), number of very heavy precipitation days (R30mm), maximum 1-day precipitation amount (Rx1day), and simple daily precipitation intensity (SDII) that measure precipitation frequency, intensity, and duration were selected with time series data on the flooded areas and estimated flood damage cost from 1985 to 2020. The ARDL-ECM bound test indicates an existence of a long-run relationship among all the variables. The empirical results of pairwise Granger causality analysis further reveal that flooded area, R30mm, and Rx1day have significant positive causal impacts on the flood damage cost in both short and long-runs, in the current period. This implies that any increase in any of these variables will cause an increase in the flood damage cost. Unidirectional causality exists from the flooded area, R30mm, Rx1days, and SDII to flood damage cost, and from R30mm and SDII to flooded area. These extreme precipitation variables could serve as indicators of flood events and economic flood damage. This study advances the knowledge of the causal link between extreme precipitation indices and economic damage from flood events.

1. Introduction

The frequency and intensity of climate extreme events driven by climate change have increased steadily in recent times. In particular, heavy-precipitation-induced flood events have continued to wreak havoc in many regions and countries (FloodList, 2022). Extreme precipitation events are regarded as unusual changes in climate conditions that potentially cause severe impacts leading to several economic losses and damage to structures, farmlands, and loss of lives (Jiang and Tan, 2022; Rahmani and Harrington, 2019). The recent increase in extreme precipitation events which accounted for the major natural disasters globally has been regarded as an evidence of climate change (H. Liu et al., 2022; Mondal et al., 2022). According to the available data

provided by the World Meteorological Organization (WMO), there were more than 1100 disasters between 1970 and 2019 that are attributed to extreme water-related climate events, which resulted in economic losses of 3.64 billion US dollars and more than 2 million death globally (WMO, 2019). Extreme climate events, especially flood events are regular occurrences in South Korea due to the country's strategic location in the monsoon climate region, thereby causing significant social and economic losses. According to the National Emergency Management Agency's annual report, about 95% of occurrence natural disasters in South Korea are related to extreme precipitation events. In recent decades from 2009 to 2018, the flood damage cost accounted for 89% of the total economic damage from various disasters (NEMA, 2018), with flood events causing economic damages worth 636.6 billion Korean won

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in 2012 due to heavy precipitation and strong wind from Typhoons Tembin and Bolaven (Kim and Sohn, 2018). Public facilities, which include roads, water supplies, and harbors followed by farmlands accounted for the most flood damage costs in South Korea (Lee et al., 2017). The most recent heavy-precipitation-induced flood event in 2022 is regarded as a record-breaking in 80 years with about 137 mm/hr in the capital and extending to the central region of the country (Choe, 2022).

The societal perspective on disasters such as floods does not only centered on their magnitude but also on their economic impacts, i.e., economic damage associated with the floods as it relates to the socio-economic sustainability of the society (Blöschl et al., 2015). The vulnerability of society to the events of extreme precipitation is further compounded due to the increasing population and urbanization (Gimeno et al., 2022). Indeed, extreme climate events characterized by increasing frequency and intensity of precipitation cause disasters and catastrophes; thus, threatening the sustainability of many cities and agricultural settlements in rural settings (Eini et al., 2022; Wang et al., 2017). However, there is still limited knowledge regarding the influence of precipitation changes on flood events and associated economic damage (Sharma et al., 2018). Thus, it is imperative to understand the economic damage of flood-related disasters and climate change drivers to aid in efficient budget planning for prevention and post-disaster management. Under this backdrop, an important and relevant research question arises on what constitutes the precipitation characteristics that cause flood events and subsequent economic damage.

Many studies have attempted to analyze the damage cost from natural disasters, specifically flood-related disasters using disaster modeling and regression analysis (Lee et al., 2017). However, few studies associated the flood damage costs with the precipitation indices. Ávila et al. (2016) investigated the relationship between flash floods and landslides and spatio-temporal changes in precipitation in the south-eastern region of Brazil using correlation analysis (Ávila et al., 2016). It was found that maximum 1-day and 5-day consecutive precipitation positively influence the flash flood and landslide events with a statistically significant correlation. Santos and Fragoso (2016) assessed the relationship between flood events and precipitation thresholds of amount and duration in northern Portugal (Santos and Fragoso, 2016). The authors reported that a minimum threshold of precipitation characteristics should be considered for flood triggering. Diakakis (2012) examined the correlation between rainfall conditions and flood triggering in northeast Attica, Greece (Diakakis, 2012). The results obtained indicated that among the different rainfall conditions investigated, only peak storm intensity significantly correlated with flood triggering. Romanescu and Stoleriu (2017) attributed the 2010 summer flood in the eastern part of Romania to the climate instability that resulted in heavy precipitation rates of 42 mm/30 minutes and caused huge economic damage (Romanescu and Stoleriu, 2017). Dao et al. (2020) investigated the precipitation threshold for floods in the Seoul region of South Korea and found that flood-induced rainfall varied between 37 and 62 mm/hr (Dao et al., 2020a). Furthermore, a precipitation intensity threshold of 55 mm/hr that could cause flood was reported for Busan metropolitan city in South Korea (Dao et al., 2020b). While the findings from these studies provide significant contributions on the subject under consideration, the correlation analysis as majorly used does not indicate causation. Besides, the economic damage is not often considered in the analysis, therefore, creating an important knowledge gap in this regard.

Econometric modeling is an effective tool for time series data to determine the causal impact of an event using some relevant and associated variables. For example, Granger causality analysis is considered an effective method for establishing the causal relationship as well as indicating the quantitative strength of such relationships among the variables (Granger, 1988). This method has been widely used to establish the causal effect of climate change and variability on various forms of human endeavors. Yang et al. (2020) investigated the potential causal relationship between climate variability and social systems in form of

migration and social crisis (Yang et al., 2020). Xin et al. (2022) analyzed the relationship between innovation in climate change mitigation technologies and CO₂ emissions from the chemical industry in the USA (Xin et al., 2022). Demirhan (2020) investigated the cointegration relationship between climate change and wheat production using autoregressive distributed lag models (Demirhan, 2020). Zhu et al. (2022) assessed the influence of temperature changes on the extreme precipitation indices in Inner Mongolia using autoregression models and Granger causality (Zhu et al., 2022). Yang et al. (2022) investigated the causal impact of soil moisture on terrestrial water storage and flood potential index based on the Granger causality test (Yang et al., 2022). The ARDL-ECM framework leading to the granger causality comes into play with more accurate results when there are cointegration relationships among the variables (Engle and Granger, 1987). Despite the growing application of this method, no study has employed the ARDL-ECM and Granger causality to investigate the causal link between climate extreme events and economic damage.

Meanwhile, climate indices of precipitation and temperature are considered important indicators for extreme events and for assessing climate change and variability (Adelodun et al., 2022a). The expert teams on climate change detection and indices (ETCCDI) and Sector Specific Climate Indices (ET-SCI) are specialized teams endorsed by the World Meteorological Organization (WMO) to develop various indices ranging from moderate to extreme indices that provide scientifically robust events of daily change and variability of extremes (Zhang et al., 2011). The climate extreme indices have been extensively used to investigate the occurrence of extreme events (Adelodun et al., 2022b; Deng et al., 2022; Gimeno et al., 2022). However, many of these studies failed to relate the calculated extreme indices to the flood events and associated economic damage due to a lack of data, thereby prompting the challenges to determine the appropriate indices and precipitation characteristics that accurately describe the cause or aid flood events and economic damage.

Considering the aforementioned limited knowledge, there is a need to investigate the appropriate precipitation characteristics that influence flooding and consequently severity of the economic damage (Ávila et al., 2016; Sharma et al., 2018). Besides, since changes in extreme precipitation is an indication of climate change, quantifying the causal impacts of precipitation characteristics on flood damage can be useful for estimating the cost of climate change (Davenport et al., 2021). Moreover, the need for a dynamic approach that could aid the forecasting of severity and economic damage from extreme climate events, which have become a priority of many governmental institutions, especially in Europe and Asia (Ávila et al., 2016; Lee et al., 2017). Thus, there is a need to investigate the causal link between climate change-induced extreme events and economic damage. The main aim of this study is to investigate the causal impact relationship between flood damage cost, flooded area, and extreme precipitation indices in the Chungcheong region of South Korea using the autoregressive distributed lag-error correction model (ARDL-ECM) and pairwise Granger causality analysis. To the best of our knowledge, this is the first study to investigate the causal relationship between extreme precipitation indices and flood damage cost using the ARDL-ECM approach and pairwise Granger causality analysis, which indicates the novelty behind this study. Further, this study is expected to advance the understanding of the causal link between precipitation characteristics and economic damage from flood events.

