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The Impact of Climate and Socioeconomic Change on Typhoon Losses in China

By **Laura A. Bakkensen**
Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC), Yale University
laura.bakkensen@cmcc.it

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SUMMARY China currently suffers from the impacts of tropical cyclones, with an average of 9 landfalls per year leading to approximately $3.9 billion in damages and 472 lives lost. In this analysis, we estimate the impact of socioeconomic and climatic changes on these disaster losses. We first calculate historical impact functions including typhoon damage, fatality, injury, homelessness, and people affected. We then use C-STORM, the China-Specific Typhoon Outcomes integRated assessment Model, to estimate the impact of climate and socioeconomic change on losses over the next one hundred years. Our results show that climate change will reduce the overall frequency of landfalls but increase the frequency of intense storms at landfall. We estimate that socioeconomic change will increase damages by approximately 118% across China, while development will decrease other losses including fatalities and injuries. Overall, climate change is expected to slightly reduce the expected losses from typhoons, with damages, fatalities, injuries, homelessness, and people affected decreasing by approximately 7%. However, disagreement remains across climate models and these general trends mask underlying heterogeneous losses across provinces. These findings are important to inform public policy on typhoon warnings, public adaptation, and risk management planning.

Keywords: Economic Damages, China, Natural Disasters, Climate Change

JEL: D81, N55, O1, Q54, R5

1 Introduction

Eastern coastal China is at high risk for typhoon landfalls and contains approximately one quarter of the Chinese population and nearly 55 percent of gross national product (Fangjin and Ziniu, 2010). From 1960 to 2010, an average of 7.3 landfalls per year struck mainland China and 8.9 landfalls per year including Taiwan, Macau, and Hong Kong[1]. As a result, China suffers from approximately $3.9 billion (2010 $USD) in direct economic damages from typhoons and an average of 472 lives lost each year. Damages have increased over the past three decades due to socioeconomic growth while fatalities have remained relatively constant (Zhang, Liu, and Wu, 2009). The number of landfalls per year has decreased slightly over the second half of the twentieth century (Fangjin and Ziniu, 2010), yet the power of storms in the Western Pacific Ocean has increased by about 75 percent from 1970 to 2000 (Emanuel, 2005). There is uncertainty with respect to future impacts due to climate and socioeconomic change over the next one hundred years.

Typhoons, a type of tropical cyclone, are meteorologically identical to hurricanes except located in the Western Pacific Ocean rather than the Atlantic or Eastern Pacific Oceans (Emanuel, 2005). Wang et al. (2012) reviews the relevant natural science literature surrounding extreme weather events in China, including typhoons. They find consistency among results that cyclones in the Western North Pacific experience large interannual and interdecadal variability in frequency, intensity, genesis, and track (Chan and Xu, 2005; Jones et al., 2007; Sheperd and Knutson, 2007). Many factors drive this result, including sea surface temperatures (Emanuel, 2005; Webster et al., 2005), El Nio-Southern Oscillation (Elsner and Liu, 2003) and other large scale circulation patterns (Zhau and Cui, 2008), as well as more remote factors through teleconnectivity (Wang, 2012). Scientists are still uncertain about the impact of climate change on tropical cyclone formation, strength, and termination. Data limitations in the historical record make it hard to find evidence of climate change in current typhoon patterns (Knutson et al., 2010). Various models have been used to project typhoon characteristics under climate change scenarios, although cyclone intensity and path are predicted with less confidence than frequency. Similarly, global estimates of cyclone changes are thought to be more accurate than regional predictions (Wang et al., 2012). Gualdi et al. (2008) found a decrease in the number of typhoons in the Western North Pacific ocean in future climate with increased carbon dioxide concentrations. These results are mirrored by work from Stowasser et al. (2007) and Zhao et al. (2009). However, Emanuel et al. (2008) found an increased frequency in typhoons in the same region. The specific impact for Chinese landfalls remains uncertain, as changes of typhoons in the Western North Pacific Ocean do not necessarily translate equivalently to changes in landfall characteristics in all locations. Thus, further research is needed specific to China.

We investigate the impact of socioeconomic and climate change on typhoon losses in mainland

[1]Calculated by the author using IBTrACS v03r03 data (Levinson et al., 2012)

China, Hong Kong, Macau, and Taiwan. This paper adds to the literature in four ways. First, we modestly expand the theoretical foundation laid by Mendelsohn and Saher (2011) by including multiple outcomes and a calculation for the impacts of socioeconomic change. Second, we develop C-STORM, the China-Specific Typhoon Outcomes integRated assessment Model. Drawing from Mendelsohn, Emanuel, Chonabayashi, and Bakkensen (2012), we refine their methodology and apply it to a Chinese context, setting up the possibility that this framework may be applied to additional countries and regions around the globe. Third, we employ a spatially-refined county-level dataset for mainland China as well as Taiwan, Macau, and Hong Kong and estimate typhoon loss functions. With the results, we use typhoons simulated in both current and future climate to calculate spatially-refined impacts of both climate and socioeconomic change. Unlike previous literature focusing on damages and fatalities, we also include homeless, injured, and affected results. Lastly, we calculate impacts on average and high-intensity tail characteristics to test if the frequency, intensity, or path of tail events will be more harmful in the future.

Although some previous literature exists quantifying the expected climate change impacts of tropical cyclones at the global (Bakkensen, 2013; Mendelsohn et al., 2012), Atlantic basin (Hallegate 2007), and United States (Nordhaus, 2012; Mendelsohn, Emanuel, and Chonabayashi, 2011) levels, only one working paper has considered the impacts on China. Shi (2013) uses Chinese government data and only considers direct economic damages. Further, the work does not include Taiwan, Macau, or Hong Kong. A Chinese-language literature exists on typhoon impacts, but access to translated articles is difficult. More broadly, the disaster impacts literature is growing (see reviews by Cavallo and Noy, 2009; and Kousky, 2012), and several paper have investigated factors influencing damages (Toya and Skidmore, 2007; Kellenberg and Mobarak, 2007) as well as fatalities (Kahn, 2005; Sadowski and Sutter, 2005). Little work has systematically focused on additional losses such as injury, homelessness, and number affected.

The paper is organized as follows: Section 2 provides a theoretical framework for the analysis. Section 3 describes the C-STORM integrated assessment model and data used. Section 4 presents the model results and discussion. Section 5 concludes. The appendix provides additional model results.

2 Theoretical Foundation

The theoretical foundation for this analysis is from Mendelsohn and Saher (2011) and has been applied to tropical cyclones in the United States by Mendelsohn, Emanuel, and Chonabayashi (2011) as well as Mediterranean hurricanes by Bakkensen (2013). In this analysis, we extend the damages theory to also include other losses such as fatalities, homelessness, injury, and people affected.

We assume that L_{ij} is a vector of losses from tropical cyclone i in location j. These losses can take many forms, including direct economic damages from capital and infrastructural destruction, human fatality, both temporary and permanent homelessness, injury, and affected people requiring assistance. Losses are based on both a vector of characteristics from storm i when it makes landfall at location j, X_{ij}, and local socioeconomic factors, Z_{ij}, in location j when storm i hits:

$$L_{ij} = L(X_{ij}, Z_{ij})$$

Losses increase in the intensity of the storm, $\frac{dL}{dX} > 0$, but losses can either increase or decrease in socioeconomic characteristics. For example, as income increases, there may be more capital in harm's way to be damaged. On the other hand, if protection is a normal good, actors may take steps to reduce the magnitude of impacts through adaptation. Thus, the direction of impact for socioeconomic variables remains an empirical question.

The probability, Π_{ij}, that storm i will make landfall in location j during a given period of time depends on both the storm characteristics, X_{ij}, and the climate, C:

$$\Pi_{ij} = \Pi(X_{ij}, C)$$

The probability of landfall decreases as the strength of the storm increases, $\frac{d\Pi}{dX} < 0$. The direction of impact of climate is an empirical question.

Expected losses in a given region, E[L], equal total losses multiplied by the probability of landfall, integrated over all landfalls and locations within the region:

$$E[L] = \iint\limits_{IJ} \Pi(X_{ij}, C) L(X_{ij}, Z_{ij}) dJdI$$

With this framework, the impact of socioeconomic and climate change is calculated. The socioeconomic change impact, SC, is equal to expected losses after a change in socioeconomic characteristics minus the expected losses before the change, holding all other factors including climate constant at the current levels:

$$SC = E[L(Z_1, C_0)] - E[L(Z_0, C_0)]$$

Additionally, CC, the impact of climate change on cyclone losses, is equal to the expected losses after a change in climate minus the magnitude of expected losses before the climate has changed:

$$CC = E[L(Z_1, C_1)] - E[L(Z_1, C_0)]$$

To separately isolate the impacts of SC and CC, it is important to hold everything else constant at the correct levels. For SC, we hold climate constant at the present value. For CC, we hold socioeconomic factors constant at the future level. This ensures that climate change impact calculations are not obfuscated by contemporaneous changes and represent a realistic future state of the world when climate will likely be different.

3 Data and Methodology

We us an integrated assessment model to calculate the impact of climate and socioeconomic change on typhoon damages in China. This model was first developed for extreme events in general by Mendelsohn and Saher (2011). Mendelsohn, Emanuel, Chonabayashi, and Bakkensen (2012) refined the model for tropical cyclones, developing the Tropical Cyclone Integrated Assessment Model (TCIAM). Bakkensen (2013a) improved upon the TCIAM by enhancing the historical dataset, including controls for underlying cyclone risk rates and storm intensity. This analysis develops a detailed Chinese tropical cyclone integrated assessment model called the China-Specific Typhoon Outcomes integRated assessment Model (C-STORM).

Figure 1 below shows the six steps of the C-STORM model, which follow directly from Mendelsohn, Emanuel, Chonabayashi, and Bakkensen (2012) in steps 1, 2, and 3. Steps 4, 5, and 6 parallel their analysis, but are applied in a more spatially-refined analysis for China instead of the globe and also include additional unexplored cyclone outcomes using data from Bakkensen (2013b). C-STORM begins with an emissions trajectory which is translated to climate outcomes by four general circulation models. Third, the climate results are downscaled to resolve cyclones using a cyclone generating model from Kerry Emanuel. Fourth, socioeconomic characteristics are projected from the year 2000 to 2100. Fifth, we estimate functional relationships between explanatory variables and cyclone impacts using historical data. We value the simulated storm landfalls using the functions from step five. Lastly, we separately calculate the impact of climate and socioeconomic change on typhoon damage, fatality, injury, loss of homes, and number affected. Below are additional details of the C-STORM steps.

1. Emissions Trajectory The first step of C-STORM sets an anthropogenic emissions scenario. We use the Intergovernmental Panel on Climate Change Special Report: Emissions Scenarios trajectory A1B. The A1B path assumes balanced and convergent economic growth with a mixture of fossil and renewable energy sources. The trajectory lies between emissions trajectories A2, a higher bound, and B1 and B2, both lower bounds. The scenario focuses on economic growth rather than environmental preservation (Nakicenovic et al., 2000). Figure 2 below details the emissions pathways for carbon dioxide (CO_2), Nitrous Oxide (N_2O), Methane (CH_4), and Sulfur Dioxide (SO_2)[2].

Comparing SRES A1B with other SRES scenarios, A1B has a higher estimated temperature increase than B1, A1T, and B2, yet is expected to be cooler than A2 and A1F1. In the forthcoming IPCC report, the AR5, new concentration pathways are developed called Representative Concentration Pathways (RCPs). Comparing the SRES A1B scenario, it is most similar to, but slightly higher than, the RCP6. Figure 3 below shows a comparison of SRES and RCP estimated temperature increases (Rogelj, Meinshausen, and Knutti, 2012).

[2]While sulfur dioxide is not a greenhouse gas, it can have indirect effects on climate through atmospheric chemistry relevant to global mean temperature (Unger et al., 2006).

