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LETTER

Evidence of reduced vulnerability to tropical cyclones in the Republic of Korea

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Abstract

On average, three tropical cyclones (TCs) affect the Republic of Korea each year, causing extensive damage. To alleviate the TC-induced disasters, the Korean government has invested nearly 4% of its annual budget in recent decades in prevention efforts; however, the effectiveness of this costly program has not been evaluated. This study determined whether any evidence shows a reduced vulnerability to TCs in Korea over 1979–2010 by utilizing multi-linear regression. Homelessness, casualties, and property losses were individually examined. These explained variables were normalized into the socio-economic circumstances of 2005 before the regression to eliminate the effect of changing exposure by dealing with population and wealth at provincial levels. Three potential explanatory variables based on nationwide weather-station data were considered, including the maximum wind, maximum rainfall, and number of affected stations over each TC's damaging period. In addition, the annual per capita income, showing a quasi-linear increasing tendency, was used as an additional explanatory variable to examine how vulnerability is altered. The results revealed that each empirical model of homelessness, casualties, and property losses can account for 47%, 57%, and 57% of each variance, respectively, which is highest when considering all four explanatory variables. Consistently negative coefficients of the per capita income terms for all damage types suggest that the vulnerability to TCs has been significantly reduced. This finding appears to be partly the result of the national prevention effort, although it also can be attributed to other unintended adaptation factors, such as building codes, industrial structures, and land use.

1. Introduction

A number of coastal countries over the globe experience extensive socio-economic damage from tropical cyclones (TCs), amounting to approximately 13 600 casualties and 22 billion US dollars in losses every year (http://emdat.be). Previous studies consistently argued that TCs will become stronger in association with global warming (Knutson *et al* 2010). Thus, the possible impact of TC intensity changes on socio-economic damage is one of our main concerns. TC-induced damage is well correlated with the maximum wind speeds of TCs, which to the nth power is generally proportional to the amount of losses (Pielke 2007, Murnane and

Elsner 2012, Zhai and Jiang 2014). Recent studies also suggested that empirical models of damage show better performance when more of the relevant TC intensity parameters are considered independent variables, such as the TC size, wind direction, and sustained periods of gusts, in addition to the maximum wind speed (Czajkowski and Done 2014, Zhai and Jiang 2014). However, some studies focused more on the possible impact of socio-economic growth on losses. According to these studies, both human and property losses are reduced by improvements in societal economic capability, which can enhance adaptation and prevention measures (Kahn 2005, Toya and Skidmore 2007, Bakkensen 2013a, 2013b, Kousky 2014). However,
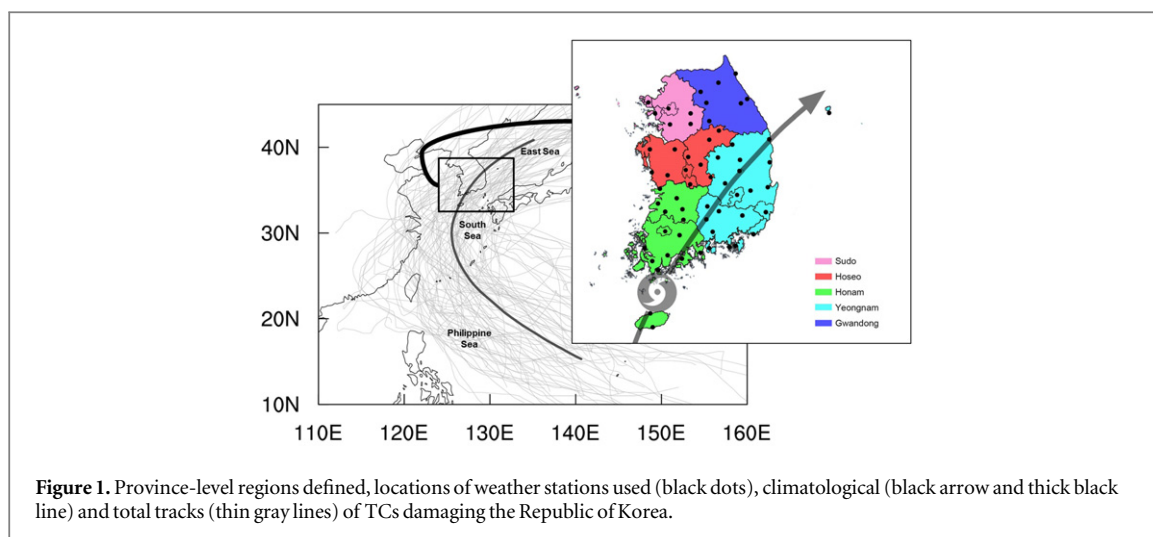
Figure 1. Province-level regions defined, locations of weather stations used (black dots), climatological (black arrow and thick black line) and total tracks (thin gray lines) of TCs damaging the Republic of Korea.

this negative correlation is not likely valid for all cases. For example, in some countries, the economic growth can increase TC-induced damage due to an increase in high-value properties in coastal areas, such as vacation spots (Pielke *et al* 2008, Zhang *et al* 2009). Developing countries show a positive correlation between economic growth and damage amount, until they exceed a certain tipping point of per capita income that likely leads citizens to make rational choices for disaster avoidance (Kellenberg and Mobarak 2008). Furthermore, a positive correlation can be found in countries exposed to more catastrophic events (Schumacher and Strobl 2011). Whether there exists a general relationship between socio-economic losses and other factors, including hazard intensity and societal growth, is difficult to say.

