

**Assessing the Global Threat of Coastal Flooding: A Mortality Risk Model**

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## **ABSTRACT**

Coastal flooding, caused by sea level rise (SLR), storm surge, and tropical cyclones, is a growing threat. Previous studies have documented mortality associated with historical coastal flooding and developed predictions of mortality risk based on SLR and human development. This study updates those estimates and provides a new model by including new mortality data from events between 2010 and 2020 and an updated method for estimating the population exposed to coastal flooding events. Primary data sources include the Emergency Events Database (EM-DAT) and the Sea Level Impacts Input Dataset by Elevation, Region, and Scenario (SLIDERS) model. We first characterize trends in exposed populations and mortality associated with coastal flooding between 1990 and 2020. A mixed effect regression model estimates mortality associated with coastal flooding and investigates the influence of variables including Human Development Index (HDI), country population, and event frequency. The frequency of coastal flooding events between 1990 and 2020 has increased, while there was an overall decrease in recorded deaths associated with coastal flooding events. The association between mortality and coastal flood exposure is reduced in countries with higher populations. This result suggests countries with larger populations may buffer risks in exposed regions. Results showed significant reduction in mortality risk, by approximately 34% (95% CI, 17-47%), associated with an increase of approximately 61 million in country-level population. Additionally, a 7% increase (95% CI, 3-11%) in mortality risk with each additional occurrence of coastal flooding events was observed. By leveraging this knowledge, decision-makers can develop targeted policies and interventions to enhance community preparedness, reduce vulnerability, and ultimately save lives in the face of increasing coastal flooding risks.

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## **GENERAL AUDIENCE ABSTRACT**

This study aims to explore the association between coastal flooding deaths and socio-economic variables globally. Additionally, it seeks to analyze trends in coastal flooding mortality, exposed populations, and flooding frequency across global regions, as well as income regions differentiated by the World Bank, from 1990 to 2020. Coastal flooding mortality data for every coastal flooding event were sourced from EM-DAT, a widely utilized disaster database. We utilized a climate model to retrieve the population exposed to coastal flooding for every event. Human Development Index (HDI) data and country population from 1990 to 2020 were taken from United Nations Development Programme (UNDP) and World Bank databases, respectively. A statistical model was used to estimate mortality risk associated with coastal flooding events and to investigate the influence of variables including Human Development Index (HDI), population, and event frequency. The frequency of coastal flooding events between 1990 and 2020 has increased, while there was an overall decrease in recorded deaths associated with coastal flooding events. The association between mortality and coastal flood exposure is reduced in countries with higher populations. This result suggests countries with larger populations may buffer risks in exposed regions. Results showed significant reduction in mortality risk, by approximately 34% (95% CI, 17-47%), associated with an increase of approximately 61 million in country population. Additionally, a 7% increase (95% CI, 3-11%) in mortality risk with each additional occurrence of a coastal flooding event was observed.

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## **Chapter 1- Introduction**

### **1.1. Overview**

The purpose of this study is to examine the relationship of socioeconomic factors like Human Development Index (HDI) and demographic factors like country-level population with coastal flooding mortality risk at global scale. We calculate the mortality risk as the ratio of coastal flooding mortality to the population exposed to coastal flooding. Here we are developing the model by including all coastal flooding related events around the globe from 1990 to 2020. This thesis is documented in three chapters. Chapter 1 gives the background on global disaster databases, models and approaches to estimate the exposed population. Chapter 2 is the main backbone of the study which provides the introduction, methods and results of the study. Chapter 3 is the conclusion and recommendation of this thesis.

### **1.2. Background**

#### **1.2.1. Increasing threat of coastal flooding worldwide**

Coastal flooding arises from the interplay of various atmospheric factors and oceanic factors, such as fluctuations in mean sea level, tidal patterns, storm surges, wave action, river flow, and precipitation (Marcos et al., 2019). Coastal flooding occurs when various factors come together, with storm surges and wind waves (tropical cyclones and extra-tropical storms) being large contributors which can lead to very high-water levels along the coast causing widespread damage (Marcos et al., 2019). Nearly half of the globe's population resides within 94 miles from a coast and these settlements are facing major social, economic and environmental risks due to rapid population growth and climate change (Dedekorkut-Howes et al., 2020). On a global scale, coastal regions with low elevation [areas less than 10 meters above mean sea level (MSL)] serve

as habitats for an estimated 700 million individuals and contribute approximately US\$13 trillion to the global economy (Hallegatte et al., 2013; Kirezci et al., 2023; Marcos et al., 2019; McGranahan et al., 2007; Milne et al., 2009; Nicholls & Cazenave, 2010; Vitousek et al., 2017). In the 21<sup>st</sup> century, the increase in coastal flooding occurrence is recognized as one of the major natural threats that might impede the socioeconomic wellbeing of coastal populations (Kron, 2013; Vafeidis et al., 2019; Wong et al., 2014). Recent studies have projected that low lying coastal communities might face a doubling of coastal flooding frequency with the estimated sea level projections and emission trajectory (Taherkhani et al., 2020; Vitousek et al., 2017).