Figure 1: C-STORM Methodology

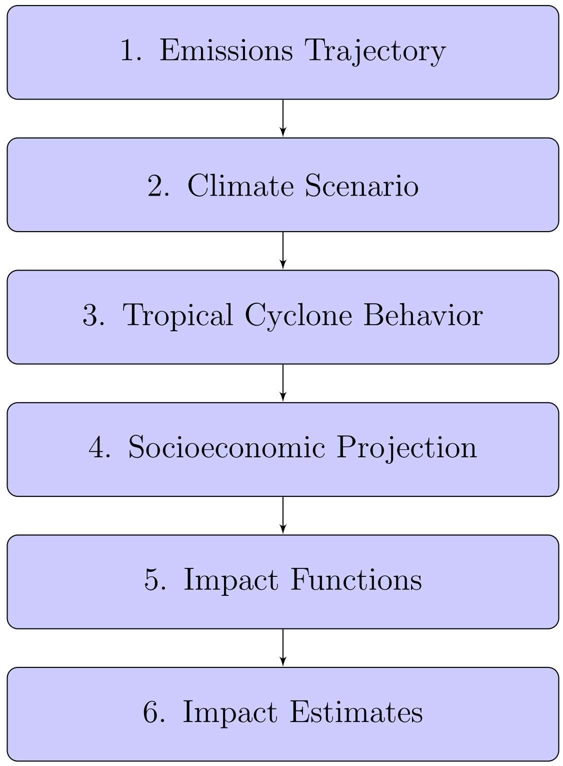


Figure 2: IPCC SRES Anthropogenic Emissions Scenarios (Houghton et al., 2001)

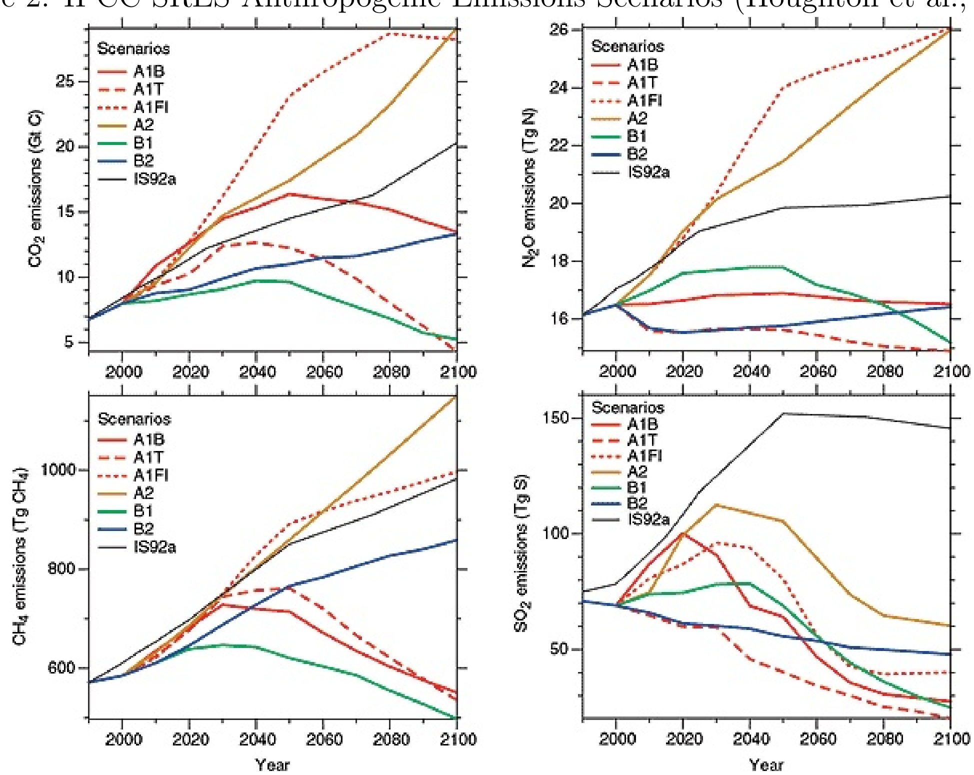
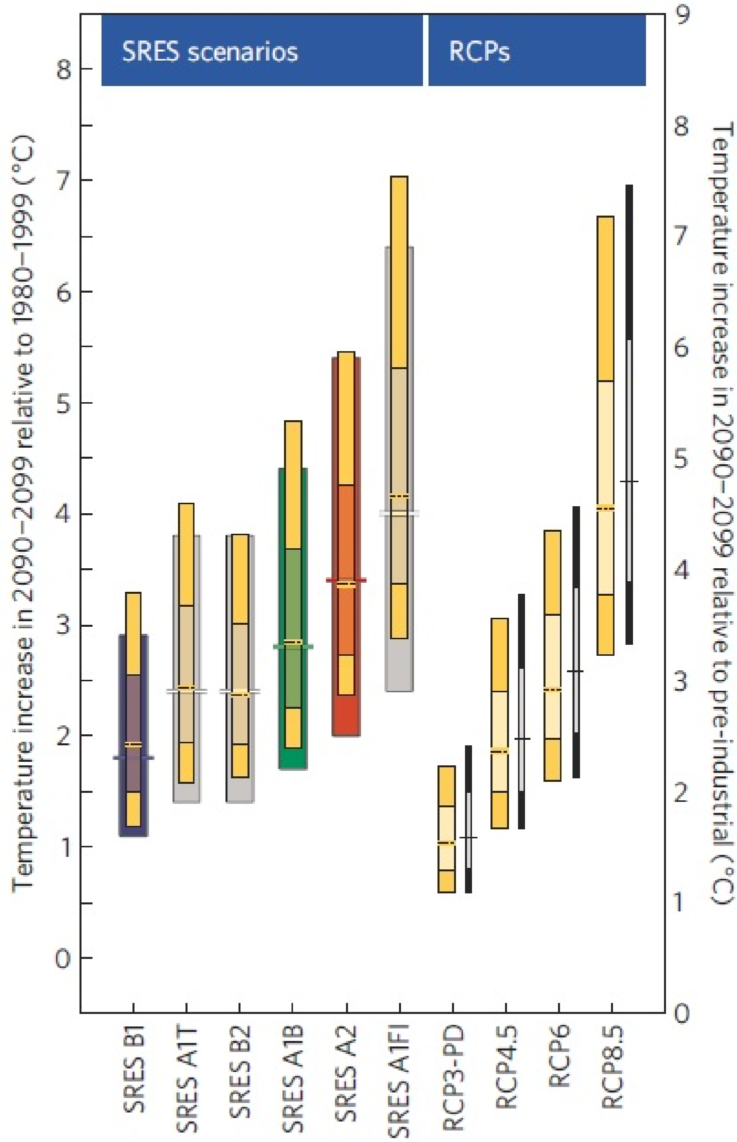
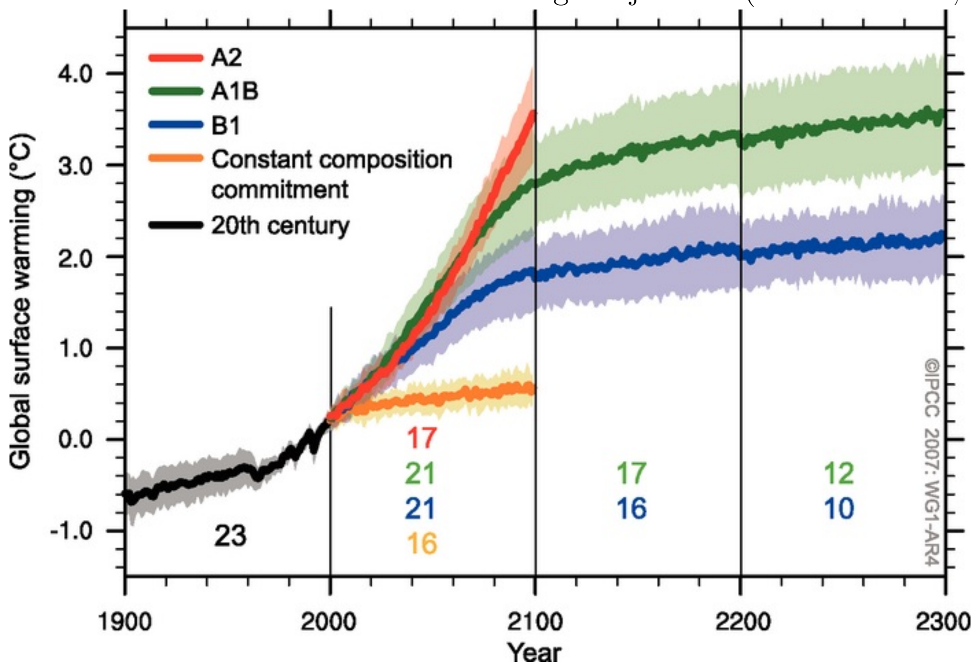


Figure 3: IPCC SERS versus RCP secnarios (Rogelj, Meinshausen, and Knutti, 2012)



2. Climate Scenario General circulation models translate emissions trajectories into climate outcomes. Figure 4 below depicts estimates of global surface warming from a hierarchical ensemble of climate models. Mean surface warming equals approximately 2.8°Celsius with a likely range of between 1.4 and 4.4°Celsius (Solomon et al., 2007). Similar to Mendelsohn et al. (2012), we employ four climate models: Centre National de Recherche Meteorologiques version CM3 (CNRM; Gueremy et al., 2007), European Centre for Medium Range Weather Forecasts-Hamburg version 5 (ECHAM; Cubasch et al., 1997), Geophysical Fluid Dynamics Laboratory version CM2.0 (GFDL; Manabe et al., 1991) and Model for Interdisciplinary Research on Climate version 3.2 (MIROC; Hasumi and Emori, 2004). Each climate model predicts a different change in mean surface temperature. Outputs range across the likely warming estimated by the IPCC, with mean predicted increases of 2.9°C for CNRM, 3.4°C for ECHAM, 2.7°C for GFDL, and 4.5°C for MIROC (Mendelsohn et al., 2012).

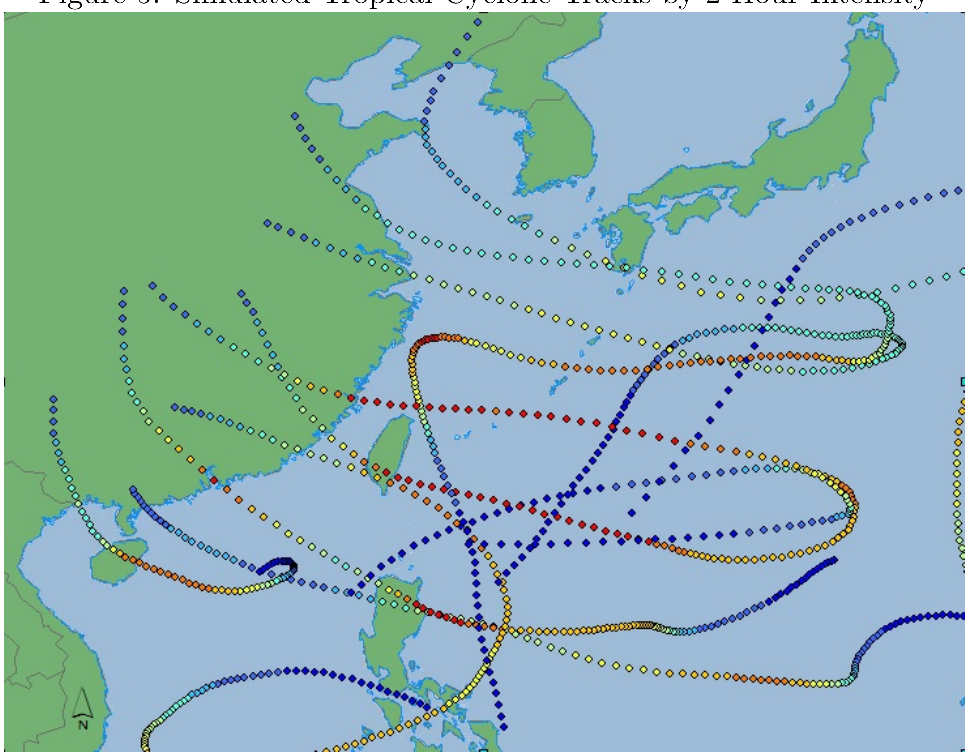
Figure 4: IPCC SRES Mean Surface Warming Projections (Solomon et al., 2007)