2. Materials and methods

2.1. Study area and data sources

Chungcheong region, which comprises Chungcheongbuk-do in the north and Chungcheongnam-do in the south, is located between Latitude 35°58' N - 36°00' N and Longitude 127°38' E - 125°32' E at the west-central region of Republic of Korea, herein referred to as South Korea,

and on the east end of the Asian continent (Fig. 1). In 2020, there were approximately 5.6 million inhabitants with total area of about 16,642 km². The study area is one of the provinces in South Korea that witness year-in year-out flood events due to the extreme weather condition and its geographical location. The annual average temperature is 11.7°C while the annual precipitation amount ranges from 1165.97 mm to 1326.39 mm with an average value of 1239.7 mm measured between 1974 and 2020. The summer (June to August) and autumn (September to November) seasons are characterized by increased and prolonged precipitation intensities, which aid the frequent flood events in the region, especially the inundation of farm settlements (Adelodun et al., 2022a).

The topographic features consist of mountainous and lowland areas with about 67% of land areas at an altitude of <100 m and a relatively low slope of <5 degrees (KOSIS, 2022a). The mountain system in the study area is majorly divided into the Sobaek Mountains in the east and Noryeong Mountains on the northwest side with many other smaller mountains that contribute to the hydrological processes such as waterfalls along the several valleys that are used for agricultural production. These features demonstrate the characteristics of the East and West Korean Peninsula (Cho et al., 2016).

Further, the Chungcheong region largely belongs to the Geum River basin in the south and partly the Namhan River basin, the mainstream of the Han River basin that houses the Chungju dam, in the northeast. It is also intersected by several major rivers, including the Geum River, the Yeongsan River, and the Nakdong River while the western part borders the Yellow sea. The major land use/land cover of the study area includes vegetation cover, built area, agriculture, and water body, which comprise 8078.56 km², 3622 km², 3096.34 km², and 546.86 km², respectively (Fig. 1). The paddy fields, supported by the flat terrain,

account for the 23% of total rice fields in South Korea.

The flood events are reoccurring occurrences in Chungcheong province which often lead to huge economic damages and loss of lives. According to the state media, in August 2010, the heavy rainfall caused the Geum River to overflow, causing significant damage to agriculture and public infrastructure including 80 acres of agricultural land and destruction of 36 buildings in Jecheon city, North Chungcheong region. In 2017, flood damage from heavy rainfall resulted in the damage of more than 500 houses and destruction of several public facility including 5000 hectares of farmland and death of 37,000 chicken from 14 poultry farms across Chungcheong region (Kim, 2017). The 2020 flood resulted in inundation of over 5000 hectares of farmland with maximum daily rainfall intensity of 427.5 mm in Chungju, Chungcheong province (FloodList, 2020). According to the Korea meteorological administration (KMA), 290 mm precipitation was recorded in 24 hours in August 2020 which resulted in the damages of public facility and agricultural settlements. The farmland and public facilities accounted for 10% and 87% of the total damage cost, respectively, with 10 missing people and 4 injured in the Chungcheong region in 2020 (KOSIS, 2022b). The recent 2022 flood was caused by heavy rainfall of up to 327 mm in Jecheon and 269 mm in Cheongju, which affected many areas in Chungcheong region, including Cheongju, Daejeon, and Sejong where several property were damaged, more than 305 hectares of farmland were inundated, and loss of lives was recorded (KMA, 2022). All the flood events and economic damage in the study area are primarily attributed to the changes in extreme precipitation patterns.

The daily precipitation data series (1985 – 2020) in 10 synoptic stations, which are homogeneously spread over the Chungcheong province, was retrieved from the Korean Meteorological Administration (KMA, 2022). The precipitation data period is considered due to the data

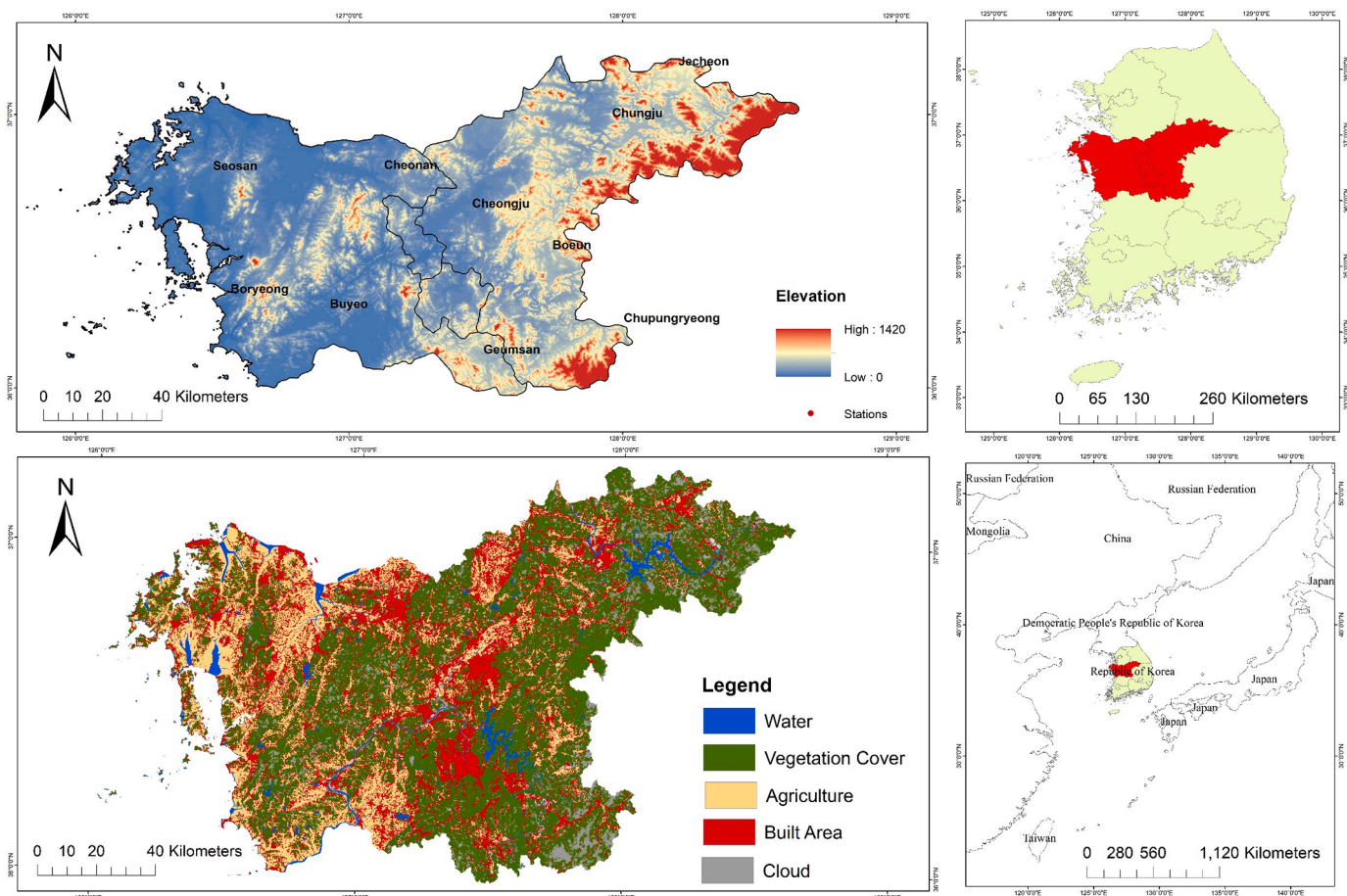


Fig. 1. Map of the study area showing its location, elevation, land use/land cover, and the spots of synoptic stations.

availability for the flood events and the associated cost of damage in the study area. Similarly, the annual data series on the flooded area (ha) and flood damage cost (millions of Korean won) estimated from flood events were obtained from the Korean statistical database (KOSIS, 2022b). The damage cost data herein refers to direct economic damage data on the loss of public facilities, farmlands, and buildings, among others, due to pluvial-induced flood events, which are estimated after each flood events and compiled annually.

2.2. Precipitation extreme indices

Four extreme precipitation indices, consisting of consecutive wet days (CWD), number of very heavy precipitation wet days (R30mm), maximum 1-day precipitation amount (Rx1day), and simple daily precipitation intensity (SDII), were computed using the ET-SCI methodology in ClimPACT2 tool (Alexander and Herold, 2016), which also involved data quality control checks. The data were also checked for homogeneity before computing the indices (Adelodun et al., 2022a). The selected indices are among the 11 extreme precipitation-based indices defined by the ETCCDI to assess different characteristics of climate extremes (http://etccdi.pacificclimate.org/indices_def.shtml) and also recommended by the World Meteorological Organization (WMO, 2009). The selected extreme precipitation indices i.e., Rx1day and SDII, R30mm, and CWD reveal the changes in the intensity, frequency, and duration, respectively, of the extreme climate events (Felix et al., 2021; Quan et al., 2021). These extreme precipitation indices are commonly considered for water-related extreme events such as floods and landslides (Ávila et al., 2016; Deng et al., 2022; Eini et al., 2022; Goyal et al., 2022).