This study aims to determine if any evidence of reduced vulnerability to TCs can be found in the Republic of Korea, which is a suitable place to seek evidence of reduced vulnerability given that both the economy and hazards are noticeably growing. The country is affected by an average of three TCs annually, and it recently has been struck by more catastrophic TCs with higher wind speeds and heavier rainfalls than in past years (Kim *et al* 2006, Choi *et al* 2010, Park *et al* 2011, 2014). The country not only invested a large portion, approximately 4%, of its annual budget in disaster prevention but also achieved a high level of economic progress over the past decades. The per capita income in 2010 is approximately five times that in 1979.

The rest of this article is organized as follows. Section 2 introduces the data used and the methods of calculating the explanatory and explained variables, socioeconomic normalization, and regression. Section 3 illustrates how well the empirical models work and whether any evidence of reduced vulnerability exists. Finally, section 4 provides a summary and discussion.

2. Data and methods

Changes in vulnerability to TCs were examined using a multi-linear regression method. The number of homeless, casualties, and property losses are considered explained variables. On behalf of explanatory variables, weather station-based variables were used, including the maximum winds, maximum rainfall, and number of weather stations affected by TCs. Most preceding studies only considered wind-related parameters as possible determinants for damage and disregarded rainfall (e.g., Murnane and Elsner 2012, Czajkowski and Done 2014, Zhai and Jiang 2014) because the best-track data, widely used to represent TC intensity, provide only the maximum wind speeds and radii of gusts. For this reason, weather-station data were applied here to determine the rainfall intensity. In addition, Korea has a dense nationwide network of weather stations to supply high-quality wind and rainfall information.

2.1. Explanatory variables: weather-station data

Sixty weather stations within Korea were utilized to obtain TC-intensity parameters (figure 1). The maximum values of wind speed and rainfall amount based on daily weather station data over the damage period for each TC case were regarded as explanatory variables. The definition of damage period is explained in detail in section 2.2. Because the affected area is another important intensity parameter (Czajkowski and Done 2014, Zhai and Jiang 2014), the number of affected stations was calculated by counting stations at which either the daily maximum wind speed or the daily accumulated rainfall exceeded critical thresholds. Using a method similar to that of Donat *et al* (2011), the critical values of maximum wind speed and rainfall were set at each station's 90th percentiles, averaging 7.9 m s^{-1} and 29.7 mm, respectively. These threshold values were regarded as the lower limits at which to incur the losses.

2.2. Explained variables: socio-economic loss data and normalization

The data on socio-economic losses were obtained from the National Disaster Information Center (NDIC) of the Korean government. The data are officially verified by the government and are open to the public through the web site, http://safekorea.go.kr. Although the NDIC data provide information on the number of homelessness, number of casualties, and amount of property losses for each natural disaster, along with the duration of the disaster, the data do not specify the sources of damage. Thus, damage is defined as TC-induced damage when the reported damage period overlaps with any days on which a TC center is located within 5° from the coastline of Korea. The TC-location information was obtained from the best-track data issued by the Regional Specialized Meteorological Centers—Tokyo. We considered TCs of the magnitude of typhoons (maximum wind $\geqslant 64$ knots), tropical storms (34 knots $\leqslant$ maximum wind < 64 knots), and tropical depressions (maximum wind < 34 knots). The TC best-track data are composed of 3 or 6 h intervals, which are too coarse to determine a more accurate damage period over Korea. Thus, the data were linearly interpolated into 1 h intervals, as in Park *et al* (2011, 2014). The union of the two defined damage periods, one from the NDIC and the other from the best-track data, is considered the damage period. According to this approach, 92 TCs caused damage over the period of 1979–2010 (table 1). In some cases, the damage period is too long, e.g., >10 days. This consequence is caused by (1) two TCs successively affecting Korea or (2) a TC arriving during a monsoon period. Here, because these cases can also be used to evaluate changing vulnerability, we took all 12 cases into account to have as many samples as possible. Excluding these cases does not significantly change our results.

Property losses include the direct damage of industrial, public, and private facilities in total economics, and the losses are adjusted by the value of money in 2005. Basically, data on light property losses are not gathered, but there is no objective criterion for light loss. Casualties include the number of deaths, missing persons, and injuries of both the insured and uninsured. The homeless are defined as people who lost their homes due to a disaster. The finest level of loss data are provided at the city levels, referred to as Si, Gun, and Gu in Korean. However, the data are not well organized for use in analysis; thus, it is necessary to reorganize them individually. Because the number of city-level districts is too large to take all of them into account, province-level aggregate data were used in this study, including the Sudo, Hoseo, Honam, Yeongnam, and Gwandong areas (figure 1). There are more than 260 city-level districts in the country.