3. Tropical Cyclone Behavior While a few general circulation models have a spatial resolution fine enough to resolve hurricanes (Gualdi, Scoccimarro, and Navarra, 2008; Hasegawa and Emori, 2005; Knutson and Tuleya, 2004), many are currently still too coarse. Because of this, we use simulated cyclone track output from Emanuel, Sundararajan, and Williams' (2008) hurricane generating model. In the model, simulated storm seeds are planted in a modeled ocean. If storms develop, the subsequent tracks are recorded at two hours intervals. Simulated characteristics include latitude, longitude, minimum sea level pressure, radius of maximum wind, and maximum wind speed. These tracks are identical to the Western Pacific Ocean tracks of

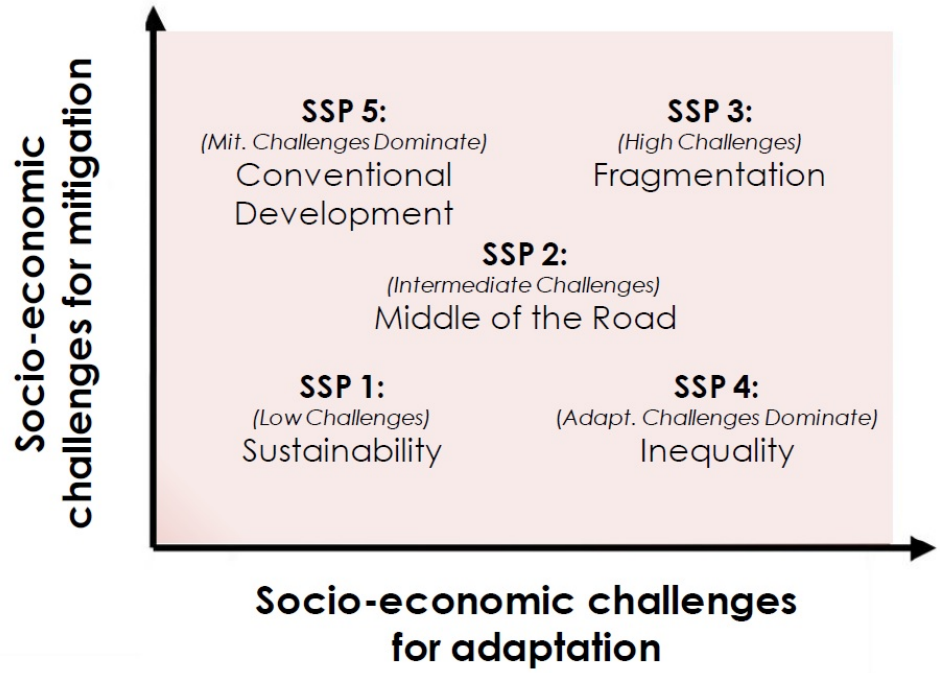
Mendelsohn et al. (2012), including 3,000 simulated storms in both current (1980-2000) and future (2080-2100) climate for each of the four climate models. Since the storms were seeded in the Western Pacific, not all storms made landfall with China. We processed tracks in ArcGIS to locate the point of first landfall in China. Storms that made landfall in Taiwan, Hong Kong, and Macau were allowed to continue and make landfall on mainland China and both landfalls were recorded. In addition, landfalls on mainland China within 50 kilometers of Hong Kong and Macau are counted also as landfalls for mainland China and the respective Special Administrative Regions, to account for near misses.

Figure 5: Simulated Tropical Cyclone Tracks by 2-Hour Intensity



4. Socioeconomic Projection The IPCC A1B emissions trajectory assumes that global population will be 7.1 billion and world Gross Domestic Product will be $529 trillion in the year 2100 (Nakicenovic et al., 2000). But these global scenarios do not include country-level projections. Thus, we use the United Nations medium-projections for future country-level population coupled with a constant income per capita growth rate of 2 percent as our base socioeconomic change assumptions. For sensitivity, we also include the five Shared Socioeconomic Pathways (SSPs), developed to offer a common set of socioeconomic projections at the country and regional levels (O'Neill et al., 2011). Multiple institutions model country-level population and gross domestic product with common setups, but output differs due to varying model assumptions. We use results from the Organisation for Economic Co-operation and Development (OECD) Environmental and Growth model. Separate pathways are provided for mainland China, Taiwan, Hong Kong, and Macau.

Figure 6: Five Shared Socioeconomic Pathways (O'Neill et al., 2011)



SSP1 represents an optimistic pathway with few challenges for mitigation and adaptation, leaving a world with fewer people and higher incomes. SSP2 represents a middle of the road scenario for gross domestic product and population, with global incomes and populations growing at a modest pace and cross-country income disparities slowly shrinking (O'Neill et al., 2011). The SSP 2 storyline assumes that from 2010 to 2100, incomes in mainland China will increase by more than 1,000%, raising from \$7,616.23 per person to \$105,498.65 in the year 2100. This will be coupled with more than 40% decrease in population density. Taiwan and Hong Kong are expected to enjoy income growth of 175% and 275%, respectively over the same period, with population density decreasing by 26 percent in Taiwan but increasing by 20 percent in Hong Kong. Macau is expected to experience the slowest income growth, with only a 50 percent increase in income and 34 percent increase in population over the next 90 years. SSP3 envisions a fragmented future world with many challenges to mitigation and adaptation, resulting in higher populations and sluggish income growth. SSP4 represents an unequal world with middle incomes and population growth. SSP 5 describes a world with very high incomes and larger populations. See Table 9 in the Appendix for a full summary of pathway results.

5. Impact Functions We use historical data to estimate the relationship between cyclone outcomes including direct economic damages, fatalities, injuries, number of homeless, and number affected.

We estimate outcome-specific functions based on historical data using Ordinary Least Squares in the following form:

$$ln\ Impact_{ij} = \beta_0 ln\ Income_i j + \beta_1 ln\ Pop_i j + \beta_2 ln\ Intensity_{ij} + \beta_3 ln\ Distance_{ij} + u_{ij} \quad (1)$$

Where $Impact_{ij}$ is the impact of cyclone landfall i in location j. We consider five specific impacts: direct economic damages, number of lives lost, homeless, injured, and affected. We assume these outcomes are a function of both socioeconomic and cyclone characteristics at the location of landfall. Socioeconomic characteristics include per capita income (Income) and population density (Pop). Cyclone characteristics include the minimum sea level pressure (Intensity) and distance of closest approach (Distance, equal to 0 if the storm makes direct landfall and the natural log of the distance of closest approach if the storm does not make direct landfall). We use the natural log of all variables in the regression, so estimated coefficients are interpreted as elasticities.

Table 1: Tropical Cyclone Landfall Summary Statistics

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Damages (million $USD)	886	826	5,240	0.01	138,741
Fatalities (ppl)	1062	393	6051	1	138,866
Injuries (ppl)	463	869	7236	1	138,849
Homeless (ppl)	319	56,401	144,204	23	1,110,020
Affected (ppl)	832	564,646	1,964,036	3	29,600,000
Income per capita (PPP $USD)	1410	$11,420	$11,994	$374	$67,723
Population density (ppl/km.sq.)	1410	448	1,526	0.01	33,922
Max. wind speed (kts)	1233	66	24	18	141
Min. sea-level pressure (mbar)	1354	972	24	885	1,012

We use data from Bakkensen (2013) to run impact functions using global historical data on typhoon landfalls. The dataset contains more than 1000 landfalls from 1960 to 2010, representing approximately 40 percent of all landfalls during this period. Historical typhoon outcomes are from EM-DAT International Disaster Database. Very low impact landfalls that do not meet EM-DAT's inclusion criterion are omitted. Outcomes include direct economic damages, lives lost, and number injured, homeless, and affected (CRED, 2012). Historical cyclone characteristics are from NOAA IBTrACS v03r03 (Levinson et al., 2012). Country-level time series data on population density and income per capita were taken from the Penn World Table v7.01 and Columbia CIESIN's Gridded Population of the World v3. County-level socioeconomic controls for the year 2000 are from China Data Online as well as country census data from the United States, India, the Philippines, Australia, Japan, and at the state-level for Mexico. We calculate county variables as a fraction of country aggregates and assume the fractions do not change over time, thereby creating a panel of county-level socioeconomic data. Lastly, simulated cyclone tracks are from Kerry Emanuel of

M.I.T. and are a subset of the sample used by Mendelsohn et al. (2012). We do not aggregate data to the year-county level, as other studies have done. Instead, the panel is unbalanced as some locations receive more than one landfall in a year. Locations receiving no landfalls are excluded from the sample. Table 1 details the sample summary statistics.

6. Impact Estimates In the final step of C-STORM, we use the impact functions from step 5 to estimate outcomes from the simulated cyclone landfalls in step 3. Holding climate constant, we first change socioeconomic conditions through the storylines in step 4. We then calculate the impact of socioeconomic changes from 2000 to 2100 on typhoon outcomes. Second, holding society constant at year-2100 projected conditions, we vary climate to calculate the impact of climate change on typhoon outcomes in China. Results from various steps are presented in section 4 below.

4 Results

In this section, we present results regarding the impact of climate change on tropical cyclone landfall behavior (from Step 3 of C-STORM) as well as the impact of socioeconomic and climate change on typhoon impacts (from Steps 5 and 6 of C-STORM). Extended results are found in the appendix.

Tropical Cyclone Behavior Climate affects tropical cyclones, although debate remains surrounding the impact of projected climate change scenarios on tropical cyclone behavior. Using the simulated tropical cyclones, we calculate the impacts of climate change on cyclone intensity, frequency, and geographic distribution at landfall. Table 2 summarizes the average results. With regard to frequency, there is disagreement across the climate models. The CNRM and ECHAM models find modest increases in the frequency of simulated cyclone landfalls in mainland China, Hong Kong, Macau, and Taiwan, while the GFDLCM and MIROC models find decreases in landfall frequency of approximately 28 and 16 percent, respectively. Averaging across the models, we find overall the frequency of landfalls is expected to decrease by 7 percent, or to approximately 8.26 landfalls per year across mainland China, Hong Kong, Macau, and Taiwan. Additionally, we find a decrease in the average intensity of typhoon landfalls, with the maximum wind speed decreasing by about 3 percent and the minimum sea level pressure increasing by 0.09 percent[3]. Here, three of the four models agree, while MIROC reports an increase in intensity of storms both in terms of maximum wind speed and minimum sea level pressure.

We also look at the distribution of storm characteristics across provinces. Figure 7 displays the province-level impacts of climate change on storm frequency and intensity, calculated by

[3]Unlike maximum wind speed, minimum sea level pressure has an inverse relationship with intensity: as a storm intensifies, the barometric pressure falls

Figure 7: The Impact of Climate Change on Average Regional Landfall Characteristics