2.3. Variables description and data analysis

2.3.1. Variables used and model specification

The annual time series data of six variables for 1985 - 2020 are used in this study. The flood damage cost (FDC) is selected as the dependent variable, while the explanatory variables are flooded area (FA), consecutive wet days (CWD), the number of very heavy precipitation wet days (R30mm), maximum 1-day precipitation amount (Rx1day), and simple daily precipitation intensity (SDII). Detailed information about the variables is presented in Table 1. All the variables were log-transformed (natural logarithms) to reduce the non-normal distribution and minimize the effect of heteroscedasticity in the data series (Abulibdeh, 2022; Zhang et al., 2021). It is worthy of note that the log transformation of the data series does not affect the cointegration relationship and other important properties of the variables but only improves the linearity by normalizing the highly skewed data series. The original data series of the variables before the log transformation is shown in Fig. 2.

The linear form of the model to examine the long- and short-runs, and causality relationships between the flood damage cost, flooded area, and extreme precipitation indices are specified in Eq. 1 while the

log-linear based econometric model is presented in Eq. 2:

$$FDC_t = f(FA_t, CWD_t, R30_t, Rx1day_t, SDII_t) \quad (1)$$

$$\ln FDC_t = \alpha + \beta_1 \ln FA_t + \beta_2 \ln CWD_t + \beta_3 \ln R30_t + \beta_4 \ln Rx1day_t + \beta_5 \ln SDII_t + \varepsilon_t \quad (2)$$

Where α is a constant term, β_1 to β_5 are coefficients of the model, ε_t is the stochastic error term, and t represents the time series of the study i.e., $t = 1, 2, \dots, 35$. The respective log forms of the variables are $\ln FDC$, $\ln FA$, $\ln CWD$, $\ln R30$, $\ln Rx1day$, and $\ln SDII$, as used in the model.

2.3.2. Stationarity test and optimal lag determination

The stationarity test also known as the unit root test is essential for time series data stability to ensure efficient and reliable estimates of the parameters. A stationarity test was conducted for each of the variables of interest in this study to avoid spurious regression issues. Previously, hydro-meteorological time series are assumed to be stationary. However, the introduction of econometric analysis in the field of hydrology and water resources has overcome the shortcomings associated with assumption of stationarity of hydro-meteorological time series variables (Zhang et al., 2021). The Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (PP) (Phillips and Perron, 1988) tests, which are the most common methods for testing the stationarity of data series were applied to the log-transformed 6 variables used in this study. Furthermore, in order to account for the possible structural break points in the series, which the ADF and PP failed to consider, we applied Zivot and Andrews (ZA) stationarity test (Zivot and Andrews, 1992). The ZA considered and treated the break-point endogenously as a modification of the Perron stationarity test (Perron, 1989). The null hypothesis of ADF, PP, and ZA is that the time series is non-stationary i.e. has a unit root and was tested at a significance level of 5%. However, the alternative hypothesis states that the series is stationary i.e. has no unit root.

In the ARDL-ECM model, the selection of appropriate lag length is necessary as too many lag lengths could result in loss of degrees of freedom, cause multicollinearity, serial correlation in the error terms, and also leads to misspecification errors. In other words, the selection of appropriate lag length in the ARDL-ECM model addresses the endogeneity issue. In this study, the selection of optimal lag length for the ARDL-ECM model is based on Akaike Information Criteria (AIC).

2.3.3. ARDL-ECM cointegration test

The autoregressive distributed lag-error correction model (ARDL-ECM) bound test was employed as a cointegration test to verify the existence of stable relationships among the variables in this study. These relationships include long-run and short-run, and the dynamics of the variables' coefficients. Unlike other conventional cointegration test methods such as Johansen and Engle-Granger tests, the ARDL-ECM bound test proposed by Pesaran et al. (2001) addresses autocorrelation issue while the selection of an appropriate lag length i.e., optimal lag, and also caters to the endogenous concern where ARDL-ECM can be used to analyze the long-term relationship of variables that are integrated of order 0 i.e. $I(0)$, 1 i.e. $I(1)$, or both (Pesaran et al., 2001). Besides, the results from these conventional methods are affected when the data contain structural breaks (Abulibdeh, 2022). However, the critical bounds introduced by Pesaran et al. (2001) are applicable for large sample sizes ranging from 500 to 40000, and using such for a small sample size could give a biased estimate. The applicable mechanism for a small sample size (30 to 80 observations) introduced by Narayan (2005) is, thus, considered as it fits the data sample size in our study (Narayan, 2005). The estimation results obtained from the ARDL-ECM technique are unbiased and considered efficient (Abulibdeh, 2022; Ali et al., 2019). Furthermore, the ARDL-ECM cannot be applied when the variables are integrated of order 2 i.e., $I(2)$.

The ARDL-ECM cointegration test among the variables was verified using Eq. 3 based on the model specification as presented in Eq. 2. The

Table 1
Definition of variables used in this study.

Variables	Description	Measurement unit
FDC	Flood damage cost i.e. Cost of Economic damage from flood events i.e.	Korean won (millions)
FA	Flooded area	km ²
CWD	Consecutive wet days i.e. maximum number of consecutive days when precipitation ≥ 1 mm.	day
R30mm	The number of very heavy precipitation days i.e. annual days with precipitation ≥ 30 mm.	day
Rx1day	Maximum 1-day precipitation amount i.e. annual maximum 1-day precipitation.	mm
SDII	Simple daily precipitation intensity i.e. the ratio of annual total precipitation to the number of wet days (≥ 1 mm).	mm/day

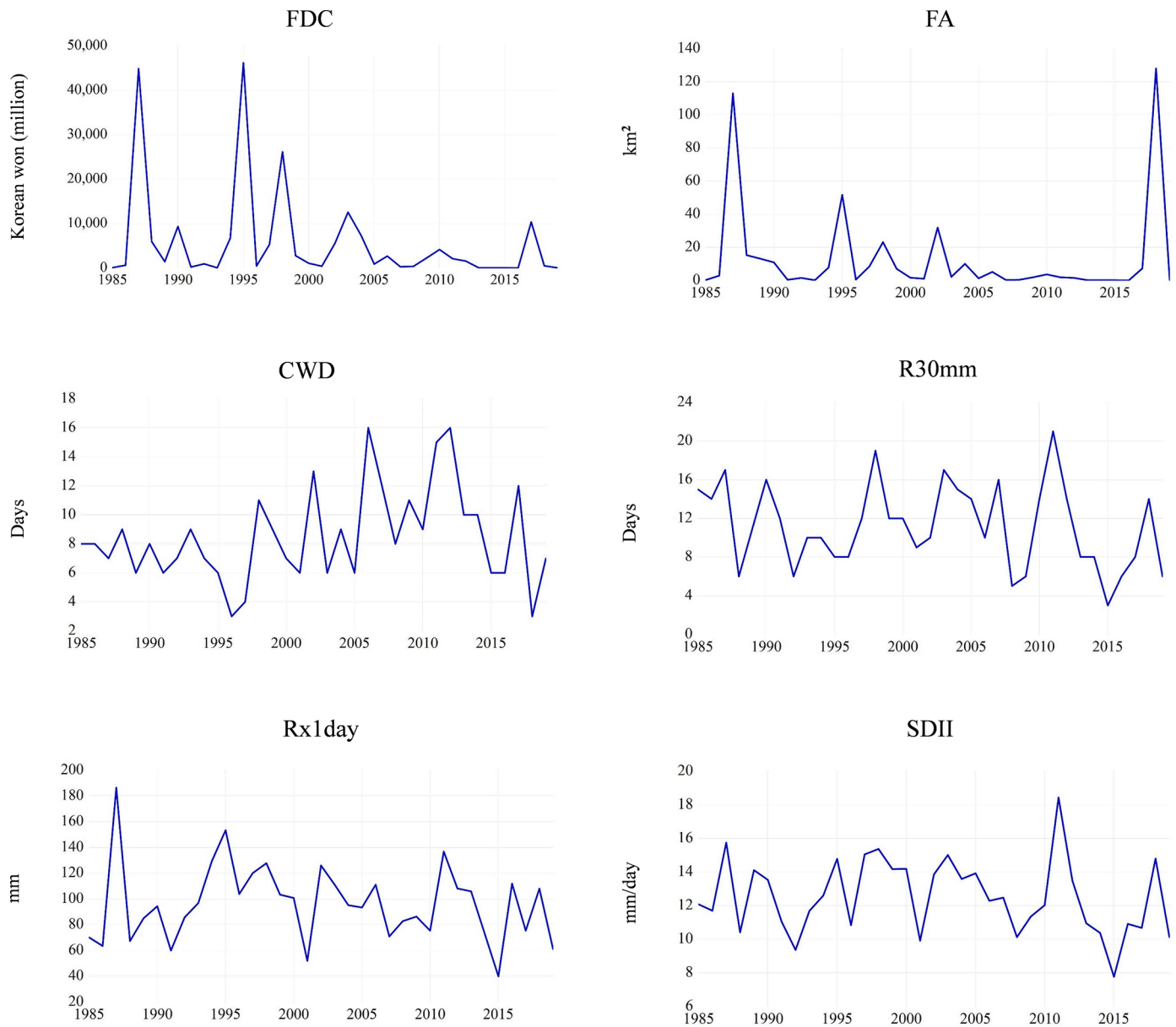


Fig. 2. Trends of variables in their natural form (before taking their logarithms).