### **1.2.2. Traditional Approach to Mortality Risk Model**

Recent studies have used published estimates of country-level mortality due to coastal flooding and estimated the population exposed with socio-demographic data to develop a mortality risk model (Lindersson et al., 2023; Lloyd et al., 2016; Patt et al., 2010). Mortality and exposed population due to coastal flooding are the main components of the mortality risk model.

In line with previous research methodologies, Hu et al. (2018) utilized the approach outlined by Jonkman (2005) to ascertain mortality rates, calculated as the ratio of total fatalities to the overall population impacted by flooding. Hu and co-authors have used the EM-DAT database for both mortality and exposed population data to obtain the mortality rate. Similarly, studies by Lloyd et al. (2016) and Lindersson et al. (2023), conducted on a global scale, also relied on mortality data sourced from the EM-DAT global disaster database. However, they independently determined the exposed population. While the former study derived exposed population estimates from the Dynamic Interactive Vulnerability Accessibility (DIVA) model at the national level, the latter study utilized data from Google Earth Engine, leveraging Global Human Settlement Population products at administrative levels 2 and 3.

### 1.2.3. Global Mortality Disaster Database

We explored several options for global disaster databases to acquire coastal flooding mortality data for our study, with detailed descriptions of these databases are provided in Table 1 below.

**Table 1| List of Global Disaster Database**

| Database      | Description   | Limitations  | Scope  | Availability  |
|---------------|---|--|--|---|
| NatCatSERVICE | NatCatSERVICE, a global commercial database of natural disaster data, was established in Munich in 1974 and offers comprehensive and reliable information on insured, economic, and human damages brought on by natural hazards.                                      | Although data is accessible to everyone online, it must be purchased via NatCatservice.  | Used in risk assessment, management, and available to the insurance, finance industries, and research enthusiasts. | <a href="https://www.munichre.com/en/solutions/for-industry-clients/natcatservice.html">https://www.munichre.com/en/solutions/for-industry-clients/natcatservice.html</a> |
| SIGMA         | Since 1970, Swiss Re has been compiling information on both natural and human-caused catastrophes across the world in its SIGMA database which provides metadata on each incident, including the date, location, damages, and victims' numbers (Mazhin et al., 2021). | SIGMA's database is not accessible to the general public outside of the annual journal, client programs, publications, and conferences, even though EM-DAT and NatCatSERVICE also offer comparable data. | Assist those making decisions in the re/insurance sector focus on risk and find strategic opportunities.           | SIGMA annual journal.   |
| GLIDE         | According to Mazhin and co-authors, Global unique disaster Identifier (GLIDE) is a coordinating platform between various disaster damage databases, facilitating communication between different databases (for eg:   | Serves as a forum for coordination and is not concerned with distributing factual data or disaster-related paperwork.  | Facilitates communication between different global disaster databases.   | Publicly accessible at <a href="https://glidenumber.net/glide/public/search/search.jsp">https://glidenumber.net/glide/public/search/search.jsp</a> .                      |

disasters recorded in EM-DAT and BD-Catnat database has same GLIDE number).