To reduce spatiotemporal changes in socio-economic factors that are able to significantly alter exposure to TCs (Neumayer and Barthel 2011, Chavas

et al 2013), we utilized normalizing factors based on the population and per capita wealth at the province level, following Pielke *et al* (2008). Equation (1) expresses the method used to obtain nationwide aggregate normalized loss data from the province-level data caused by the *i*th case of landfall TC

$$A_{i,2005} = \sum_r \left\{ A_{i,y,r} \times \left(P_{2005,r} / P_{y,r} \right) \right\},$$

$$C_{i,2005} = \sum_r \left\{ C_{i,y,r} \times \left(P_{2005,r} / P_{y,r} \right) \right\},$$

$$D_{i,2005} = \sum_r \left\{ D_{i,y,r} \times \left(\left(P_{2005,r} \times W_{2005} \right) / \right. \right.$$
$$\left. \left. \left(P_{y,r} \times W_y \right) \right) \right\}, \tag{1}$$

where $A_{i,2005}$, $C_{i,2005}$, and $D_{i,2005}$ indicate the nationwide aggregate homelessness, casualties, and property loss, respectively, which are normalized to the reference year 2005. The variables $A_{i,y,r}$, $C_{i,y,r}$, and $D_{i,y,r}$ represent the number of province-level homeless, number of casualties, and amount of property loss over region r in a relevant year y, respectively. The variables $P_{y,r}$ and $P_{2005,r}$ are the province-level populations over region r in year y and 2005, respectively. Similarly, W_y and W_{2005} present per capita wealth in year y and 2005, respectively.

2.3. Empirical model design and vulnerability

Because many previous studies utilized per capita income as an indicator of resistance to disasters, higher income is often associated with less damage and vice versa (Kahn 2005, Toya and Skidmore 2007, Bakkensen 2013a, 2013b, Kousky 2014). Annual per capita income was included as an explanatory variable in addition to the three TC-intensity parameters above. Equation (2) describes the loss model suggested for the *i*th case of landfall TC

$$D_{i,2005} = Y \times V_i^\alpha \times R_i^\beta \times N_i^\gamma \times I_y^\delta,$$

$$\alpha = \frac{a}{S_{\log_{10} V}}, \quad \beta = \frac{b}{S_{\log_{10} R}}, \quad \gamma = \frac{c}{S_{\log_{10} N}},$$

$$\delta = \frac{d}{S_{\log_{10} I}}, \tag{2}$$

where $D_{i,2005}$ is the normalized loss by the *i*th case and Y is the intercept. The variables V_i^α, R_i^β, and N_i^γ indicate the maximum wind, maximum rainfall, and number of affected stations, respectively, which are the intensity parameters of the *i*th case. The parameter I_y^δ represents the per capita income in year y in which the *i*th case occurred. The per capita income was adjusted to reflect 2005 monetary value. The variables α, β, γ, and δ are the exponential coefficients of the maximum wind, maximum rain, number of affected stations, and per capita income, respectively. The exponential coefficients are composed of coefficients a, b, c, and d divided by $S_{\log_{10} V}$, $S_{\log_{10} R}$, $S_{\log_{10} N}$, and $S_{\log_{10} I}$, i.e., standard deviations of common logarithms

Table 1. List of TCs damaged Republic of Korea.

Name	Year/month	Name	Year/month	Name	Year/month	Name	Year/month	Name	Year/month
IRVING	1979/8	HAL	1985/6	ROBYN	1990/7	TINA	1997/8	MATSA	2005/8
JUDY	1979/8	JEFF	1985/8	ZOLA	1990/8	WINNIE	1997/8	NABI+KHANUN	2005/9
IDA	1980/6	KIT	1985/8	ABE	1990/9	OLIWA	1997/9	EWINIAR	2006/7
NORRIS	1980/8	LEE + MAMIE	1985/8	HATTIE	1990/10	YANNI	1998/9	WUKONG	2006/8
ORCHID	1980/9	ODESSA + PAT	1985/8	CAITLIN	1991/7	NEIL + OLGA	1999/7	SHANSHAN	2006/9
JUNE	1981/6	BRENDA	1985/10	GLADYS	1991/8	ANN	1999/9	MAN-YI	2007/7
OGDEN	1981/7	NANCY	1986/6	MIREILLE	1991/9	DAN	1999/10	PABUK	2007/8
AGNES	1981/8	ROGER	1986/7	JANIS	1992/8	BILIS+PRAPIROON	2000/8	NARI	2007/9
CLARA	1981/9	VERA	1986/8	POLLY	1992/8	SAOMAI	2000/9	KALMAEGI	2008/7
CECIL	1982/8	ABBY	1986/9	TED	1992/9	CHEBI	2001/6	MORAKOT	2009/8
ELLIS	1982/8	THELMA	1987/7	PERCY	1993/7	TORAJI	2001/7	DIANMU	2010/8
KEN	1982/9	VERNON	1987/7	ROBYN	1993/8	RAMMASUN	2002/7	KOMPASU	2010/9
FORREST	1983/9	DINAH	1987/8	BRENDAN	1994/7	RUSA	2002/8	MALOU	2010/9
ALEX	1984/7	noname	1988/8	DOUG+ELLIE	1994/8	SOUDELOR	2003/6	MERANTI	2010/9
ED	1984/7	JUDY	1989/7	SETH	1994/10	MAEMI	2003/9		
HOLLY	1984/8	KEN	1989/8	FAYE	1995/7	MINDULLE	2004/7		
GERALD	1984/8	VERA	1989/9	JANIS	1995/8	MEGI	2004/8		
JUNE	1984/8	OFELIA	1990/6	PETER	1997/6	SONGDA	2004/9		