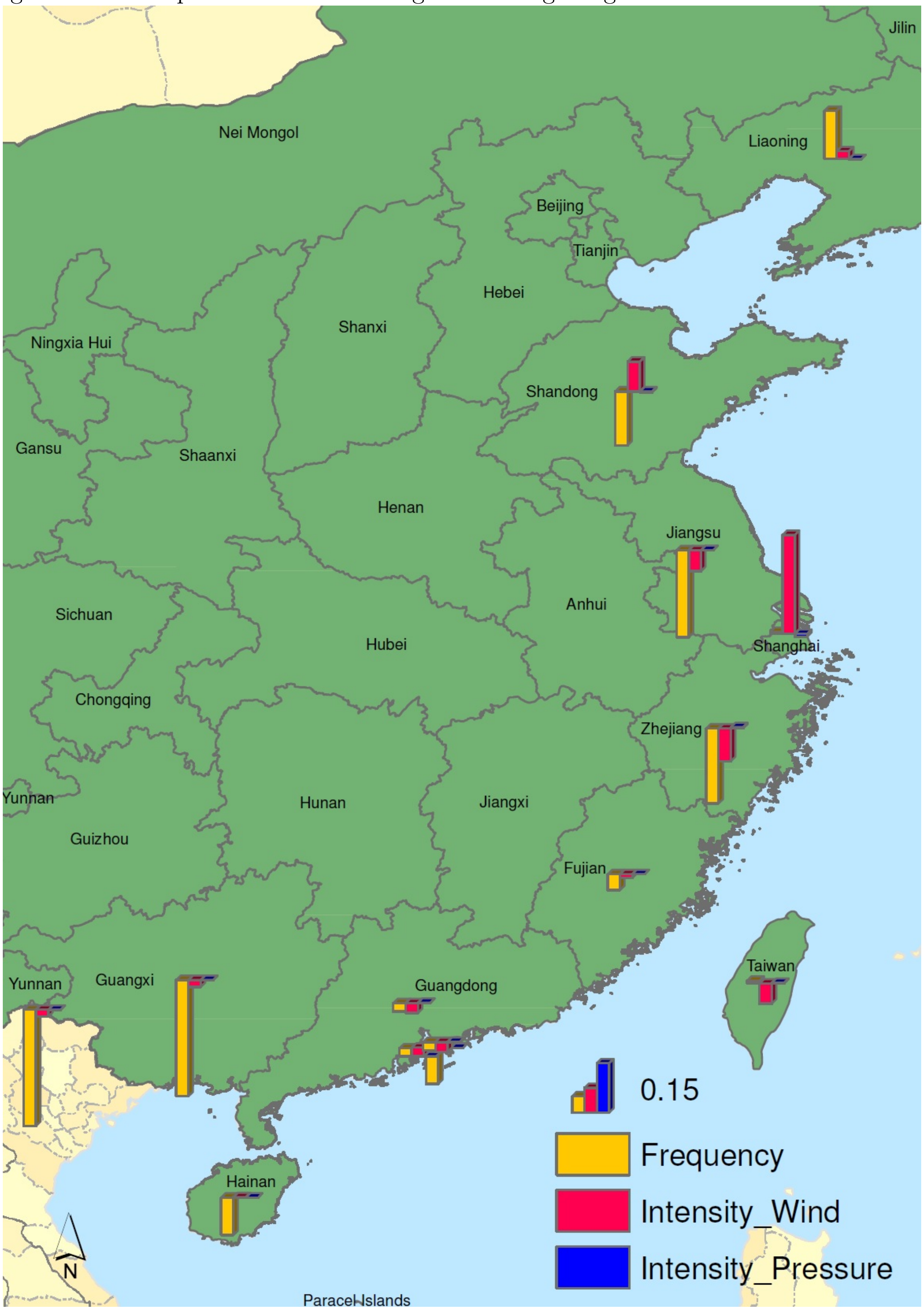


Table 2: Climate Change Impact on Cyclone Landfall Characteristics

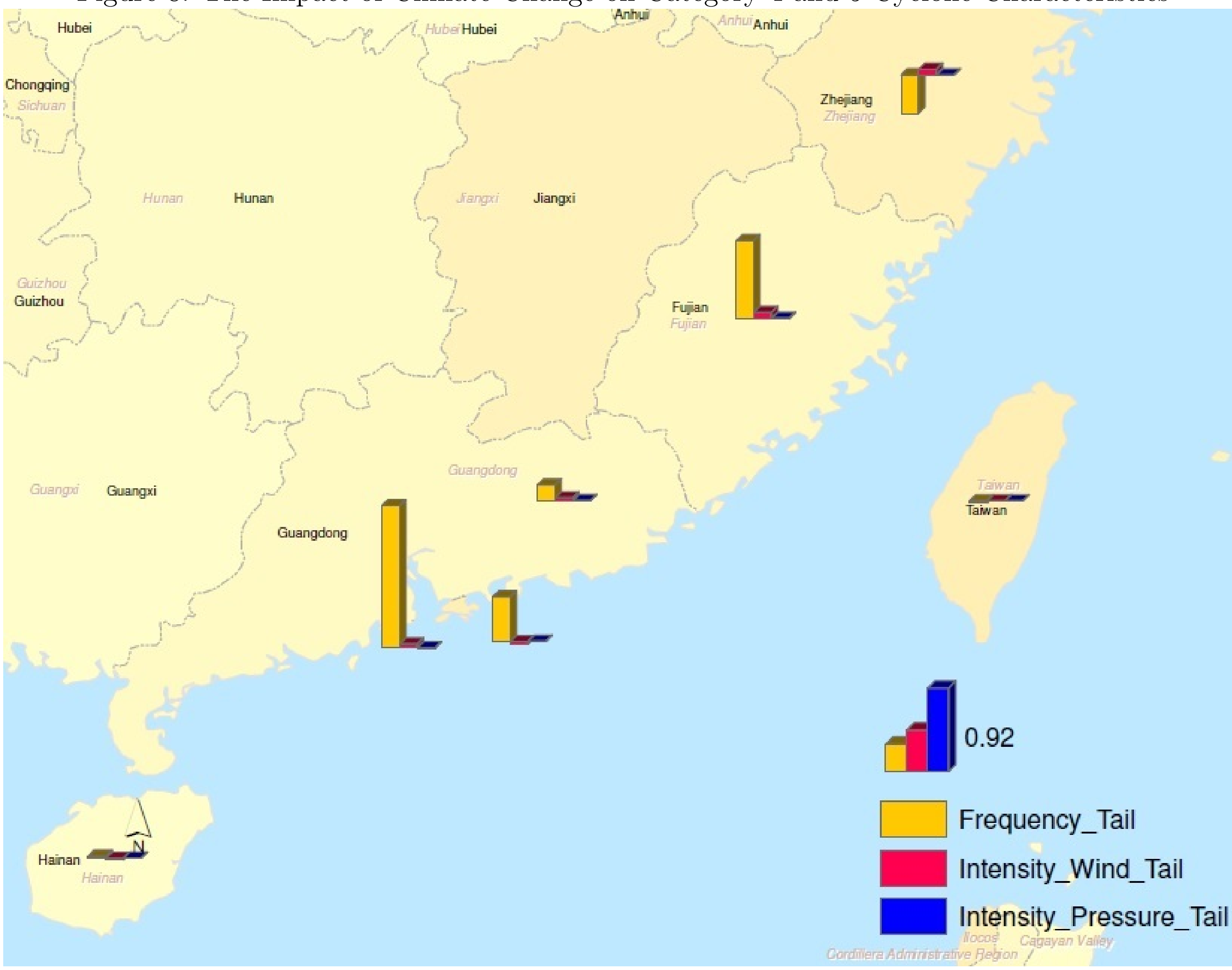
Climate Model	Frequency (%)	Max. Wind (%)	MSLP (%)
CNRM	6.93	-1.80	0.06
ECHAM	8.50	-4.11	0.16
GFDLCM	-27.98	-13.11	0.58
MIROC	-16.26	8.57	-0.44
Average	-7.20	-2.61	0.09

the unweighted average across the four climate models. See the appendix for the model-specific results. We find geographic variation in climate change impacts. Southeastern China is expected to experience a reduction in the frequency of storms, with a decrease of between 15 and 30 percent in Yunnan, Guangxi, Zhejiang, and Jiangsu provinces. These regions can also expect a small decrease, of between 2 to 10 percent, in the maximum wind speed of the average storm. In contrast, the far Northeastern province of Liaoning is expected to see around a 15 percent increase in the frequency, due to increased occurrence of storms in higher latitudes. Coupled with the increase in frequency, Northeastern mainland China also can expect increases in the average intensity of storms, by around 10 and 30 percent in Shandong province and Shanghai, respectively. Thus, future work and policy should focus on these regions, to ensure that actors are properly planning for the changing risks. Average landfall frequency and intensity in Hong Kong, Macau, and Taiwan are expected to remain relatively constant over the next century.

Next, we investigate climate change impacts on the tail of the typhoon distribution and present statistics on changes in the frequency and intensity of Category 4 and 5 storms in Figure 8. These results show an increased frequency of intense storms. Macau and Fujian Province experience more than a doubling of intense storms, and Guangdong Province and Hong Kong see increases of less than 50 percent. Taiwan and Hainan remain relatively stable. Average intensity increases minimally. Thus, strategic planning for more frequent high category storms is important. We caution over-interpretation of the results, however, as these statistics are driven by relatively few observations. We recommend that future work use a much larger dataset of several thousand simulated high category storms for each model and climate scenario to better characterize the underlying tail distribution. We also only present results for Southeastern China, as the rest of mainland China receives relatively few intense storms and therefore more prone to outliers driving the results.

Impact Functions We next turn to Step 5 of C-STORM, estimating the impact functions. We run the regressions presented in the Methodology section using Ordinary Least Squares. Extensive model testing was preformed in Bakkensen (2013b) including both cross sectional and error component models. Table 3 shows the results for the valuation functions. Robust standard errors are included in the parentheses. Each column represents a different typhoon loss, including

Figure 8: The Impact of Climate Change on Category 4 and 5 Cyclone Characteristics



damages, fatalities, injuries, homeless, and total number affected. Explanatory variables include per capital income, population density, as well as the minimum sea level pressure at landfall and the distance of closest approach, if the storm was not a direct hit. Our model takes a log-log functional form, and therefore estimated coefficients can be interpreted as elasticities. We also present C-STORM results using an East Asia-Specific valuation function in the Appendix. The results are qualitatively identical, except for damages.

Table 3: Historical Impact Functions

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Ln Damages	Ln Fatalities	Ln Injured	Ln Homeless	Ln Affected
Ln Income Per Capita	0.447***	-0.616***	-0.469***	-0.665***	-0.890***
	(0.0741)	(0.0439)	(0.0809)	(0.128)	(0.0837)
Ln Population Density	0.0688	0.165***	0.265***	0.0357	0.105
	(0.0548)	(0.0314)	(0.0678)	(0.0876)	(0.0672)
Ln Pressure	-29.48***	-9.707***	-18.91***	-23.60***	-20.11***
	(3.150)	(2.240)	(4.052)	(5.040)	(3.331)
Ln Distance	-0.396***	-0.189***	-0.217***	-0.243***	-0.260***
	(0.0400)	(0.0210)	(0.0449)	(0.0481)	(0.0366)
Constant	216.7***	74.34***	136.8***	176.4***	156.0***
	(21.68)	(15.48)	(27.95)	(34.59)	(22.89)
Observations	856	1,020	448	307	802
R-squared	0.223	0.229	0.165	0.198	0.192

The model results are consistent with our ex-ante expectations. First, it is important to note that the socioeconomic elasticities are less than one at the 99 percent confidence interval. Thus, we caution the use of normalization assumptions that implicitly assume an elasticity of one (Hsiang and Narita, 2012; Nordhaus, 2010; Pielke et al., 2008; Pielke and Landsea, 1998). This implies some level of adaptation through both development and population density. Richer and more urban areas are protective. Development is very protective, as fatalities, injuries, homelessness, and total number affected decreases quickly with increases in income per capita. We estimate elasticities of between -0.89 and -0.47 for these impacts. Damages, on the other hand, increase with development with an estimated elasticity of 0.48. This shows that development increases the capital stock in harm's way. This drives up damages. However, damage increases do not keep pace with economic growth, implying some protection taking place. Similarly, while we find that increases in population increase all losses, with estimated elasticities of between 0.04 and 0.27, we do not find that these losses are proportional with population.

For the typhoon variables, more intense storms characterized by lower minimum sea level pressure leads to higher loss across all impacts. Damages are highly nonlinear with respect to pressure, as a 1 percent decrease in pressure leads to an average increase of 29 percent in damages. Fatalities are the least sensitive to storm intensity, which could be evidence of the effectiveness of hurricane warning and evacuation programs, as well as the relative randomness of the deaths that do occur. We also find, consistent with intuition, that losses drop at roughly the one-third power as, conditional on not making landfall, the distance of closest approach of a typhoon increases.

Impact Estimates With the impact functions from Table 3 above, we estimate the changes in typhoon losses from both socioeconomic and climate change in Step 6 of C-STORM. First, we calculate the impact of socioeconomic change on typhoon losses. To do so, we hold climate constant at the current level. We only vary socioeconomic factors to isolate the impact of changes in human communities. Recall that for our main future baseline results, we use the United Nations medium-scenario projections for population and a 2% constant growth rate for per capita income. Results are presented in Table 4.