|              |  |  |  |  |
|--------------|--|--|--|--|
| BD<br>CATNAT | BD CATNAT is a database that records natural disaster events, providing accessible and reliable long-term information. CATNAT.net has been recording natural disaster events since 2001, and in 2007, Ubyrisk Consultants took over its management to create the BD Catnat database. | Since they have just been collecting data since 2001 and lack the past data needed for historical research analysis of certain events.<br><br>It is open to the public, but a subscription is required to access the data. | This database seeks to provide long-term, accessible, and trustworthy information to support decision-making for disaster preparedness, enhance awareness of environmental dangers, and help in identifying vulnerabilities and setting priorities.  | Publicly accessible at <a href="https://gdc.unicef.org/resource/bd-catnat-database">https://gdc.unicef.org/resource/bd-catnat-database</a> .   |
| DesInventar  | Desinventar-Sendai is a tool for recording disaster loss, created by the United Nations Office for Disaster Risk Reduction (UNDRR) and is used for monitoring Sustainable Development Goals (SDGs), under Goals 1, 11, and 18.   | This database does not have worldwide coverage; it only includes data from 82 developing nations.  | The main purpose of DesInventar is to gather comprehensive and reliable data about disasters, which can then be used to support efforts in reducing the impact of these events. It also provides a database where participating nations can enter and monitor important information about disasters. | Data can be downloaded from the tool “Desinventar Sendai 10.1.2”<br><br>Publicly accessible at the website ( <a href="https://www.desinventar.net/DesInventar/main.jsp?countrycode=gl">https://www.desinventar.net/DesInventar/main.jsp?countrycode=gl</a> ) |
| EM-DAT       | The World Health Organization (WHO), the Belgian government, and the Centre  | Although EM-DAT data is available back to 1900, the  | Its main goal is to offer accurate and thorough  | Publicly available at EM-DAT website.  |

for Research on the Epidemiology of Disasters (CRED) work together to manage EM-DAT. It gathers information from sources like non-governmental organizations, UN agencies, insurance firms, research institutes, and press agencies and provides core data of nearly 23,000 mega disasters that occurred globally from 1900 to the current day (EM-DAT, 2022).

reliability of historical data is less reliable than it is for more recent years (Barredo, 2007).

information about significant disasters that have happened all over the world.

(<https://public.EM-DAT.be>)

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## **1.2.4. Exposed population for coastal flooding**

### **1.2.4.1 DIVA model**

The DIVA model provides information on coastal vulnerabilities like coastal floodplain population, capital value at loss, land at loss, wetland at loss and potential adaptation costs (Hinkel & Klein, 2009). Previous studies have used the DIVA model estimated exposed population to coastal flooding (Fang et al., 2020; Lloyd et al., 2016; Nicholls et al., 2021; Wolff et al., 2016). DIVA is no longer publicly available.

### **1.2.4.2 EM-DAT**

EM-DAT defines its total exposed population as the sum of number of people injured, number of people who became homeless after the disaster and number of people requiring immediate assistance. Hu et al. (2018) performed global trend analysis of flooding exposed population using EM-DAT total exposed population. However this estimate of exposed population is not

complete, since many people may be exposed but are not injured or have home damages that require seeking assistance.

#### **1.2.4.3 The Global Flood Database**

In this database all major flood events (coastal, riverine, tropical cyclone, heavy rainfall) are taken from the Dartmouth Flood Observatory (DFO) starting from 2000 to 2018 with spatial resolution of 250m, and their exposed populations are estimated from Global Human Settlement Layer (GHSL) (Tellman et al., 2021). This database only has a record of 913 all cause flooding events and the majority of them are riverine flooding. Reimann et al., (2024) utilized total exposed population from the global flood database for flood risk assessment accounting for social vulnerability; however, since this database focuses primarily on riverine flooding, it has minimal coverage of coastal flooding events.

#### **1.2.4.4 DSCIM-Coastal**

Data-driven Spatial Climate Impact Model (DSCIM) is a modeling platform which provides a sea level rise impact module (Depsky et al., 2022). It contains two sections: Sea Level Impacts Input Dataset by Elevation, Region, and Scenario (SLIIDERS) and pyCIAM. The SLIIDERS dataset is similar to DIVA in terms of concept as it is divided into similar coastal segments, with yearly estimates of population within each segment by elevation, designed for coastal impact modeling.

### **1.3. Objectives**

The main goals of this research are to explore the relationship of coastal flooding mortality risk with socio-economic variables at global scale with the latest available data and to investigate the trend in coastal flooding mortality and exposed population by global region and country income

category specified by World Bank on the basis of Gross National Income (GNI). We carefully took the following steps to achieve our goal and have explained them in detail in Chapter 2:

- i. Gather coastal flooding related mortality data from EM-DAT by selecting coastal flooding related events only.
- ii. Estimate coastal population potentially exposed to flooding at segment level from SLIDERS
- iii. Investigate the trend of coastal flooding mortality
- iv. Gather socioeconomic data for mortality risk model
- v. Implement and interpret the negative binomial regression (mixed effect model) of mortality risk