of the maximum wind, maximum rain, number of affected stations, and per capita income, respectively, to compare the magnitudes of α, β, γ, and δ directly with each other. We conducted a multi-linear regression after applying common logarithms to both sides. Thus, the zero values of loss are not included when training each model of homelessness, casualties, and property loss. The number of TCs considered is displayed by parentheses in table 2.

Considering the meaning of the exponential coefficient of the per capita income term, the term implies the degree of vulnerability to TCs. The damage amount is generally determined by exposure, vulnerability, and strength of the event (Neumayer *et al* 2014). To the extent that our model successfully captures the intensity of the physical hazard itself, and furthermore, that normalization of the damage data successfully removes the effect of spatiotemporal variability of exposure, then the other factor, that is, the per capita income term, largely represents changes in vulnerability. Hence, because the per capita income in Korea has quasi-linearly risen (figure 4(d)), the negative sign of its coefficient indicates the vulnerability has been reduced and vice versa.
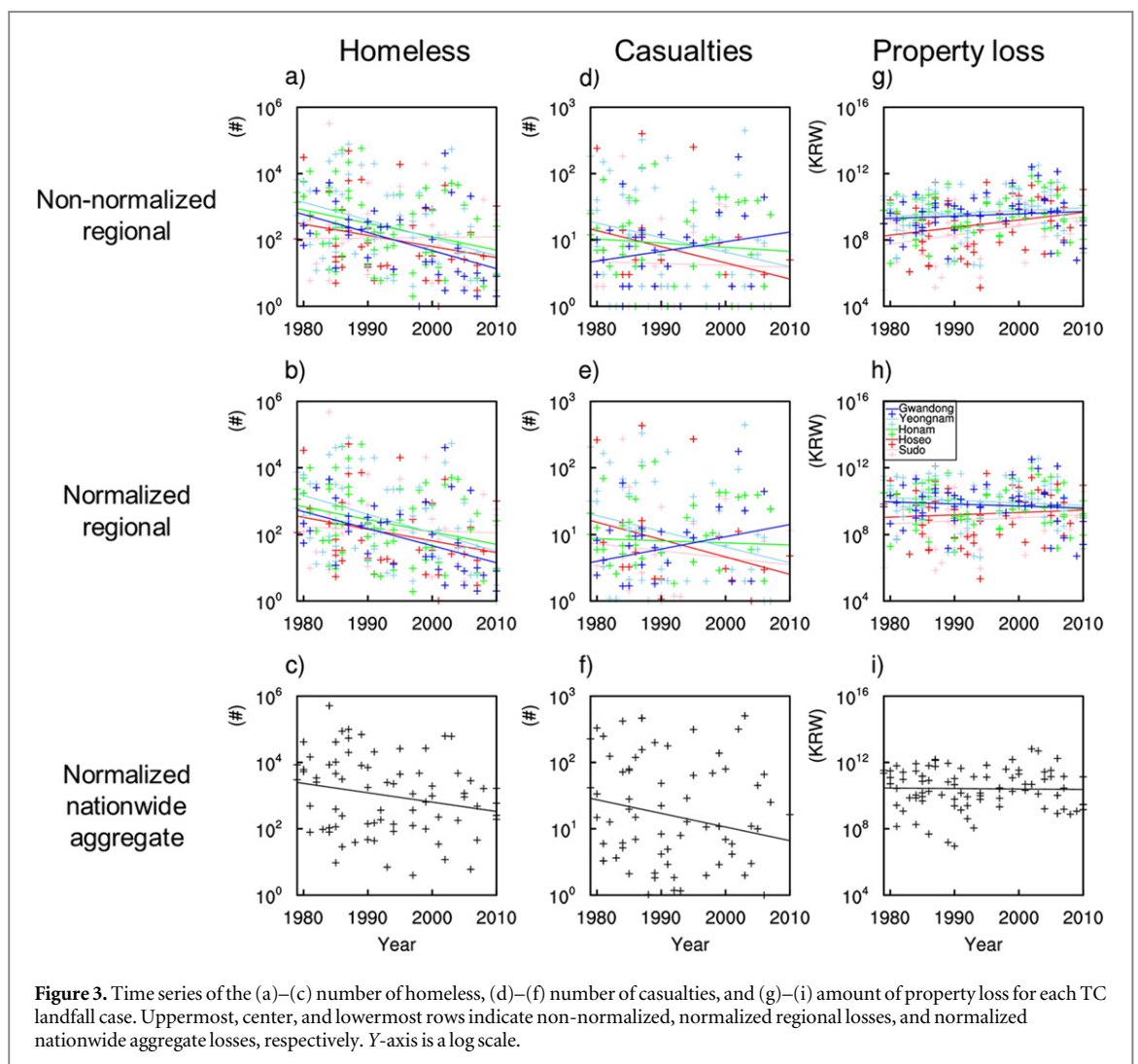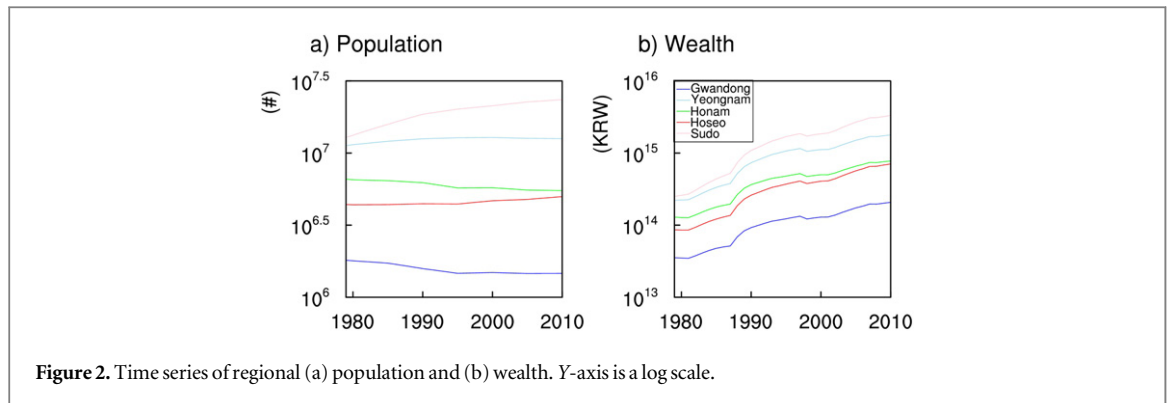
3. Results