Table 4: The Impact of Socioeconomic Change on Typhoon Losses

	Damages (Billion $USD/yr)	Fatalities (Ppl/yr)	Injuries (Ppl/yr)	Homeless (Ppl/yr)	Affected (Ppl/yr)
Current Baseline	3.9	472	837	33,837	4,200,000
2100 Baseline	8.5	151.8	343	10,260	840,513
% Change	117.8%	-67.8%	-59.1%	-69.7%	-78.0%

We find that socioeconomic change will have a dichotomous impact on typhoon losses. Given the much richer future world and the positive income elasticity of damages, China suffers from an almost 120% increase in damages, from approximately $3.9 to $8.5 billion in expected annual losses. Keep in mind that due to the economic growth, China will be much richer so this represents a smaller fraction of gross domestic product relative to today. Nonetheless, it is important to quantify the estimated impacts in order to properly manage the changing risks. The other losses, including fatalities, injuries, homelessness, and total number affected, are expected to decrease with socioeconomic growth as we find that growth is protective. However, these results should be interpreted with caution. With proper planning and effort, they represent realistic targets for future loss reductions. But as each storm can be dangerous, we must continue with efficient warning and evacuation plans as these results are not guaranteed.

We present the regional impacts of socioeconomic change on typhoon losses in Table 5. As all of mainland China has the same rate of socioeconomic growth in the United Nations projections, the results are the same across mainland China. The variation across locations is due to changes in population growth rates by the United Nations. Taiwan is expected to have the greatest reduction in population density, at around -39 percent, it has the least increase in damages coupled with the greatest reduction in other losses. However, the vast changes in socioeconomic condition across the century dominate relatively small regional differences in income and population, leading to

Table 5: The Impact of Socioeconomic Change on Regional Typhoon Losses

Location	Damages	Fatalities	Injuries	Homeless	Affected
Mainland China	119.8%	-67.6%	-58.7%	-69.6%	-79.9%
Hong Kong	121.1%	-67.0%	-57.5%	-69.5%	-79.7%
Macau	126.8%	-64.6%	-52.3%	-69.0%	-78.7%
Taiwan	112.8%	-69.8%	-63.0%	-70.1%	-80.8%

little variation in expected impacts from socioeconomic change across mainland China, Hong Kong, Macau, and Taiwan.

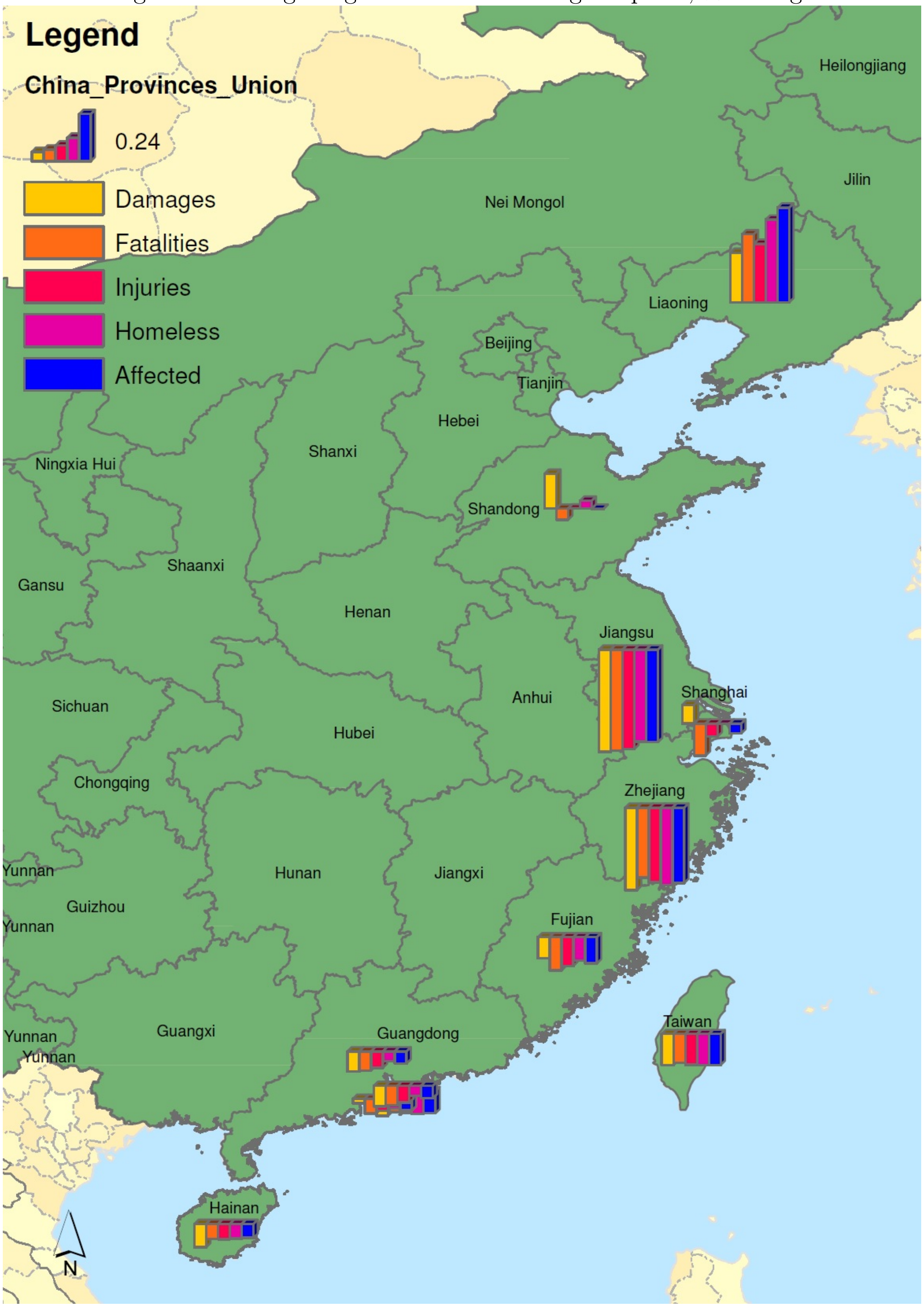
Table 6: The Impact of Climate Change on Typhoon Losses

	Damages (Billion $USD)	Fatalities (People)	Injuries (People)	Homeless (People)	Affected (People)
2100 Baseline	8.5	151.8	343	10,260	840,513
CNRM	7.6%	8.2%	9.6%	17.8%	15.8%
ECHAM	7.2%	4.1%	3.6%	0.5%	0.7%
GFDLCM	-46.9%	-33.6%	-39.6%	-43.9%	-41.2%
MIROC	2.1%	-10.1%	-4.5%	1.3%	-1.8%
Average	-7.5%	-7.9%	-7.7%	-6.1%	-6.6%

Next, we discuss our results regarding the impact of climate change on typhoon damages in mainland China, Hong Kong, Macau, and Taiwan. Table 6 summarizes the average results across the four climate models: CNRM, ECHAM, GFDLCM, and MIROC. Two models, CNRM and ECHAM, predict increases across all typhoon losses, with an average of 7 percent increases in damages and between 1 and 17 percent increases in homelessness. This is driven mainly due to the increased frequency of landfall in both models, although ameliorated by small reductions in intensity. The results of the MIROC model predict modest impacts, with small increases in damages and homeless given the larger pressure elasticities and increase in storm intensity, and moderate reductions between 2 and 10 percent in other losses. GFDLCM remains the most optimistic model, predicting large decreases in both storm intensity and frequency leading to reductions of between 33 and 46 percent in all losses. Overall, the impacts of climate change are more complex than changes in intensity and frequency. Storm paths are also influenced by climate, leading to differing frequencies and intensities of landfall across geographic space with different underlying socioeconomic factors at play. However, the changes in storm frequency still are a dominant force in these climate change impact results.

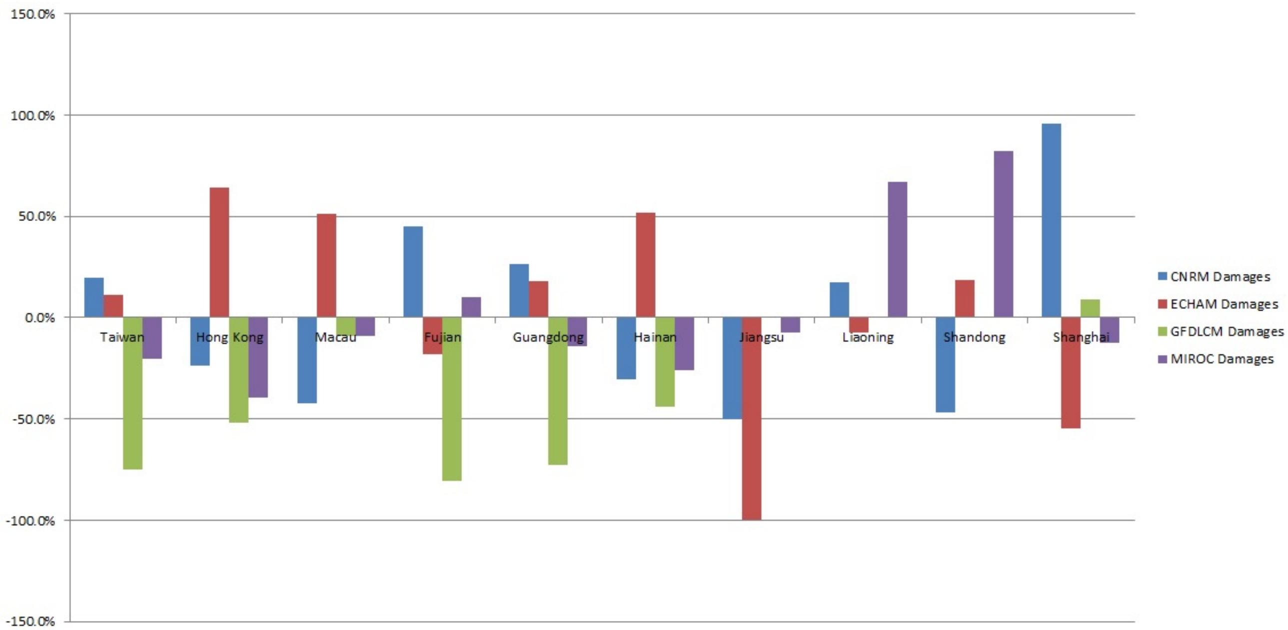
We present our spatially disaggregated results in Figure 9 calculated by an equal-weighted average across the four climate model outcomes. As foreshadowed in our regional typhoon landfall characteristics, we find heterogeneous climate change impacts across China. Given reductions in

Figure 9: Average Regional Climate Change Impacts, % Change



the average storm frequency and intensity, Southeastern China, Hong Kong, Macau, and Taiwan have expected decreases across all typhoon losses, with Zhejiang and Jiangsu Provinces seeing almost 50 percent reductions. Given the increases in frequency and intensity, Northeastern China including all losses in Liaoning, as well as damages in Shangdong and Shanghai are expected to increase. This is important for both public and private planning.