test was performed on the log-transformed level of the variables.

$$\begin{aligned} \Delta \ln FDC_t = & \alpha_1 + \sum_{i=1}^k \beta_{1i} \Delta \ln FDC_{t-i} + \sum_{i=0}^l \gamma_{1i} \Delta \ln FA_{t-i} + \sum_{i=0}^m \varphi_{1i} \Delta \ln CWD_{t-i} \\ & + \sum_{i=0}^n \partial_{1i} \Delta \ln R30_{t-i} + \sum_{i=0}^p \tau_{1i} \Delta \ln Rx1day_{t-i} + \sum_{i=0}^q \Psi_{1i} \Delta \ln SDII_{t-i} \\ & + \Phi_{11} \ln FDC_{t-1} + \Phi_{12} \ln FA_{t-1} + \Phi_{13} \ln CWD_{t-1} + \Phi_{14} \ln R30_{t-1} \\ & + \Phi_{15} \ln Rx1day_{t-1} + \Phi_{16} \ln SDII_{t-1} + \varepsilon_{1t} \end{aligned} \quad (3)$$

Where Δ is the first difference operator; α_1 is the constant term; k , l , m , n , p , and q are maximum lag lengths as determined by the AIC; Σ is the short-run section of the model equation; β_{1i} , γ_{1i} , φ_{1i} , ∂_{1i} , τ_{1i} , and Ψ_{1i} are short-run correlation coefficients; Φ_{11} , Φ_{12} , Φ_{13} , Φ_{14} , Φ_{15} , and Φ_{16} are long-run correlation coefficients; $\ln FDC$, $\ln FA$, $\ln CWD$, $\ln R30$, $\ln Rx1day$, and $\ln SDII$ are the variables of interest; ε_{1t} is the stochastic error term that is free from serial correlation and heteroscedasticity.

The null hypothesis of the ARDL-ECM bound test is no cointegration i.e. $H_0: \Phi_{11} = \Phi_{12} = \Phi_{13} = \Phi_{14} = \Phi_{15} = \Phi_{16} = 0$ and the alternative

hypothesis is $H_1: \Phi_{11} \neq \Phi_{12} \neq \Phi_{13} \neq \Phi_{14} \neq \Phi_{15} \neq \Phi_{16} \neq 0$ i.e. there is cointegration. The null hypothesis is rejected when the ARDL-ECM F-statistic value is greater than the critical value of the upper bound $[I(0)]$ at a significance level of 5%, indicating cointegration among the investigated variables.

2.3.4. Long-run and short-run estimation

The cointegration relationship among the variables is established after passing the bound test of ARDL-ECM where the null hypothesis is rejected. The long-run equilibrium coefficients or simply put correlation coefficients are, thus, estimated using Eq. 4.

$$\begin{aligned} \Delta \ln FDC_t = & \alpha_1 + \sum_{i=1}^k \beta_{1i} \Delta \ln FDC_{t-i} + \sum_{i=0}^l \gamma_{1i} \Delta \ln FA_{t-i} + \sum_{i=0}^m \varphi_{1i} \Delta \ln CWD_{t-i} \\ & + \sum_{i=0}^n \partial_{1i} \Delta \ln R30_{t-i} + \sum_{i=0}^p \tau_{1i} \Delta \ln Rx1day_{t-i} + \sum_{i=0}^q \Psi_{1i} \Delta \ln SDII_{t-i} \\ & + \varepsilon_{1t} \end{aligned} \quad (4)$$

Thereafter, the short-run dynamics of the investigated variables are estimated using the error correction model in Eq. 5.

$$\begin{aligned} \Delta \ln FDC_t = & \alpha_1 + \sum_{i=1}^k \beta_{1i} \Delta \ln CD_{t-i} + \sum_{i=0}^l \gamma_{1i} \Delta \ln FA_{t-i} + \sum_{i=0}^m \varphi_{1i} \Delta \ln CWD_{t-i} \\ & + \sum_{i=0}^n \delta_{1i} \Delta \ln R30_{t-i} + \sum_{i=0}^p \tau_{1i} \Delta \ln Rx1day_{t-i} + \sum_{i=0}^q \Psi_{1i} \Delta \ln SDII_{t-i} \\ & + \lambda ECT_{t-1} + \varepsilon_1 \end{aligned} \quad (5)$$

Where ECT_{t-1} is the error correction term with lagged periods. This indicates the speed of adjustment in long-run equilibrium with lag representation after the shock in the short-run. The value of the coefficient (λ) of the error correction term (ECT_{t-1}) must be negative or falls between 0 and -1 and statistically significant for the short-run dynamics to converge to the long-run equilibrium (Danish et al., 2019).

2.3.5. Diagnostic tests

The post-estimation tests are also conducted to verify the reliability of the coefficients and stability of the model to avoid misspecification and bias in the model (Rahman and Alam, 2022). The diagnostic tests conducted were normality, serial correlation, heteroscedasticity, linearity, and stability tests using Jarque-Bera statistic, Breusch-Godfrey (BG) Lagrange Multiplier (LM) test, Breusch-Pagan-Godfrey and ARCH tests, Ramsey RESET (Regression Specification Error Test), and cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests, respectively.

2.3.6. Causality test

The direction of causality between the investigated variables is necessary for policy implementation after estimating the long and short-term relationships. This study employs the pairwise Granger's causality test. The test is performed for each pair of variables to indicate the existence and direction of causality among the variables. The lag-order selection for the Granger causality is based on the AIC as previously considered. The model equation governing the pairwise Granger causality test between two-time series or variables as described by Shahzad et al. (2021) (Shahzad et al., 2021) is presented in Eq. 6.

$$\Delta Y_t = \alpha_1 + \sum_{i=1}^n \phi_{Yt} \Delta Y_{t-i} + \sum_{i=1}^n \delta_{Yt} \Delta X_{t-i} + \mu_{Yt} \quad (6)$$

Where Δ is the first difference operator and μ_{Yt} represents the white noise error.

3. Results

3.1. Definition and descriptive statistics of the variables

The definitions and statistical descriptions of the variables used in this study are presented in Tables 1 and 2, respectively. The average values of the flood damage cost, flooded area, consecutive wet days, number of very heavy precipitation days, maximum 1-day precipitation

Table 2
Descriptive statistics of the variables used in this study

Description	lnFDC	lnFA	lnCWD	lnR30	lnRx1day	lnSDII
Mean	6.869	0.417	2.061	2.332	4.520	2.513
Median	7.296	0.679	2.079	2.398	4.556	2.508
Maximum	10.739	4.852	2.773	3.045	5.228	2.914
Minimum	0.241	-6.571	1.099	1.099	3.686	2.048
Std. Dev.	2.546	2.820	0.400	0.436	0.318	0.179
Skewness	-0.784	-0.793	-0.405	-0.664	-0.313	-0.198
Kurtosis	3.164	3.140	3.337	3.112	3.199	2.905
Jarque-Bera	3.520	3.590	1.120	2.587	0.631	0.241
Probability	0.172	0.166	0.571	0.274	0.729	0.887
VIF		1.8631	1.0497	3.8214	3.3430	7.9524

amount, and simple daily precipitation intensity in their natural log forms are 6.869, 0.417, 2.061, 2.332, 4.520, and 2.513, respectively. Similarly, the Jarque-Bera statistics and its respective probability values (> 0.05) showed that all the variables are normally distributed, indicating that the variables could be further explored to establish relationships among them and it is very unlikely to give spurious findings. Furthermore, the multicollinearity among the explanatory variables was also tested using the variance inflation factor (VIF) to quantify the extent of variance inflation of the estimated coefficients. The variables were found to have VIF less than 10 with an average value of 3.61, which indicates no multicollinearity among the variables (Raza and Lin, 2022). The trend of the variables in their original states before the log-transformed is also presented in Fig. 2. Similarly, the spatial distribution of annual mean precipitation indices for the duration (CWD), frequency (R10mm), and intensity (Rx1day) and (SDII) is presented in Fig. 3a while the annual mean of flood area and damage cost inventory are presented in Fig. 3b.