Even though the Republic of Korea is not a vast country, the change in the exposure to TCs can vary by region. The country is located in Northeast Asia, and TCs that affect the country climatologically move from the Philippine Sea to the East Sea via the South Sea of Korea (see figure 1). Thus, the Southeastern part of the Korean peninsula is generally subject to the danger semicircle, i.e., the right half circle of the TC direction of progress where wind speed is much greater than that in the left half circle. Accordingly, the Yeongnam area is most exposed to TCs. Approximately 29%, 45%, and 44% of the total homelessness, casualties, and property losses, respectively, are found in this region where the population and wealth represent only approximately 28% of the total economy. In addition, each region shows a distinct socio-economic growth rate. For the past three decades, the Korean population has significantly changed. A noticeable increase is only found in the Sudo, Hoseo, and Yeongnam areas; the population has decreased in other regions (figure 2(a)). The time series of regional wealth show consistent positive trends due to a sharp increase in per capita wealth, although the rates vary among regions (figure 2(b)). These regional variations strongly suggest that the exposure changes need to be viewed from both spatial and temporal sides.

The normalization technique described in section 2 was applied to the raw damage data with consideration of the above regional factors. Figure 3 shows the non-normalized and normalized losses in each area, as well as the national aggregation of losses. The

overall trends decrease after the normalization. Homelessness showed consistently negative trends for all areas after normalization (figure 3(b)). This finding indicates that in recent years, housing damage by flooding and wind gusts has decreased, possibly due to improved flood control and/or changes in building codes. Casualties also show negative trends, except in Gangwon, for both normalized and non-normalized time series (figures 3(d) and (e)). Property losses show increasing trends before the normalization. After normalization, however, the trends become negligible (figures 3(g) and (h)). Consequently, the normalized aggregates in the numbers of homeless and casualties for the entire nation have decreased considerably, whereas property losses have decreased slightly (figures 3(c)–(i)).

In contrast, intensity parameters have consistently strengthened in terms of the maximum wind, maximum rainfall, and number of affected stations (figures 4(a)–(c), in close agreement with previous studies. For example, Park *et al* (2014) determined that the maximum wind speed of TCs at landfall over East Asia has significantly increased because large-scale environments are favorable for TC development. Increased sea-surface temperature, weakened vertical wind shear, and anomalous cyclonic low-level circulation in the vicinity of the East Asian land mass can intensify TCs. Moreover, TC-induced rainfall has increased as well due to upper-tropospheric jet shifts and low-level moistening (Kim *et al* 2006, Park *et al* 2011). The increase in the number of affected stations is attributable to enhanced TC landfall intensity, which can lead to an increase in the number of weather stations where wind speed and/or rainfall amounts exceed their threshold values used in determining if a station is affected by a TC.