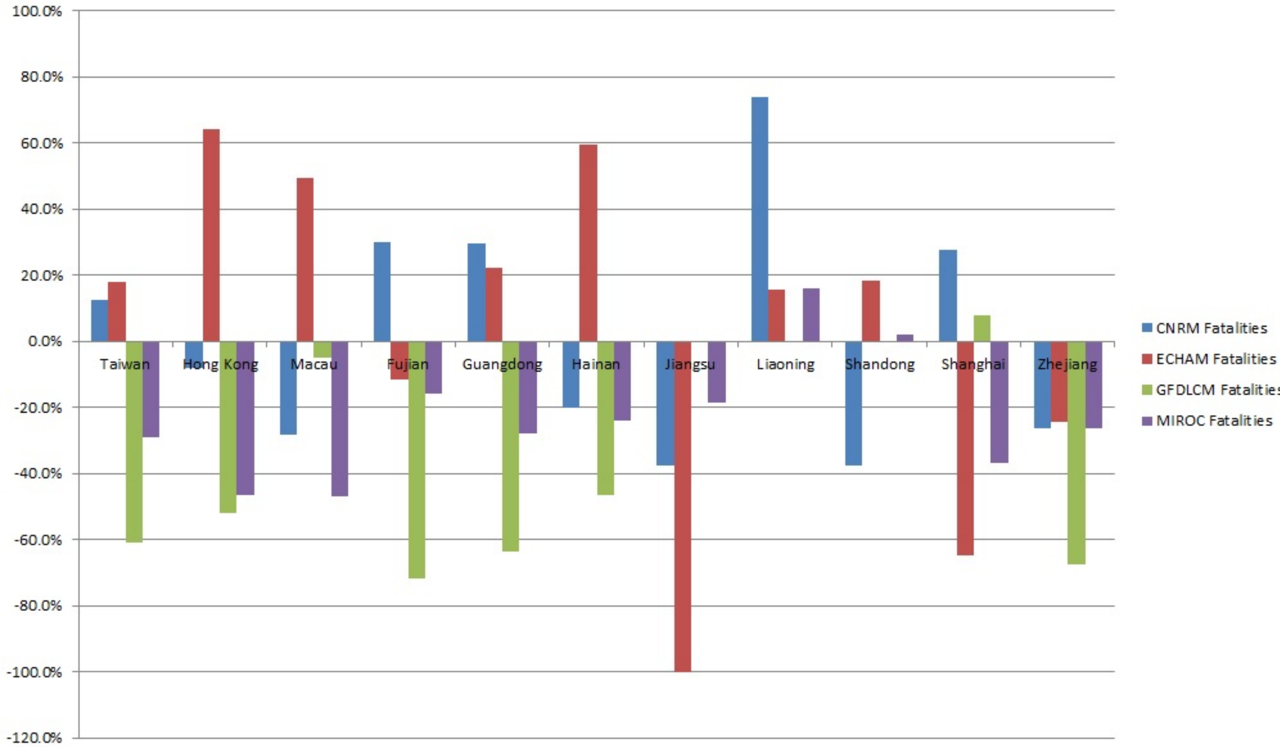
Figure 10: Climate Change Impacts on Regional Typhoon Damages, % Change



Lastly for our climate change results, we present detailed results for climate change damages and fatalities to illustrate areas of consensus and disagreement across climate models. We use fatality results because they are characteristic of the reductions also seen in injury, homelessness, and total affected. We present results regarding damages because they are not. We include figures for injury, homeless, and affected in the appendix. Figure 10 displays the regional impacts of climate change on typhoon damages. We find qualitative agreement across all four models only in Jiangsu Province, with expected reductions in damages. Six of the ten regions have two models predicting increases while the other two predict decreases. In line with the aggregate averages, GFDLCM consistently predicts reductions in damages across much of mainland China as well as Taiwan, Hong Kong, and Macau.

We present parallel results for fatalities in Figure 11. In this figure, we graph the province-level estimated impacts of climate change on typhoon fatalities. Overall, while disagreement across the models remains, a few trends are present. First, the GFDLCM model remains optimistic, predicting large reductions in fatalities across all regions except Shanghai. The MIROC model predictions are also more similar with GFDLCM, leaving the CNRM and ECHAM models as the main drivers of most pessimistic outlooks, especially in Guangdong, Taiwan, and Liaoning regions. Jiangsu continues to be a region of agreement across the models. Zhejiang has the

Figure 11: Climate Change Impacts on Regional Typhoon Fatalities, % Change



closest agreement across the four model. All together, these results highlight the importance of continued advancements in the underlying scientific understanding of the impacts of climate change on typhoons. Also, we recommend using a larger sample of simulated storms, as it is possible that even with 3,000 tracks, we have not yet reached a law of large numbers allowing our simulated sample to approach the true population.

Sensitivity Analysis Finally, we test the sensitivity of some of our model assumptions. For parsimony, we present only the results for damages and fatalities. The results for injury, homeless, and affected are similar to those of fatalities. Table 7 shows the sensitivity results across the socioeconomic change impacts. Row 1 describes the future baseline percent change in damages and fatalities dues to socioeconomic change. It represents a future state of the world consistent with medium population projections from the United Nations and a constant 2 percent rate of income growth. All other rows in the table should be compared to this one. Rows 2 through 6 vary the socioeconomic change assumption by instead using those of the Sustained Socioeconomic Pathways (SSP). The SSP are storylines rather than projects used by the United Nations. Finally, we test the sensitivity of the model in response to the model parameters by including the highest and lowest values within the 95 percent confidence interval of the estimated elasticities of per capita income and population density.

We find several important notes. First of all, damages experience a larger spread in estimated

Table 7: Socioeconomic Impact Sensitivity

	Damages	Fatalities
Future Baseline	117.7%	-67.8%
SSP 1	125.3%	-75.2%
SSP 2	116.7%	-72.4%
SSP 3	67.1%	-58.0%
SSP 4	119.7%	-74.7%
SSP 5	178.6%	-81.1%
Income -95%	-60.5%	-87.6%
Income +95%	1125.5%	-15.6%
Population -95%	7.7%	-78.0%
Population +95%	349.1%	-52.6%

impacts. This is likely due to the fact that fatalities is bounded by a 100 percent reduction in lives lost, while the positive increases in damages are unbounded in theory. Thus, we see fatalities results within approximately 20 percent of the future baseline figure, although fatalities are most sensitive when the income elasticity increases, moving closer to zero. This weakens the protective tendencies of development, leading to fewer fatalities avoided. Damages are sensitive to model assumptions. The impact of the SSP 1, 2, and 4 assumptions are similar to the future baseline. Damages increase the least in the SSP 3, where the future world is relatively poorer and more populated. Damages are very sensitive to the income and population elasticities. Therefore, it behooves future work to think carefully about these relationships and related assumptions.

Table 8: Climate Impact Sensitivity

	Damages	Damages	Damages	Damages	Fatalities	Fatalities	Fatalities	Fatalities
	CNRM	ECHAM	GFDLCM	MIROC	CNRM	ECHAM	GFDLCM	MIROC
Future Baseline	7.6%	7.2%	-48.9%	2.1%	8.2%	4.1%	-33.6%	-10.1%
SSP 1	11.0%	3.3%	-50.7%	4.4%	5.9%	9.4%	-30.5%	-14.0%
SSP 2	10.5%	3.5%	-50.7%	4.1%	6.1%	8.6%	-30.8%	-13.5%
SSP 3	9.8%	4.7%	-50.7%	3.7%	6.8%	6.8%	-31.7%	-12.4%
SSP 4	11.1%	4.0%	-50.9%	4.1%	5.8%	8.6%	-30.4%	-13.8%
SSP 5	10.9%	3.0%	-50.7%	4.6%	5.8%	9.7%	-30.4%	-14.1%
Income -95%	9.9%	6.0%	-49.8%	3.0%	8.6%	3.7%	-33.7%	-9.8%
Income +95%	5.2%	8.5%	-47.5%	1.2%	7.8%	4.5%	-33.4%	-10.5%
Population -95%	9.5%	6.8%	-50.3%	2.2%	8.6%	3.8%	-33.9%	-9.8%
Population +95%	2.8%	8.1%	-46.4%	1.7%	7.7%	4.5%	-33.2%	-10.6%
Pressure -95%	12.2%	6.4%	-57.6%	9.6%	9.6%	3.4%	-36.6%	-7.5%
Pressure +95%	5.1%	8.4%	-41.2%	-4.5%	7.6%	5.0%	-31.2%	-12.3%

Lastly, we present the results of the climate impact sensitivity in Table 8. We employ the same tests as described above and apply them to both damages and fatalities across all four climate models. We also add a test for the sensitivity of the estimated intensity elasticity. Overall, we find the across-model sensitivity dominates the within-model sensitivity. This is logical for the socioeconomic sensitivity tests, as we hold socioeconomic factors constant in this analysis. Thus, the variation is driven by changes in the path of the storm leading to different types of human communities being hit. While we found large sensitivity to the income and population for socioeconomic damages, we do only find small aggregate-level sensitivity to the changes in the intensity coefficient. Thus, socioeconomic variable elasticities as well as across-model agreement are main areas of sensitivity in the model.

5 Conclusion

In this paper, we estimate the impact of climate and socioeconomic change on typhoon losses in mainland China, Hong Kong, Macau, and Taiwan. To do so, we first extend the theoretical framework based on Mendelsohn and Saher (2011). We then construct C-STORM, the China-Specific Typhoon Outcomes integRated assessment Model. This model synthesizes the forefront of natural science knowledge with economic valuation tools. Using simulated typhoon data generated from the results of four climate models, we value the simulated losses using global valuation functions for damages, fatalities, injury, homelessness, and number affected. We then characterize spatially-explicit changes in landfall characteristics due to climate change and separately estimate change in typhoon losses due to climate and socioeconomic change. We find that China is likely to see fewer storms overall, but an increase in the strongest storms. Additionally, we find an increase in future baseline damages by 118% due to socioeconomic change, while other losses are expected to decrease due to increased protection from economic development. Overall, the long term socioeconomic changes coupled with some disagreement across climate model output drive loss changes.

There are important policy implications of this work. First, we must keep in mind that the projected reductions in losses are not deterministic. They will not occur automatically but rather highlight the potential for a century of economic growth coupled with efficient adaptation. Second, they highlight the importance of public adaptation, as well as public leadership to educate the general public about typhoon risks. Clear and credible advanced warning is important to prevent unnecessary deaths. Lastly, it is important for governments to consider these long term changes in underlying risk rates and the types of storms a specific location may face. With that said, China is already hit frequently by storms each year, so adapting optimally to the current levels of risk will help combat future risks as well.

This research leaves several directions for future work. First, a careful study of the costs and benefits of various mechanisms to reduce fatality risks is important. This will better inform and tailor evacuation and advanced warning messages for potential storm landfalls. Second, this study highlights the importance of continued advancements in scientific knowledge of climate science, as there is still disagreement across model output. Third, the results here highlight the importance of better damages data, including better understanding of how data collection may vary across types of collection agencies. This will inform the extent to which results are driven by measurement issues. Lastly, the impact of sea level rise was not included in this analysis and is an important direction for future work.

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A Extended Results

In this section of the appendix, we present additional information and results relevant to the analysis. Table 9 details the exact socioeconomic change assumptions used in the Sustained Socioeconomic Pathways as well as the United Nations medium population projections and a 2 percent per capita income growth rate. We also include a high-population growth and 2.5 percent constant growth rate for comparison. We find it is important to carefully chose SSP scenarios, as the domain across the five SSP scenarios is not always contained within the United Nations and income change assumptions. For example, the SSP predict more convergent incomes, leading to more than 1000 percent growth in income per capita in China coupled with only 50 percent increases in incomes in Macau over the next century. The SSP also predict faster rates of population shrinking in China and Macau, relative to the United Nations projections. Thus, researchers should think carefully about assumptions that fit their needs.

In Table 10, we present the results of the impact of climate change on average typhoon landfall characteristics. These are identical to the results in Figure 7, but written out for ease of numerical interpretation. After presenting the results for damages and fatalities in the main body of the paper, we include here the impact of climate change on regional typhoon injuries in Table 12, homelessness in Table 13, and number affected in Table 14. The results are similar to those of fatalities, with CNRM and ECHAM models dominating the predictions of regional increases in typhoon losses, while GFDLCM and to a lesser extent the MIROC model forecasts net reductions in impacts.