3.2. Stationarity test analysis and optimal lag length result

The results of the stationarity test based on the ADF, PP, and ZA are presented in Tables 3 and 4. The ADF and PP tests showed that the first two variables i.e. flood damage cost and flooded area are non-stationary at level (existence of a unit root) but are stationary at first difference i.e. integrated at order one [I(1)]. Conversely, other variables such as consecutive wet days, number of very heavy precipitation days, maximum 1-day precipitation amount, and simple daily precipitation intensity are all stationary at level i.e. integrated at order zero [I(0)]. The stationarity test of ADF and PP results confirmed that all variables are integrated of orders I(0) and I(1) (Table 3), an indication that ARDL is appropriate for the cointegration test to investigate long and short-run impacts. Besides, the optimal lag length obtained using the AIC that could capture the dynamic relationship in the estimation of the best ARDL model is 3. This lag length has the lowest AIC value and is thus considered accordingly.

Furthermore, flood damage cost (lnFDC) has a structural break in 2012 as indicated by the Zivot-Andrew test, which ADF and PP unit root tests were unable to detect. Other variables such as flooded area (lnFA), number of very heavy precipitation days (lnR30), and simple daily precipitation intensity (lnSDII) also showed a break in 2012. The break in 2012 could be attributed to the 2012 Typhoons Tembin and Bolaven which caused devastating floods, and loss of lives and properties in South Korea (Kim and Sohn, 2018). The stationarity test is essential to avoid using variables with data series integrated of order two or above for the ARDL model as using such variables becomes invalid for the computation of ARDL cointegration analysis.

3.3. ARDL-ECM bounds test result for cointegration

The ARDL-ECM bound test is conducted to verify long-run stable relationships among the lnFDC, lnFA, lnCWD, lnR30, lnRx1day, and lnSDII after establishing the stationarity status of these variables. The results of the ARDL-ECM bound cointegration test is presented in Table 5. The F -statistic value of 20.302 which is greater than the 5.002 critical value of the upper bound $I(1)$ at a 5% significance level when lnFDC is considered as a dependent variable showed that there is a long-run cointegration relationship with other explanatory variables i.e. lnFA, lnCWD, lnR30, lnRx1day, and lnSDII. The optimal lags structure of the ARDL model based on the AIC are (1,3,3,3,3,2). The AIC method for optimal lag selection was considered because of its superior property to obtain reliable results that can capture the dynamic relationships among the variables compared to other methods such as the Schwarz information criterion and Hannan-Quinn information criterion (Lütkepohl, 2006). Similarly, when other variables were further considered, each as the dependent variable, the F -statistics values are also greater than the critical values of the upper bound at 5% as obtained for the lnFDC

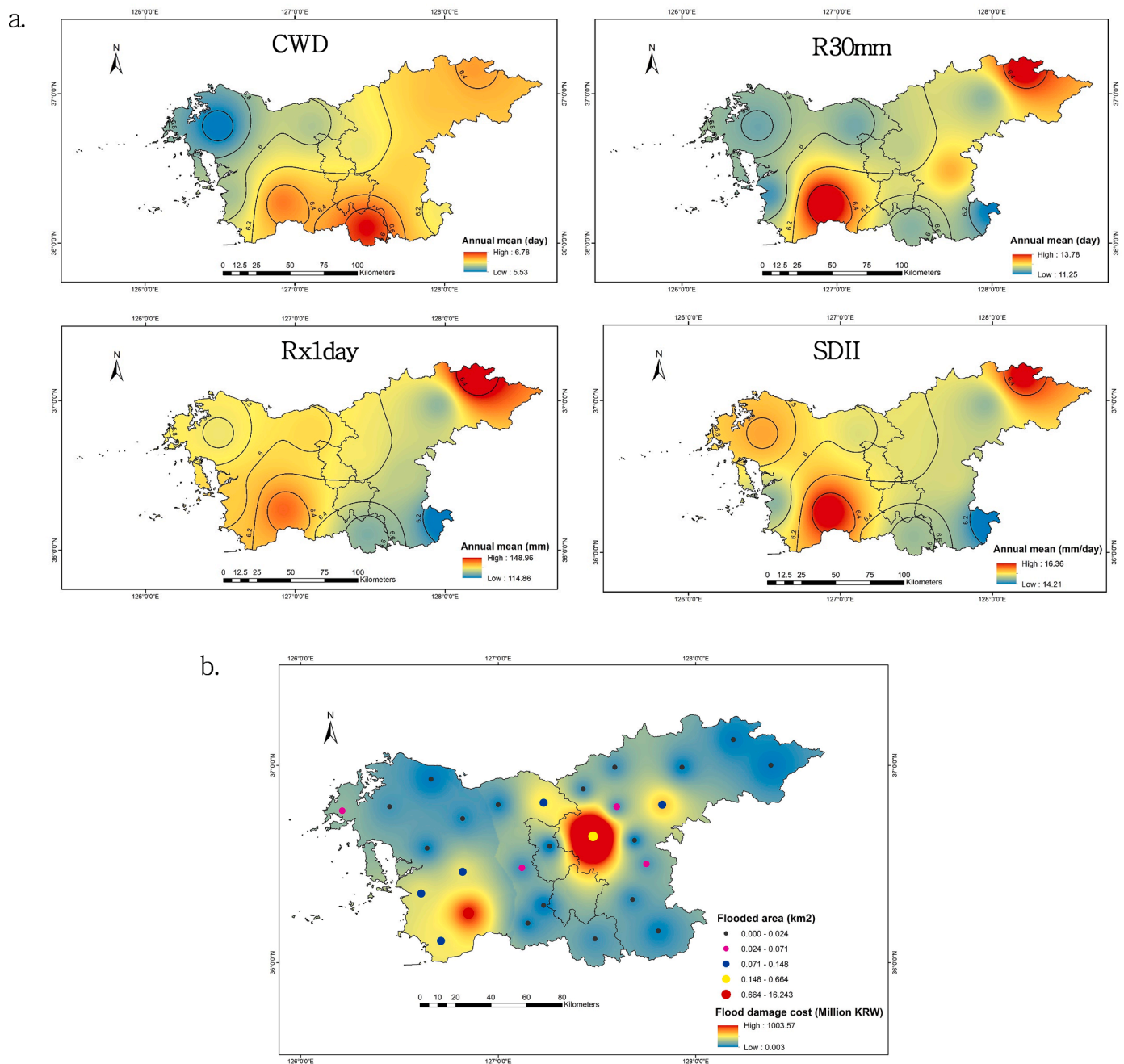


Fig. 3a. Spatial distribution of (a) extreme precipitation indices and (b) flood area and damage cost inventory over Chungcheong region during 1985-2020.

(Table 5). This confirms the existence of cointegration among the variables with each as a dependent variable.

3.4. Relationship between flood damage cost, flooded area, and precipitation indices

The results of long- and short-run estimated parameters for the relationships between the flood damage cost, flooded area, and extreme precipitation-based climate indices in Chungcheong province of South Korea over the period of 1985-2020 are presented in Table 6.

3.4.1. Long-run relationship

The flooded area (lnFA) and maximum 1-day precipitation (lnRx1day) have positive and strong impacts on the economic flood damage at 1% and 5% significance levels, respectively, which is an

indication of a long-run causal impact (Table 6). This implies that a percentage increase in the flooded area will cause a 1.62 percent increase in flood damage costs in the long-run. The increase in the flooded area leads to the possible occurrence of flood damage. Besides, agriculture accounts for one of the major land use, aside from the residential and industrial areas in the Chungcheong province, which could lead to the inundation of farmlands with significant economic losses during flood events (Ko, 2017; Yushin, 2022). The importance of the flooded area as a variable to investigate economic flood damage was also emphasized by Park and Kim (Park et al., 2020).

Similarly, an increase in the maximum 1-day precipitation amount (lnRx1day) by 1% will cause an increase in the flood damage cost by 2.66% in the long-run. This result is consistent with the findings that extreme precipitation intensity, especially a higher value of maximum 1-day precipitation amount could cause flash floods and severe damage

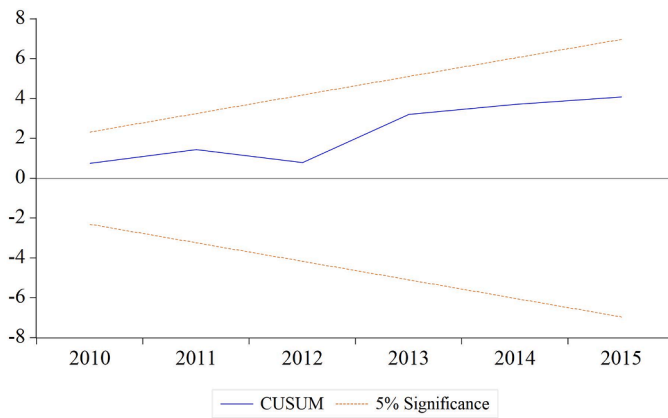


Fig. 3b. Plot of CUSUM for lnFDC model.

Table 3

Stationarity test results for ADF and PP.