Using the three intensity parameters above and per capita income as explanatory variables, a multi-linear regression model for each of the three damage types was developed. Note that the variance inflation factors among all the explanatory variables are smaller than 2.7, indicating that the model does not suffer from a multi-collinearity problem. Table 2 shows the adjusted R-squared values of each model with various combinations of one to four explanatory variables. All models show the highest adjusted R-squared values when all four explanatory variables are applied. A larger R-squared value generally indicates the model can explain a larger portion of the real variance. The models of homelessness, casualties, and property losses with four explanatory variables can account for 47%, 57%, and 57% of each variance, respectively, although all models tend to underestimate damages at both the high and low extrema (figure 5). For property losses, the use of only three variables, maximum wind, maximum rainfall, and number of affected stations, is adequate because the addition of per capita income increases the R-squared value by only 0.01–0.54. For

Figure 2. Time series of regional (a) population and (b) wealth. *Y*-axis is a log scale.

Figure 3. Time series of the (a)–(c) number of homeless, (d)–(f) number of casualties, and (g)–(i) amount of property loss for each TC landfall case. Uppermost, center, and lowermost rows indicate non-normalized, normalized regional losses, and normalized nationwide aggregate losses, respectively. *Y*-axis is a log scale.

the remaining damage types, adding per capita income is important in enhancing the *R*-squared value.

When only one explanatory variable is applied, the maximum rainfall is the most influential factor for determining the amount of all types of damage (table 2). The adjusted *R*-squared values are 0.33, 0.35, and 0.40 for the number of homeless, number of casualties, and amount of property loss when maximum rainfall is solely applied as an explanatory variable. Although the adjusted *R*-squared value for the property loss model of the number of affected stations

is 0.44, just slightly larger than that of maximum rainfall, the values for homelessness and casualties are only 0.21 and 0.26, respectively. The least influencing factor is the maximum wind for which the adjusted *R*-squared values are only 0.08, 0.14, and 0.23 for homelessness, casualties, and property losses. This finding suggests that maximum rainfall plays the most important role in determining the intensity factors for Korea, that is, most damage is caused by hydrological extremes induced by heavy rainfall. The same conclusion is reached without considering the TCs during the
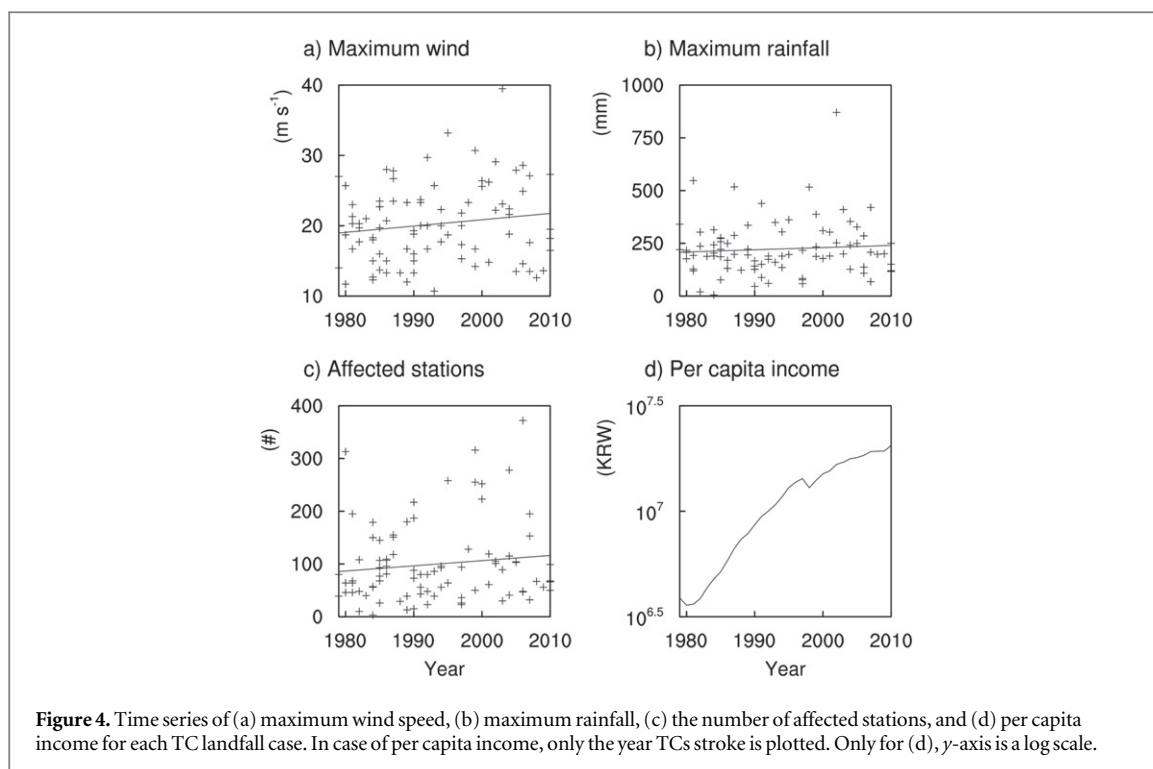
Figure 4. Time series of (a) maximum wind speed, (b) maximum rainfall, (c) the number of affected stations, and (d) per capita income for each TC landfall case. In case of per capita income, only the year TCs stroke is plotted. Only for (d), *y*-axis is a log scale.