Table 9: Shared Socioeconomic Pathway Storylines and Projections

Location	2010 Pop. Density	2100 Pop. Density	% Change	2010 Income	2100 Income	% Change
Mainland China, SSP 1	140.16	67.29	-51.99%	7,616.23	105,498.65	1285.18%
Mainland China, SSP 2	140.16	80.18	-42.80%	7,616.23	86,392.60	1034.32%
Mainland China, SSP 3	140.16	107.42	-23.36%	7,616.23	40,325.17	429.46%
Mainland China, SSP 4	140.16	58.01	-58.61%	7,616.23	82,714.86	986.03%
Mainland China, SSP 5	140.16	67.35	-51.95%	7,616.23	150,680.35	1878.41%
China, Med & 2%	145.80	116.40	-20.16%	7,616.23	45,264.27	494.31%
China, High & 2.5%	145.80	190.82	30.88 %	7,616.23	70,289.09	822.89%
Hong Kong, SSP 1	6,691.65	6,008.54	-10.21%	46,817.68	125,374.03	167.79%
Hong Kong, SSP 2	6,691.65	8,060.72	20.46%	46,817.68	128,898.47	175.32%
Hong Kong, SSP 3	6,691.65	7,865.28	17.54%	46,817.68	86,080.98	83.86%
Hong Kong, SSP 4	6,691.65	6,570.21	-1.81%	46,817.68	116,854.44	149.59%
Hong Kong, SSP 5	6,691.65	7,363.38	10.04%	46,817.68	175,626.85	275.13%
Hong Kong, Med & 2%	6,385.87	6,228.26	-2.47%	46,817.68	278,243.70	494.31%
Hong Kong, High & 2.5%	6,385.87	9,366.74	46.68%	46,817.68	432,073.64	822.89%
Macau, SSP 1	19,290.78	19,007.09	-1.47%	64,500.88	97,038.81	50.45%
Macau, SSP 2	19,290.78	25,886.52	34.19%	64,500.88	98,782.47	53.15%
Macau, SSP 3	19,290.78	26,170.21	35.66%	64,500.88	76,883.90	19.20%
Macau, SSP 4	19,290.78	20,957.45	8.649%	64,500.88	85,169.20	32.04%
Macau, SSP 5	19,290.78	23,191.49	20.22%	64,500.88	136,053.52	110.93%
Macau, Med & 2%	18,135.59	27,728.81	53.90%	64,500.88	383,337.32	494.31%
Macau, High & 2.5%	18,135.59	40,944.58	125.77 %	64,500.88	595,269.35	822.89%
Taiwan, SSP 1	713.79	393.43	-44.88%	36,129.35	130,812.86	262.07%
Taiwan, SSP 2	713.79	527.77	-26.06%	36,129.35	135,864.56	276.05%
Taiwan, SSP 3	713.79	514.97	-27.85%	36,129.35	96,195.75	166.25%
Taiwan, SSP 4	713.79	430.22	-39.73%	36,129.35	136,998.41	279.19%
Taiwan, SSP 5	713.79	482.15	-32.45%	36,129.35	182,917.13	406.28%
Taiwan, Med & 2%	639.51	391.40	-38.80%	36,129.35	214,721.54	494.31%
Taiwan, High & 2.5%	639.51	651.32	1.85 %	36,129.35	333,432.58	822.89%

Population density is in units of ppl/km sq. Income is in in units of 2010 purchasing power parity $USD.

Table 10: The Impact of Climate Change on Average Typhoon Landfall Characteristics

Location	Frequency (%)	Wind (%)	Pressure (%)
Fujian	-5.03	-1.21	0.04
Guangdong	-2.65	-3.10	0.11
Guangxi	-36.48	-2.20	-0.10
Hainan	-11.78	0.14	0.01
Jiangsu	-27.26	-6.52	0.04
Liaoning	15.16	2.48	-0.07
Shandong	-16.91	9.36	-0.33
Shanghai	0.61	30.98	-0.95
Zhejiang	-23.50	-10.23	0.41
HongKong	-11.30	1.20	-0.04
Macau	2.54	2.76	-0.07
Taiwan	0.89	-6.32	0.27

Figure 12: Climate Change Impacts on Regional Typhoon Injuries, % Change

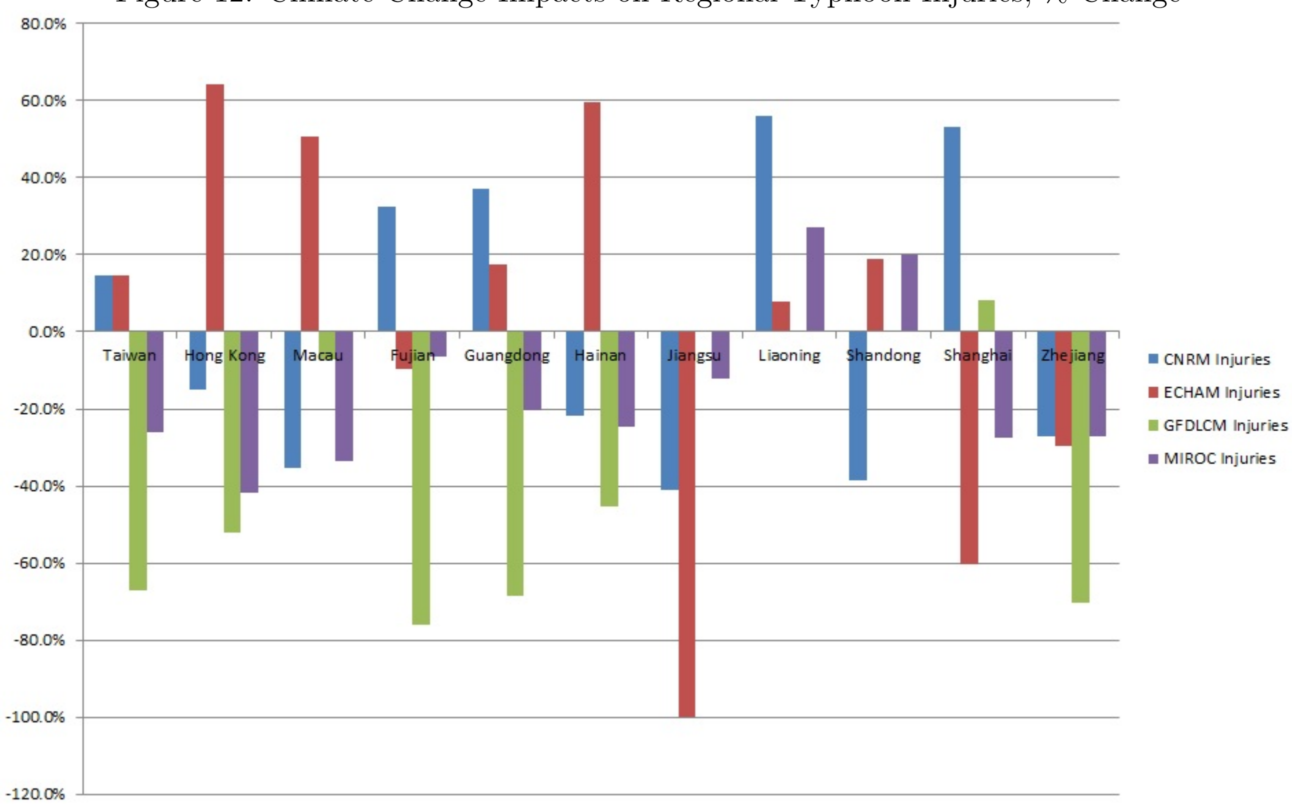


Figure 13: Climate Change Impacts on Regional Typhoon Homeless, % Change

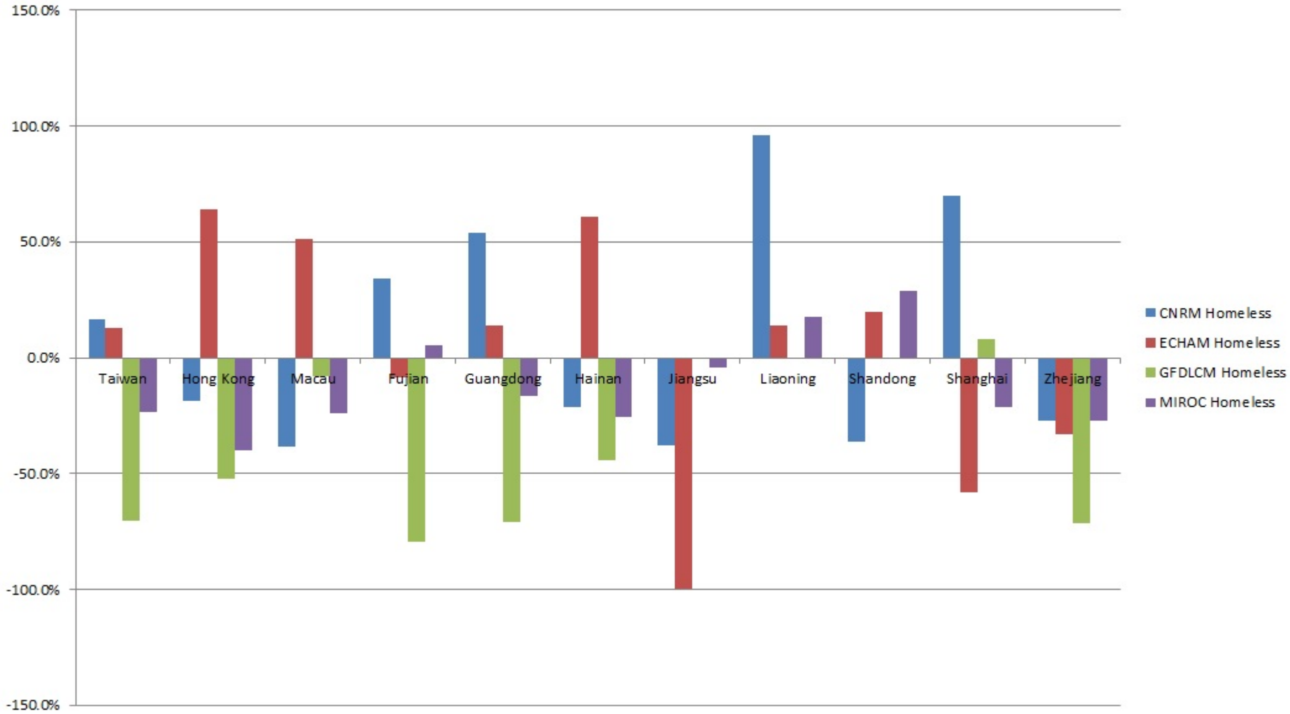
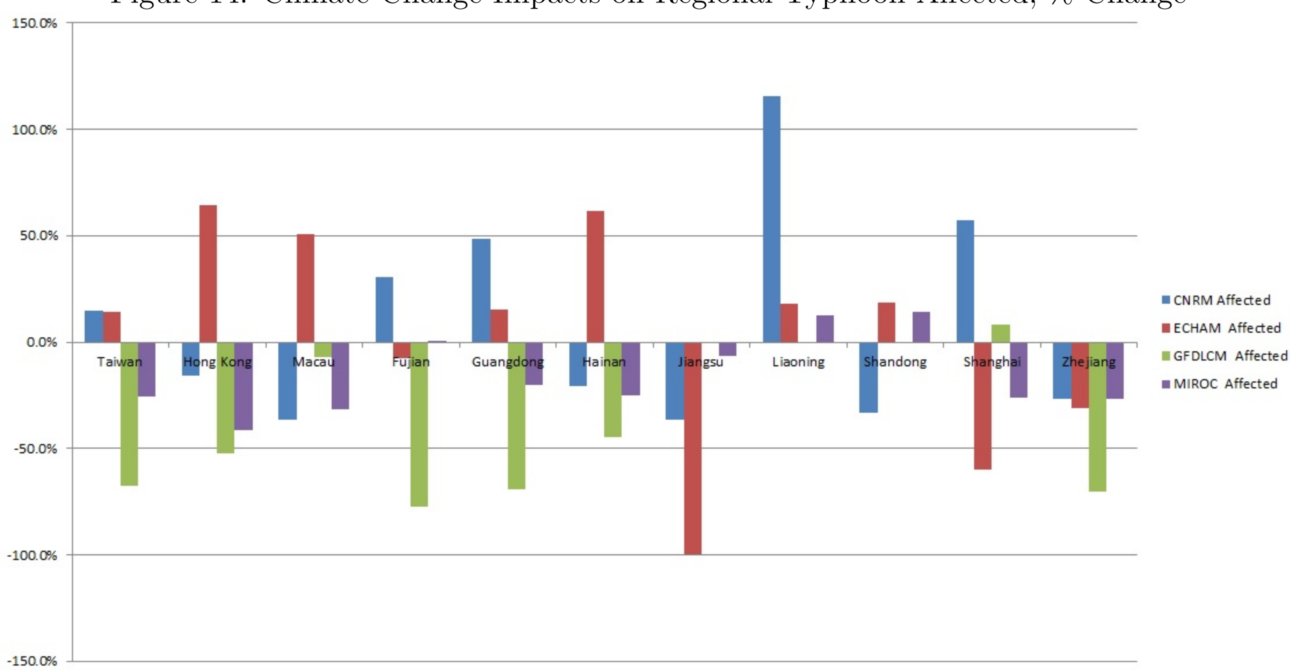


Figure 14: Climate Change Impacts on Regional Typhoon Affected, % Change



B East Asia Results

In this section, we present the results of the analysis using a valuation function unique to East Asia. We find qualitatively similar results as with the global model, except for damages. We present the results from our East Asia-specific valuation functions in Table 11. The model set up is identical to the global model in the body of the text, except the underlying sample is censored to only include locations in East Asia, including China, Macau, Hong Kong, Taiwan, Japan, and the Koreas. Thus, the sample size is reduced by 75 percent.