Variables	Augmented Dickey-Fuller (ADF)		Philips-Perron (PP)		Order of Integration (I)
	Level	First difference (Δ)	Level	First difference (Δ)	
lnFDC	-2.584 (0.107)	-5.495 (0.000)**	-2.836 (0.065)	-6.289 (0.000)**	I(1)
lnFA	-3.645 (0.042)*	-5.366 (0.001)**	-3.330 (0.080)	-7.498 (0.000)**	I(1)
lnCWD	-4.770 (0.001)**	-9.584 (0.000)**	-4.793 (0.001)**	-18.963 (0.000)**	I(0)
lnR30	-4.211 (0.002)**	-0.907 (0.769)	-4.045 (0.004)**	-12.699 (0.000)**	I(0)
lnRx1day	-5.963 (0.000)**	-4.947 (0.000)**	-5.949 (0.000)**	-20.234 (0.000)**	I(0)
lnSDII	-4.759 (0.001)**	-5.059 (0.000)**	-4.691 (0.001)**	-22.945 (0.000)**	I(0)

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

Table 4

Results of Zivot-Andrews stationarity test.

Variables	Zivot-Andrews			
	Level	Time break	First difference (Δ)	Time break
lnFDC	-5.628**	2012	-7.202**	2011
lnFA	-5.094	2012	-7.737**	1992
lnCWD	-5.965**	2014	-10.201**	1996
lnR30	-5.021	2012	-6.842**	2014
lnRx1day	-7.081**	1993	-10.947**	1986
lnSDII	-5.659**	2012	-8.790**	2014

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

Table 5

ARDL bound test results.

Variable	lnFDC	lnFA	lnCWD	lnR30	lnRx1day	lnSDII
F-statistics	20.302**	17.674**	7.771**	8.819**	14.321**	5.198*
Optimal lag structure	1,3,3,3,3,2	1,3,3,3,1,2	1,3,2,2,1,2	1,1,3,2,0,2	1,0,3,3,3,3	1,1,1,3,3,1
Critical value	1%	5%	10%			
Lower bound I(0)	5.095	3.673	3.087			
Upper bound I(1)	6.770	5.002	4.277			
CointegrationDecision	Yes	Yes	Yes	Yes	Yes	Yes

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

(Ávila et al., 2016; Du et al., 2022). Furthermore, a percentage increase in the number of heavy precipitation days (lnR30) will cause a 0.15% increase in the flood damage cost but this precipitation index is found to be statistically insignificant ($p > 0.05$), an indication that such a climate extreme index does not significantly contribute to the cost of damage from flood events in the long-run in the study area. This can probably be explained by the late insignificant increase in the occurrence frequency of the extremely heavy precipitation days with precipitation above 30 mm in South Korea (Chang et al., 2023).

However, both lnCWD and lnSDII have significant negative impacts on the economic flood damage at 5% and 1% statistical significance levels, respectively, as indicated by the negative values of the estimated coefficients of these variables. This implies that a 1% increase in lnCWD, which is classified as precipitation frequency duration, will cause a decrease in economic flood damage by 1.23%. Similarly, a percentage increase in lnSDII will lead to a decrease in economic flood damage by 12.25% in the current period.

3.4.2. Short-run relationship

The results of the short-run dynamics of the estimated model are presented in Table 6. The lnFA, lnR30, and lnRx1day variables have a strong significant influence on the flood damage cost in the short-run as indicated by their coefficients and probability values. The coefficient values of the short-run show that with a 1% increase in each of lnFA, lnR30, and lnRx1day, the economic flood damage will increase by

Table 6

ARDL long- and short-run estimation results of lnFDC as a dependent variable.

Variables	Coefficient	Standard error	t-Statistic	Prob.
<i>Long-run estimations</i>				
lnFA	1.6162**	0.1734	9.3189	0.0001
lnCWD	-1.2271*	0.3681	-3.3337	0.0157
lnR30	0.1483	0.7178	0.2066	0.8431
lnRx1day	2.6581*	0.8993	2.9557	0.0254
lnSDII	-12.2510**	2.9934	-4.0926	0.0064
<i>Short-run dynamics</i>				
Constant	25.0154**	1.6622	15.0498	0.0000
Trend	0.1168**	0.0091	12.8013	0.0000
Δ lnFA	0.9516**	0.0203	46.9202	0.0000
Δ lnFA(-1)	-0.4538**	0.0336	-13.4876	0.0000
Δ lnFA(-2)	-0.3048**	0.0228	-13.3605	0.0000
Δ lnCWD	-0.8132**	0.0817	-9.9513	0.0001
Δ lnCWD(-1)	0.5270**	0.0881	5.9845	0.0010
Δ lnCWD(-2)	0.8200**	0.0906	9.0516	0.0001
Δ lnR30	0.3180*	0.1140	2.7886	0.0316
Δ lnR30(-1)	0.3616*	0.1112	3.2524	0.0174
Δ lnR30(-2)	0.4905**	0.08816	5.5639	0.0014
Δ lnRx1day	1.5554**	0.1575	9.8766	0.0001
Δ lnRx1day(-1)	0.9421**	0.1512	6.2304	0.0008
Δ lnRx1day(-2)	0.4948*	0.1704	2.9032	0.0272
Δ lnSDII	-3.5047**	0.4282	-8.1844	0.0002
Δ lnSDII(-1)	4.4603**	0.4330	10.3000	0.0000
$ECT_{(t-1)}$	-0.9869**	0.0660	-14.9440	0.0000
R^2	0.9986			
Adjusted R^2	0.9966			
F-statistic	491.006			
Prob. F-statistic	0.0000			

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

0.95%, 0.32%, and 1.56%, respectively, in the current period. However, unlike in the long-run, lagged lnCWD and lnSDII variables have strong positive impacts on the flood damage cost in the current period such that a 1% increase in lnCWD at lag 1 and lag 2 will cause 0.53% and 0.82% increase in flood damage cost, respectively, while 1% increase in lnSDII at lag 1 will cause an increase in flood damage cost by 4.46% in the short-run. These results demonstrate the influence of antecedent soil moisture conditions that could have resulted from the consecutive wet days and daily precipitation intensity before these variables could have had significant positive influences on the economic flood damage. The influence of consecutive wet days of extreme precipitation on the soil moisture condition and flood risk has previously been emphasized (Wasko and Nathan, 2019). Similarly, in the short-run, a percentage increase in lnR30 at lag 1 and lag 2 will cause an increase in the flood damage cost by 0.36% and 0.49%, respectively, in the current period. In South Korea, it was reported that a 1% increase in annual precipitation results in an increase of economic damage by 4.52% (Lee et al., 2017). The abrupt changes in the climate as indicated by the frequency, duration, and intensity of the extreme precipitation-based climate indices may be responsible for the frequent climate-related disasters of flood events being witnessed in South Korea and many other countries (FloodList, 2022). Moreover, change in climate regime reveals an element of causality in climate change impacts based on the outcomes of statistical analysis of the stationarity detection in climate indices data series (Sauquet and Lang, 2017).

The results of short-run dynamics of the variables show that the lagged ECT is negative and highly significant ($p < 0.000$), which also affirms the long-run relationship in the model (Table 6). This implies that there is a high speed of adjustment from the short-run to the long-run if there is any disequilibrium in the model i.e., it takes an average speed of 98.69% to adjust back from the short-run to the long-run. The flooded area and all the investigated extreme precipitation indices are also found to have short-run causal impact relationships on the flood damage cost. Furthermore, the model statistical tests, including the R^2 and adj. R^2 values of 0.9986 and 0.9966, respectively; and the significant prob. value of F -statistic ($p < 0.000$) indicate that the model has a good fit and passed the overall significance test.

3.5. Diagnostic results

To test for the robustness, appropriateness, fitness, and constancy of the empirical estimation of the ARDL-ECM model and policy relevance, various diagnostic tests were conducted and the results are presented in Table 7 and Figs. 3 and 4.

The test results showed that the Jarque-Berra statistic is not significant ($p < 0.4725$) and; thus, failed to reject the null hypothesis of the normal distribution of the error terms. This implies that the residuals of the estimated model are normally distributed. Similarly, the serial correlation of the model was performed to check whether the successive values of the error terms are temporarily independent. The Breuch-Godfrey LM test also failed to reject the hypothesis of the no serial correlation as indicated by the obtained F -statistic (0.6703) and prob. value (0.5610), which indicate that there is no serial correlation problem in the model. To test for the validity of the model, a

Table 7
Results of Diagnostic test statistics for the flood damage cost ARDL-ECM.