Table 2. Adjusted *R*-squared values of the models for homelessness, casualties, and property loss. Bold indicates the highest *R*-squared for each model. NAS and IC indicate the number of affected stations and per capita income, respectively. Parentheses indicate the number of cases that incurred each type of damages. Note that for all models *F* values are statistically significant at the 95% confidence levels.

	Wind + Rain + NAS + IC	Wind + Rain + NAS	Wind + Rain	Wind + NAS	Rain + NAS	Only Wind	Only Rain	Only NAS
Homeless(75)	**0.44**	0.36	0.34	0.24	0.36	0.08	0.33	0.21
Casualties(72)	**0.55**	0.44	0.39	0.31	0.42	0.14	0.35	0.26
Property losses(86)	**0.55**	0.54	0.48	0.50	0.49	0.23	0.40	0.44

monsoon period (not shown). The relative importance of wind and rainfall intensity effects on the TC damage in Korea is possibly associated with the topography of the Korean peninsula, which is characterized by several high mountains particularly along the East coast. These mountains can protect the country against strong wind gusts, while they can strengthen rainfall intensity via low-level moisture convergence and orographic lifting (Buzzi *et al* 1998, Park and Lee 2007).

Finally, we seek evidence of reduced or enhanced vulnerability by using each regression coefficient of the explanatory variables (table 3). For all models of homelessness, casualties, and property losses, the per capita income terms exhibit negative trends, which are statistically significant at or above the 90% confidence level. This result suggests that the vulnerability to TCs in homelessness, casualties, and property losses has considerably decreased with time. An examination of the regression coefficients of other variables and their significances reveals that all coefficients of the homelessness, casualties, and property loss models are statistically significant. This indicates that all intensity parameters are influential to all damage types. In

addition, to compare the magnitudes of regression coefficients re-emphasizes that taking the maximum rainfall into account as an explanatory variable is very important in the case of Korea, given that the smallest coefficient of maximum rainfall is 0.32 while those of maximum wind and the number of affected stations are 0.21 and 0.26, respectively.

In the present study, direct connections between vulnerability reduction and prevention efforts were not investigated. However, this study suggests the possibility that the efforts may have reduced vulnerability because Korea experienced outstanding improvements in weather forecasting and prevention planning during the late 1980s and 1990s, as shown in table 4. The Korean Meteorological Administration started the TC-track forecasts after 1984, the application of numerical weather prediction after 1991, and the use of supercomputers for weather forecasting that greatly improved the prediction accuracy and lead time after 1999. In addition to forecasting, Korea has benchmarked and adopted successful disaster prevention plans from other developed countries to efficiently establish and implement its own plans. Particularly, the period of 1980–2004 was the build-up period for
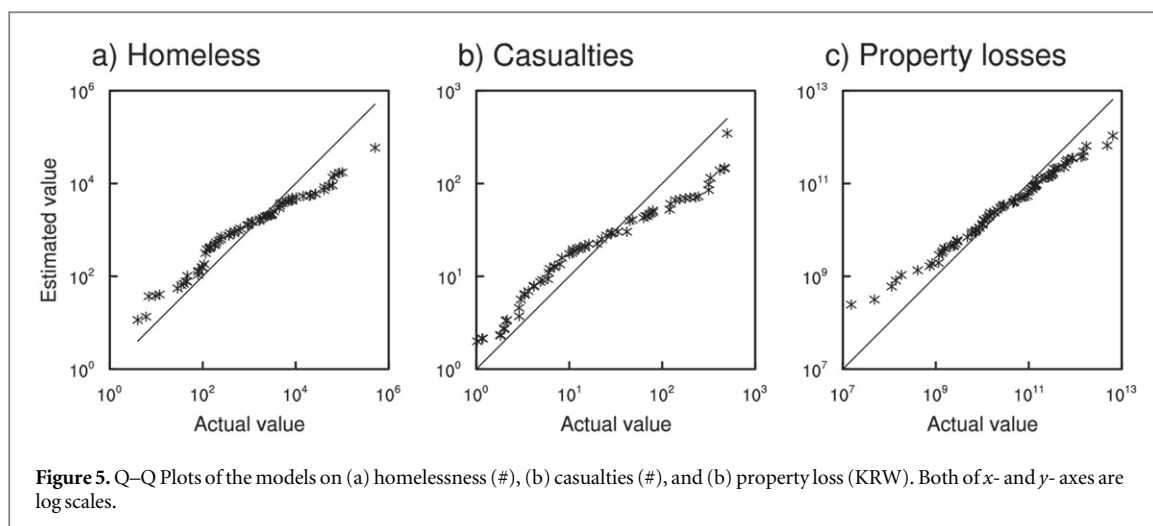
Figure 5. Q–Q Plots of the models on (a) homelessness (#), (b) casualties (#), and (b) property loss (KRW). Both of *x*- and *y*- axes are log scales.