## References

- Adnan, M. S. G., Haque, A., & Hall, J. W. (2019). Have coastal embankments reduced flooding in Bangladesh? *Science of The Total Environment*, 682, 405–416. <https://doi.org/10.1016/j.scitotenv.2019.05.048>
- Azevedo de Almeida, B., & Mostafavi, A. (2016). Resilience of Infrastructure Systems to Sea-Level Rise in Coastal Areas: Impacts, Adaptation Measures, and Implementation Challenges. *Sustainability*, 8(11), Article 11. <https://doi.org/10.3390/su8111115>
- Bakkensen, L. A., & Mendelsohn, R. O. (2016). Risk and Adaptation: Evidence from Global Hurricane Damages and Fatalities. *Journal of the Association of Environmental and Resource Economists*, 3(3), 555–587. <https://doi.org/10.1086/685908>

- Barredo, J. I. (2007). Major flood disasters in Europe: 1950–2005. *Natural Hazards*, 42(1), 125–148. <https://doi.org/10.1007/s11069-006-9065-2>
- Bevere, L., & Weigel, A. (2021). Natural catastrophes in 2020. *Swiss RE Sigma*.
- Bulleri, F., & Chapman, M. G. (2010). The introduction of coastal infrastructure as a driver of change in marine environments. *Journal of Applied Ecology*, 47(1), 26–35. <https://doi.org/10.1111/j.1365-2664.2009.01751.x>
- Camelo, J., Mayo, T. L., & Gutmann, E. D. (2020). Projected Climate Change Impacts on Hurricane Storm Surge Inundation in the Coastal United States. *Frontiers in Built Environment*, 6. <https://www.frontiersin.org/articles/10.3389/fbuil.2020.588049>
- CRED, U. (2015). The human cost of natural disasters: A global perspective. *Centre for Research on the Epidemiology of Disaster (CRED), Brussels*.
- Dasgupta, S., Laplante, B., Meisner, C., Wheeler, D., & Yan, J. (2009). The impact of sea level rise on developing countries: A comparative analysis. *Climatic Change*, 93(3), 379–388. <https://doi.org/10.1007/s10584-008-9499-5>
- Dasgupta, S., Laplante, B., Murray, S., & Wheeler, D. (2009). *Climate Change and the Future Impacts of Storm-Surge Disasters in Developing Countries* (SSRN Scholarly Paper 1479650). <https://doi.org/10.2139/ssrn.1479650>
- Dedekorkut-Howes, A., Torabi, E., & Howes, M. (2020). When the tide gets high: A review of adaptive responses to sea level rise and coastal flooding. *Journal of Environmental Planning and Management*, 63(12), 2102–2143. <https://doi.org/10.1080/09640568.2019.1708709>
- Delforge, D., Wathelet, V., Below, R., Sofia, C. L., Tonnelier, M., van Loenhout, J., & Speybroeck, N. (2023). *EM-DAT: the Emergency Events Database*.

- Depsky, N., Bolliger, I., Allen, D., Choi, J. H., Delgado, M., Greenstone, M., Hamidi, A., Houser, T., Kopp, R. E., & Hsiang, S. (2022). DSCIM-Coastal v1.0: An Open-Source Modeling Platform for Global Impacts of Sea Level Rise. *EGUsphere*, 1–47. <https://doi.org/10.5194/egusphere-2022-198>
- Diaz, D. B. (2016). Estimating global damages from sea level rise with the Coastal Impact and Adaptation Model (CIAM). *Climatic Change*, 137(1–2), 143–156. <https://doi.org/10.1007/s10584-016-1675-4>
- Em-DAT, C. / Ucl. (2024). *EM-DAT* [dataset]. [www.emdat.be](http://www.emdat.be)
- Ericson, J. P., Vörösmarty, C. J., Dingman, S. L., Ward, L. G., & Meybeck, M. (2006). Effective sea-level rise and deltas: Causes of change and human dimension implications. *Global and Planetary Change*, 50(1), 63–82. <https://doi.org/10.1016/j.gloplacha.2005.07.004>
- Fang, J., Lincke, D., Brown, S., Nicholls, R. J., Wolff, C., Merkens, J.-L., Hinkel, J., Vafeidis, A. T., Shi, P., & Liu, M. (2020). Coastal flood risks in China through the 21st century – An application of DIVA. *Science of The Total Environment*, 704, 135311. <https://doi.org/10.1016/j.scitotenv.2019.135311>
- Fauzi, D. (2021). Coastal Flood Responses in Manila Bay, the Philippines: Understanding Social Contract in the Policy-Making Processes. *Case Studies in the Environment*, 5(1), 1438458. <https://doi.org/10.1525/cse.2021.1438458>
- Franzke, C. L. E., & Torelló I Sentelles, H. (2020). Risk of extreme high fatalities due to weather and climate hazards and its connection to large-scale climate variability. *Climatic Change*, 162(2), 507–525. <https://doi.org/10.1007/s10584-020-02825-z>
- Hagen, I., Huggel, C., Ramajo, L., Chacón, N., Ometto, J. P., Postigo, J. C., & Castellanos, E. J. (2022). Climate change-related risks and adaptation potential in Central and South