Diagnostic test	Test type	F-statistic	Prob.
Normality	Jarque-Bera statistic	1.4995	0.4725
Serial correlation	Breuch-Godfrey LM test	0.6703	0.5610
Heteroscedasticity	Breusch-Pagan-Godfrey	0.7911	0.6845
	ARCH	1.1746	0.3268
Linearity	Ramsey RESET	0.2388	0.7980
Stability	CUSUM	Stable	
	CUSUMSQ	Stable	

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

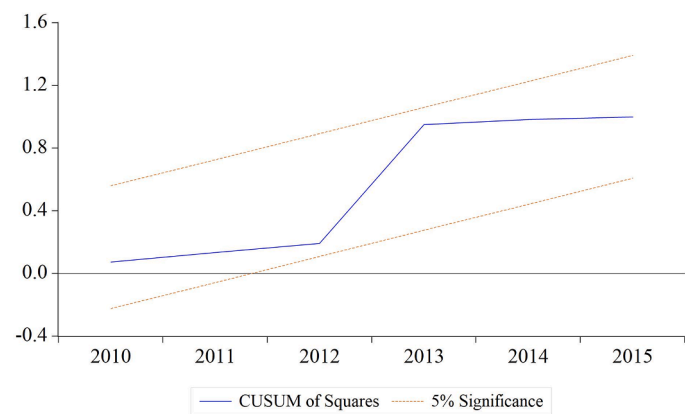


Fig. 4. Plot of CUSUM of square for lnFDC model.

heteroscedasticity test was conducted to find out if error terms exhibit constant variance. Both Breusch-Pagan-Godfrey and ARCH tests confirmed that the model is homoscedastic as shown by their insignificant p -values of 0.6845 and 0.3268, respectively, which indicates the absence of heteroscedasticity in the model. The linearity test was also conducted to test the specificity of the model i.e., the linear relationship between the dependent variable and explanatory variables. The Ramsey RESET test failed to reject the null hypothesis of a linear relationship and confirmed that the model is well and correctly specified. Furthermore, the CUSUM and CUSUM square plots test statistics within the 5% critical bounds confirmed the appropriateness and stability of the model. This implies that all the coefficients in the model are stable and the model is suitable for making a long-run decision.

3.6. Granger causality test result

The results of the pairwise Granger causality test are presented in Table 8. The results show that the flooded area and all the extreme

Table 8
The results of the pairwise Granger causality test.

Granger causality	F-statistic	Prob. value	Conclusion
lnFA $\Rightarrow$ lnFDC	3.7521	0.0625	Unidirectional
lnFDC $\Rightarrow$ lnFA	0.2364	0.6305	
lnCWD $\Rightarrow$ lnFDC	0.6290	0.4342	
lnFDC $\Rightarrow$ lnCWD	1.1473	0.2929	Unidirectional
lnR30 $\Rightarrow$ lnFDC	5.9961	0.0206	
lnFDC $\Rightarrow$ lnR30	0.0659	0.7992	
lnRx1day $\Rightarrow$ lnFDC	3.7297	0.0633	Unidirectional
lnFDC $\Rightarrow$ lnRx1day	0.9587	0.3356	
lnSDII $\Rightarrow$ lnFDC	8.7821	0.0060	
lnFDC $\Rightarrow$ lnSDII	0.0014	0.9704	Unidirectional
lnCWD $\Rightarrow$ lnFA	0.4779	0.4949	
lnFA $\Rightarrow$ lnCWD	0.2111	0.6494	
lnR30 $\Rightarrow$ lnFA	3.8080	0.0607	Unidirectional
lnFA $\Rightarrow$ lnR30	0.0079	0.9298	
lnRx1day $\Rightarrow$ lnFA	1.3533	0.2542	
lnFA $\Rightarrow$ lnRx1day	1.8537	0.1838	Unidirectional
lnSDII $\Rightarrow$ lnFA	5.2808	0.0290	
lnFA $\Rightarrow$ lnSDII	0.2742	0.6045	
lnR30 $\Rightarrow$ lnCWD	0.2024	0.6559	Unidirectional
lnCWD $\Rightarrow$ lnR30	1.5785	0.2184	
lnRx1day $\Rightarrow$ lnCWD	0.1047	0.7484	
lnCWD $\Rightarrow$ lnRx1day	0.0184	0.8930	Unidirectional
lnSDII $\Rightarrow$ lnCWD	0.0029	0.9574	
lnCWD $\Rightarrow$ lnSDII	0.6282	0.4341	
lnRx1day $\Rightarrow$ lnR30	0.0602	0.8078	Unidirectional
lnR30 $\Rightarrow$ lnRx1day	0.0046	0.9461	
lnSDII $\Rightarrow$ lnR30	0.1425	0.7084	
lnR30 $\Rightarrow$ lnSDII	0.5408	0.4676	Unidirectional
lnSDII $\Rightarrow$ lnRx1day	0.2496	0.6209	
lnRx1day $\Rightarrow$ lnSDII	0.0496	0.8253	

precipitation indices except $\ln\text{CWD}$ granger cause flood damage cost at a significance level of at least 10%. Specifically, the results reveal unidirectional causality from the flooded area ($\ln\text{FA}$), heavy precipitation days ($\ln\text{R30}$), maximum 1-day precipitation amount ($\ln\text{Rx1day}$), and simple daily precipitation intensity ($\ln\text{SDII}$) at 10%, 5%, 10%, and 1% significance levels, respectively, to flood damage cost. Furthermore, a unidirectional causality is also indicated from heavy precipitation days ($\ln\text{R30}$) and simple daily precipitation intensity ($\ln\text{SDII}$) at 10%, and 5% significance levels, respectively, to the flooded area ($\ln\text{FA}$). Thus, it can be concluded that flooded area, heavy precipitation days, maximum 1-day precipitation amount, and simple daily precipitation intensity dictate the economic flood damage in the Chungcheong region of South Korea. The previous results where it was reported that extreme precipitation indices such as consecutive wet days, maximum 1-day precipitation amount, and precipitation intensity influenced the flood events are consistent with the findings of this study (Ávila et al., 2016; Dao et al., 2020a; Du et al., 2022; Y. Liu et al., 2022).

4. Discussion and implications for policy makers

4.1. Discussion

The extreme precipitation events over the last three decades have caused severe economic damage from flood events in the Chungcheong region of South Korea. The causal influence of precipitation characteristics such as duration, frequency and intensity on flood events and economic damage plays an important role to understand the climatic factor and climate change impact on the flood damage. The positive and strong causal effect of precipitation intensity as measured by both $\ln\text{Rx1day}$ and $\ln\text{SDII}$ on the flood damage cost, which indicated significant long-run and short-run impacts can be attributed to the occurrence of heavy precipitation induced flash floods and irregular topographic features. The generating mechanisms of precipitation events in Korean Peninsula include the local convective storm events, which are largely caused by the subtropical East Asian summer monsoon, and the typhoons around the coastal regions cause severe floods over South Korea. While the local convective storm events often result in heavy precipitation during the onset of summer season due to seasonal changes in atmospheric circulation, the destructive typhoons occasionally occur during the late summer season (Song, 2023).

The environmental and climatic conditions such as upper-level divergence, abundant water vapour, and significant atmospheric instability have been reported to aid the development of convection system that is accompanied by heavy precipitation in the central region of the Korean Peninsula (Park et al., 2022). Moreover, the occurrence of a maximum daily precipitation of 290 mm occurred in 2017 was attributed to the warm and humid water vapour transported from the western North Pacific into the central region of the Korean Peninsula and was further enhanced by the southwestern wind (Park et al., 2022). Further, the influence of orographic lifting and subsequent triggering of deep convection due to the complex topographic features that are characterized by the mountain systems and lowlands with gentle slopes could also be ascribed to the localized precipitation intensity that causes the economic damage (Jeong et al., 2016). The intensity of extreme precipitation events causing the flood damage is expected to increase in the future as the climate change becomes more severe due to increasing warmer atmosphere (Cho et al., 2022). These results are consistent with previous studies in other regions with similar conditions. In Brazil, the atmospheric dynamics over the Southeastern South America region were identified as a fundamental cause of persistent precipitation intensity that resulted in flood induced damage (Marengo et al., 2023). The increased in rainfall intensity as indicated by the extreme precipitation index (Rx1day) and irregular topographic features were associated with rainfall-related disasters in Brazil (Regueira and Wanderley, 2022). Similarly, Liu et al. (2022) identified the significant role of mountain systems to enhance the flood induced damage and mortality

during extreme event of heavy precipitation in Africa and Europe (Liu et al., 2022). Moreover, Davenport et al. (2021) found that the extreme precipitation intensity aided by the climate change causes the significant cost of the United States flood damage (Davenport et al., 2021). Further, extreme rainfall events of above 6 mm per 15 minutes were found to be significantly correlated with the extent of flood damage between 1987–2013 in Sweden (Grahn and Olsson, 2019). Lastly, Kim et al. (2019) established a correlation between the changing precipitation patterns and flood damage in Cambodia but failed to find a significant relationship between increased flood risk and deforestation (Kim et al., 2019). However, Barredo (2009) failed to detect climatological impact on economic flood damage in Europe between 1970 and 2006, thereby suggesting that the flood damage was associated with socioeconomic factors (Barredo, 2009).