Table 11: Historical East Asia-Specific Impact Functions

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Ln Damages	Ln Fatalities	Ln Injured	Ln Homeless	Ln Affected
Ln Income Per Capita	-0.407**	-0.521***	-0.776***	-0.791***	-1.214***
	(0.174)	(0.0868)	(0.131)	(0.290)	(0.226)
Ln Population Density	-0.919***	-0.367***	-0.0870	-0.583**	-1.112***
	(0.224)	(0.0947)	(0.119)	(0.236)	(0.216)
Ln Pressure	-31.11***	-4.426	-20.10***	-10.66	3.143
	(9.366)	(5.011)	(7.677)	(14.48)	(13.78)
Ln Distance	-0.589***	-0.135***	-0.274***	-0.115	-0.379**
	(0.106)	(0.0503)	(0.0873)	(0.152)	(0.180)
Constant	242.3***	40.57	150.3***	92.41	7.087
	(64.76)	(34.58)	(52.87)	(100.1)	(95.13)
Observations	190	264	161	60	167
R-squared	0.260	0.229	0.259	0.302	0.336

Interestingly, we find qualitatively similar results for the cyclone elasticities, with a stronger and closer storm leading to more losses. The only unexpected result is the pressure elasticity of number affected, which is positive but not statistically different from zero. This could be due to small sample size or measurement error. In fact, three of the five model pressure elasticities lack statistical significance from zero. The socioeconomic elasticities are different. Similar to the main result, the income elasticity is negative and statistically significant for fatalities, injury, homeless, and affected, although the magnitude of the coefficients is larger, especially for affected. This implies strong adaptive potential in East Asia, but could also be due to error in the underlying data. Surprisingly, the income elasticity of damages is negative, implying that adaptation completely washes out any scale effect from more in harm's way. Unlike the global model, the population density elasticity is negative and significant for all specifications excluding the injury regression. We present the results for socioeconomic change on typhoon impacts in Figure 15 and the socioeconomic sensitivity analysis in Figure 16. Lastly, we present results for the regional impact of climate change in Figure 17. We use the world model as our main result, as the drivers of the East Asian results is still an open research question. It could be that East Asia is very effective at adapting as it develops and thereby greatly reduces typhoon impacts. On the other hand, since there is no systematic accounting scheme for disaster impact data collection, it is possible that measurement error or even strategic reporting could be attenuating or even biasing, respectively, the analysis results. Thus, we leave a detailed data collection study for future work.

Figure 15: Socioeconomic Change Impacts, % Change

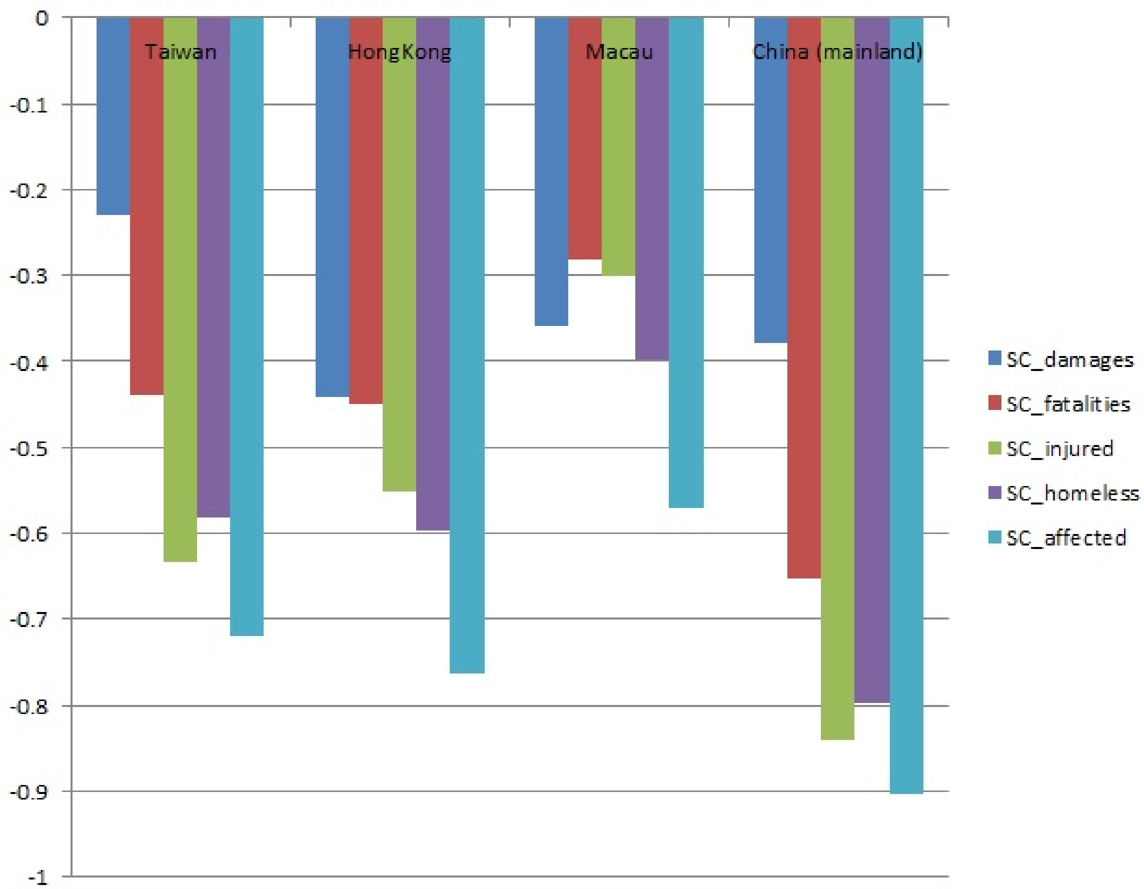


Figure 16: Socioeconomic Change Sensitivity Analysis, % Change

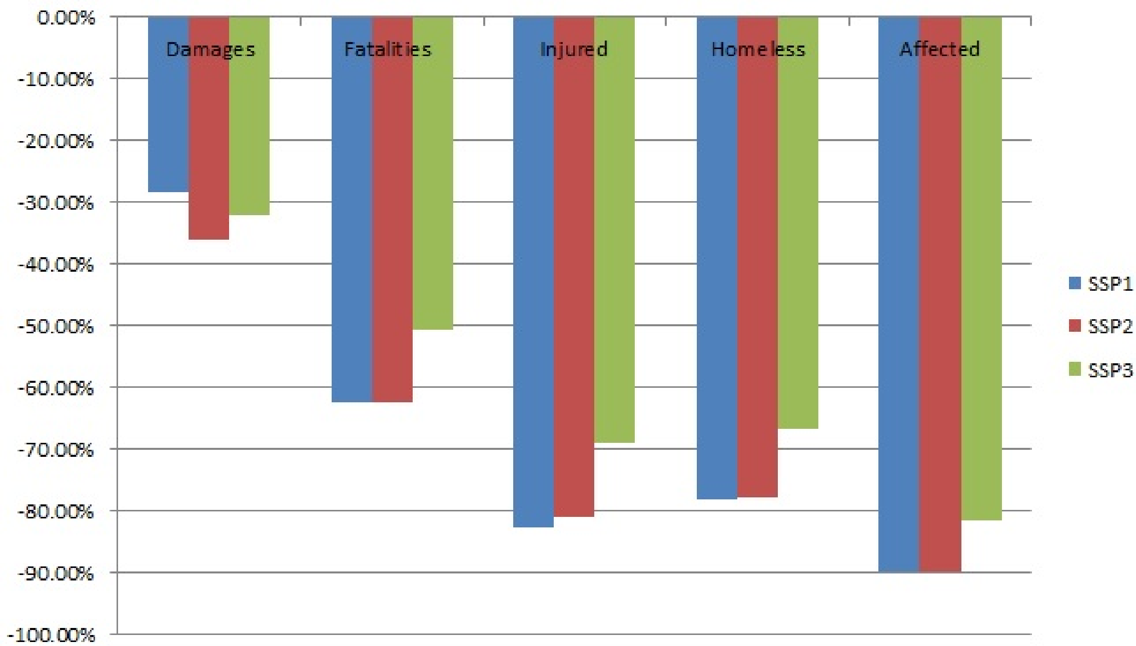
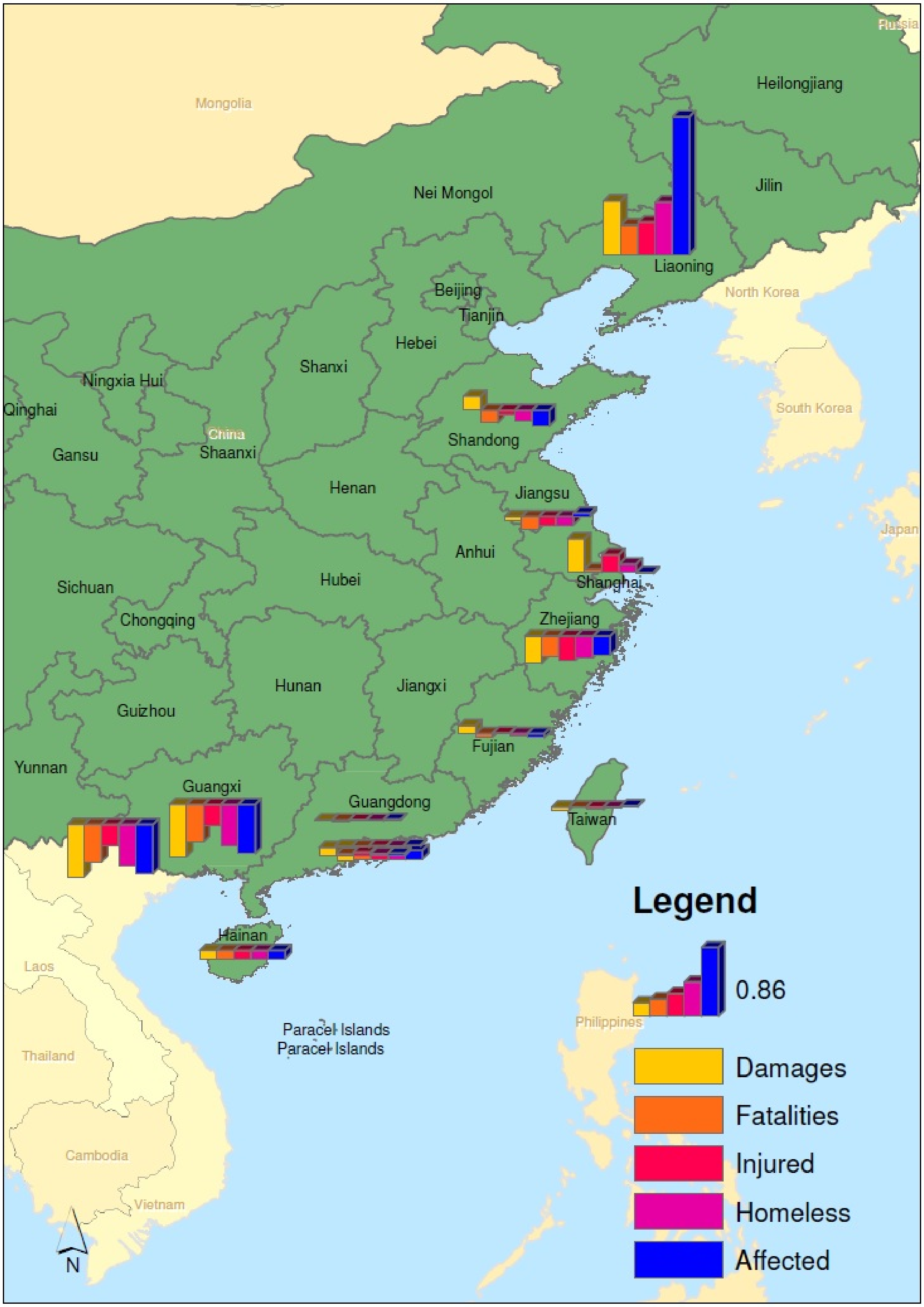


Figure 17: Climate Change Impacts, % Change



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