Table 3. Each regression coefficient of maximum wind speed, maximum rainfall, the number of affected stations, and per capita income for homelessness, casualty, and property-loss models. Parentheses represent standard error of regression coefficient. Bold (bold and italic) indicates the coefficient is statistically significant at the 90% (95%) confidence levels. NAS and IC indicate the number of affected stations and per capita income, respectively.

	Wind	Rain	NAS	IC
Homeless	**0.21** (±0.11)	*0.45(±0.12)*	*0.30(±0.12)*	*−0.35(±0.10)*
Casualties	*0.23(±0.07)*	*0.32(±0.08)*	*0.26(±0.08)*	*−0.29(±0.07)*
Property losses	*0.33(±0.10)*	*0.35(±0.13)*	*0.47(±0.13)*	*−0.17(±0.09)*

prevention. The Korean National Assembly reviewed and revised the Countermeasures Against Typhoons and Floods Act in 1981, which expanded the Disaster Relief Center. The Disaster Prevention Division was reorganized and expanded into two departments, one for disaster planning and the other for disaster prevention, in 1987. In the same year, the Korean government established the Central Civil Defense and Disaster Management Institute. The national 119 rescue service was established and expanded over 1981–1992. Thus, major improvements mainly occurred in the 1990s, and these improvements are likely be related to the decrease in vulnerability to TCs.

4. Summary and discussion

This study suggests that the national prevention effort may have reduced the vulnerability to TCs in Korea over the period of 1979–2010 on the basis of a multilinear regression method. Here, the three intensity parameters, maximum wind speed, maximum rainfall, and number of affected stations, were derived from weather station—based observations. These parameters, in addition to per capita income, were used to train the regression models for three damage types, including homelessness, casualties, and property losses, which were normalized to 2005 by considering spatiotemporal variations in socio-economic growth, including population, inflation, and

wealth. The regression models were designed such that the intensity parameters and per capita income are the explanatory variables, and the normalized damages are the explained variables. The four explanatory variables explain 47%, 57%, and 57% of the variances of homelessness, casualties, and property losses, respectively. Among these explanatory variables, maximum rainfall appears to be the most influential factor. The significant negative values of regression coefficients of the per capita income terms for all models indicate that the vulnerability to TCs is reduced.

This study shows a possible link, but not direct connections, between reduced vulnerability and prevention effectiveness. In reality, the reduced vulnerability can also result from other prevention measures, such as stricter building codes, industrial structures, and land use policy. In early years, i.e., before the 1980s, the country was largely based on agriculture and light industry, and farmland was the dominant land-use type. Many houses were wooden structures. Thus, the overall socio-economic circumstances were more vulnerable to TCs. In addition, although four explanatory variables can account for approximately half of the variances of all damage types, the remaining variances are not explained. They could be related to factors disregarded in the present study (e.g., wind direction, smaller-scale exposure changes, etc), unknown, or random. Hence, future studies should attempt to (1) resolve whether the impact of each prevention effort and other adaptation factors can be

Table 4. Representative improvements in weather forecasting and prevention plans in Korea and the years in which the improvements were made.

Year	National efforts
	• The revision of the countermeasures against typhoons and floods act
1981	• The establishment of the central disaster relief center
	• The test operation of rescue teams
1982	• The organization of the 119 rescue teams in fire station
	• The start to 24 h lead-time typhoon track forecast
1984	• The establishment of the departments on a plan and facility for preventing disasters
1987	• The establishment of the central civil defense and disaster management institute
1988	• The launch of the national 119 rescue service
1989	• The revision of the fire services act that includes that the 119 rescue teams take all of emergency rescue recovery support
1991	• The start to numerical weather prediction
	• The start to 36 h lead-time typhoon track forecast and
1992	• The launch of wide-area fire service system
1997	• The establishment of the National Disaster Management Institute
1999	• The introduction of super computer for weather forecasting
2003	• The start to 72 h lead-time typhoon track forecast
	• The establishment of the National Emergency Management Agency
2004	• The start to 48 h lead-time typhoon intensity forecast
2008	• The establishment of the National Typhoon Center

clearly divided and (2) determine what factors are responsible for the remaining variances.

Acknowledgments

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