For the extreme precipitation frequency, the positive and strong causal relationship of the $\ln\text{R30}$ with flood damage cost especially in the short-run can be attributed to the frequency of the extreme precipitation events in the study area. The frequency of extreme precipitation events in the central region of South Korea has increased over the last three decades although with different behaviour in terms of severity compared to the events of 1970s and 1980s (Adelodun et al., 2022a; Seo et al., 2017). Besides, there has been a significant regime shift in the frequency of extreme precipitation events associated with intermittent occurrence of typhoons and tropical cyclones, which correspond with increases in the upper tropospheric wind speed towards the Korean Peninsula (Chang et al., 2023). According to the available data in Korean Statistical Information Service (KOSIS), the frequency of extreme precipitation extremes between 2010 and 2020 from 12 locations in Chungcheong region was 105, among which 35 events resulted in estimated flood damage cost of more than 1 billion Korean won per event (KOSIS, 2022b). In 2020, the public facilities, farmlands, and buildings accounted for 80.3%, 14.4%, and 3.7%, respectively, of the total precipitation-induced flood damage cost in Jecheon, a city located in Chungcheong region. According to the Korea Meteorological Administration in 2020, the southern part of the Chungcheong region received up to 180 mm of precipitation amount, which resulted in 118 reports of flood-related damage (KMA, 2022). These findings are consistent with results obtained in the United States where the positive impact of extreme precipitation on flood damage was attributed to the increased in the frequency of extreme precipitation due to anthropogenic climate forcing (Davenport et al., 2021). Also reported that rather than the magnitude of events, a stronger signal change in the frequency of precipitation is strongly correlated with the increase in flood damage in the United States. Moreover, the findings from the Hanjiang River Basin in China indicated that the precipitation characteristics of high intensity, long duration, and high frequency induced flood disasters (Deng et al., 2022).

However, the finding of non-significant causal impact of consecutive wet days on flood damage cost shows that the precipitation characteristic of consecutive wet days had little or no influence on flood damage cost in the Chungcheong region. This result is consistent with previous studies where the maximum number of consecutive wet days had no significant changes when analyzed the trends of summer precipitation extreme in South Korea and Chungcheong province over a period of 1913–2012 and 1974–2020, respectively (Adelodun et al., 2022b; Baek et al., 2017). Similar results were reported by where monthly maximum consecutive 5-day precipitation had little effect on monthly flood damage compared with total monthly precipitation in the United States (Davenport et al., 2021). By contrast, Pielke and Downton (2000) found that only number of wet days and 2-day heavy precipitation, out of the ten precipitation characteristics, have significant correlation with observed flood damage in the United States (Pielke and Downton, 2000). The aforementioned findings showed that the precipitation characteristics that cause flood damage vary across regions.

The findings of the positive and strong causal impact of flooded area on flood damage cost is consistent with the similar results obtained by

(Chen et al., 2017; Porter et al., 2023). The extent of flood such as the flooded area could serve as an indicator to assess the vulnerability of an area to flood damage (Fig. 3b). Besides, the data on flooded area can easily be obtained among other parameters related to the flood characteristics (Park et al., 2020). Chen et al. (2017) considered flooded area as one of the important parameters to estimate flood waste (Chen et al., 2017). An exponential model was developed for flood waste estimation that correlated well with flooded area, amount of precipitation, and population density. Similarly, Porter et al. (2023) developed depth-damage functions for pluvial-induced flooding that relate the flood extent in terms of depth with the economic damage using regression models (Porter et al., 2023). The obtained results indicated a moderate correlation between the observed flood damage and the computed values, indicating the impact relation of flooded area on flood damage. However, the findings by Olsen et al. (2015) indicated that impact of flooded area on flood damage cost can only be accurately assessed in the long-run period while there are substantial variation for short-run due to the heterogeneity nature of drainage systems and other land use in the different cities investigated (Olsen et al., 2015). Nevertheless, it was concluded that flooded area reflects the extent of the damage and can be used for the vulnerability assessment.

4.2. Implication for policy makers

The findings of this study reveal that some important policies on adaptation and disaster mitigation strategies need to be instituted to mitigate the potential economic damage associated with changes in precipitation characteristics. Firstly, there is a need to recognize that precipitation patterns are changing due to climate change, with increasing frequency and intensity of extreme precipitation events. The implication is that the traditional approach of flood damage control may no longer be sufficient. Thus, new approaches and strategies on floodplain management that incorporate the precipitation characteristics at a specific region are required to adapt to the changing climate. The structural and non-structural investment including improved drainage system and increased green infrastructure can also be adopted to mitigate the flood risks in the advent of changing precipitation characteristics. The increasing naturally-occurring open spaces was found to be most effective approach to reduce economic damage flood events along the Gulf of Mexico coast (Brody et al., 2017).

Secondly, the precipitation characteristics should be considered by the policy makers when making decisions on land use planning. For instance, protecting the forests and grasslands along riparian zones that characterize heavy precipitation and restricting development of these areas could minimize the flood damage. Since agriculture accounts for the significant percent of land use in the study area and being one of the sectors with significant regular flood damage, there is a need to consider policies such as sustainable land use practice that could protect the agricultural sector against the precipitation-induced flood damage. Recently, nature-based land management has increasingly been suggested as an alternative approach of land use management to minimize flood damage (Chang et al., 2020). Incorporating nature-based land management strategies into flood risk management plans can provide a cost-effective and sustainable approach to reducing flood damage.

Similarly, the precipitation characteristics can inform emergency management policies, such as determining evacuation routes and shelter locations, and developing emergency response plans. Emergency management plans can help reduce flood damage by ensuring that people can quickly evacuate flood-prone areas, and by having resources ready to respond to flooding, such as sandbags, pumps, and emergency shelters. The extent of flood and damage cost can be reduced through adequate monitoring and prediction of precipitation characteristics that aid or trigger flood occurrence and consequently flood damage.

Further, policy makers may need to re-evaluate flood insurance policies to reflect the changes in precipitation patterns. This may involve revising premiums to reflect the increased risk of flooding in some areas.

More emphasis should be placed on the precipitation characteristics such as heavy precipitation days and precipitation intensity, and extreme precipitation frequency that trigger or cause flood events and associated economic damage. Besides, the indices such as Rx1day, SDII, and R30mm can serve as indicators of extreme precipitation characteristics in Chungcheong region to assess vulnerability of the flood damage and the flood damage cost.

The findings of this study, therefore, offer practical implications for floodplain management, land use planning, infrastructural design, and insurance and disaster relief policy guideline. Overall, addressing the policy implications of precipitation characteristics on flood damage will require a coordinated efforts across all levels of government agencies and society.

5. Conclusions and limitations of the study

This study investigated the causal relationship between flood damage cost, flooded area, and extreme precipitation indices in the Chungcheong region of South Korea over a period of 1985–2020 using the ARDL-ECM framework and pairwise Granger causality analysis. This region has witnessed reoccurring flood events and economic damage making it appropriate for this study. We found that flooded area, Rx1day, and R30mm have positive impacts on the flood damage cost in both short and long-runs, in the current period. In the long-run, one percent increase in the flooded area, Rx1day, and R30mm causes an increase in flood damage cost by 1.62%, 2.66%, and 0.15%, respectively, with R30mm not statistically significant (at a 5% level). In the short-run, one percent increase in each of the flooded area, R30mm, and Rx1day, the economic flood damage will increase by 0.95%, 0.32%, and 1.56%, respectively, in the current period. In the same short-run, a percentage increase in SDII at lag 1 will cause an increase in the flood damage cost by 4.46%. Furthermore, unidirectional causality was found from the flooded area, R30mm, Rx1days, and SDII to flood damage cost, and from R30mm and SDII to the flooded area. Therefore, this study concluded that the extreme precipitation indices (Rx1day, SDII, and R30mm) and flooded area cause and impacted flood damage cost and can serve as indicators of extreme precipitation characteristics in Chungcheong region to assess vulnerability of the flood damage.

The inventory data on the flood damage events may possibly contain missing data or undocumented records. Similarly, the flood damage data are only available as a total estimated amount but not classified into specific items, making it difficult to account for property-level damage. Further, there could be spatial-temporal variations in the extreme precipitation events which could likely cause a potential mismatch between the precipitation characteristics at a particular location and extent of flood damage. All these limitations put together could have introduced some level of uncertainties in the obtained results. However, these uncertainties are inevitable due to the complexity of flood events and hydrological processes, making the availability of accurate and precise data a herculean task. Nevertheless, the findings of this study provides an important insights on the causal impacts of precipitation characteristics on flood damage in Chungcheong region of South Korea. Further study is suggested to incorporate other environmental and socioeconomic variables that could possibly influence flood economic damage and extending such to other regions with reoccurring flood events.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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