- America during the 21st century. *Environmental Research Letters*, 17(3), 033002.  
<https://doi.org/10.1088/1748-9326/ac5271>
- Hallegatte, S., Green, C., Nicholls, R. J., & Corfee-Morlot, J. (2013). Future flood losses in major coastal cities. *Nature Climate Change*, 3(9), 802–806.  
<https://doi.org/10.1038/nclimate1979>
- Harman, B. P., Heyenga, S., Taylor, B. M., & Fletcher, C. S. (2015). Global Lessons for Adapting Coastal Communities to Protect against Storm Surge Inundation. *Journal of Coastal Research*, 31(4), 790–801. <https://doi.org/10.2112/JCOASTRES-D-13-00095.1>
- Hinkel, J., & Klein, R. J. T. (2009). Integrating knowledge to assess coastal vulnerability to sea-level rise: The development of the DIVA tool. *Global Environmental Change*, 19(3), 384–395. <https://doi.org/10.1016/j.gloenvcha.2009.03.002>
- Hinkel, J., Lincke, D., Vafeidis, A. T., Perrette, M., Nicholls, R. J., Tol, R. S. J., Marzeion, B., Fettweis, X., Ionescu, C., & Levermann, A. (2014). Coastal flood damage and adaptation costs under 21st century sea-level rise. *Proceedings of the National Academy of Sciences*, 111(9), 3292–3297. <https://doi.org/10.1073/pnas.1222469111>
- Hsiang, S. M., & Narita, D. (2012). Adaptation to cyclone risk: Evidence from the global cross-section. *Climate Change Economics*, 03(02), 1250011.  
<https://doi.org/10.1142/S201000781250011X>
- Hu, P., Zhang, Q., Shi, P., Chen, B., & Fang, J. (2018). Flood-induced mortality across the globe: Spatiotemporal pattern and influencing factors. *Science of The Total Environment*, 643, 171–182. <https://doi.org/10.1016/j.scitotenv.2018.06.197>

- Jones, R. L., Guha-Sapir, D., & Tubeuf, S. (2022). Human and economic impacts of natural disasters: Can we trust the global data? *Scientific Data*, 9(1), 572.  
<https://doi.org/10.1038/s41597-022-01667-x>
- Jonkman, S. N. (2005). Global Perspectives on Loss of Human Life Caused by Floods. *Natural Hazards*, 34(2), 151–175. <https://doi.org/10.1007/s11069-004-8891-3>
- Jonkman, S. N., Curran, A., & Bouwer, L. M. (2024). Floods have become less deadly: An analysis of global flood fatalities 1975–2022. *Natural Hazards*.  
<https://doi.org/10.1007/s11069-024-06444-0>
- Kirezci, E., Young, I. R., Ranasinghe, R., Lincke, D., & Hinkel, J. (2023). Global-scale analysis of socioeconomic impacts of coastal flooding over the 21st century. *Frontiers in Marine Science*, 9. <https://doi.org/10.3389/fmars.2022.1024111>
- Kron, W. (2013). Coasts: The high-risk areas of the world. *Natural Hazards*, 66(3), 1363–1382.  
<https://doi.org/10.1007/s11069-012-0215-4>
- Le, T. D. N. (2020). Climate change adaptation in coastal cities of developing countries: Characterizing types of vulnerability and adaptation options. *Mitigation and Adaptation Strategies for Global Change*, 25(5), 739–761. <https://doi.org/10.1007/s11027-019-09888-z>
- Le, T. D. N., & Awal, R. (2021). Chapter 9—Adaptation to climate extremes and sea level rise in coastal cities of developing countries. In A. Fares (Ed.), *Climate Change and Extreme Events* (pp. 145–170). Elsevier. <https://doi.org/10.1016/B978-0-12-822700-8.00003-2>
- Lindersson, S., Raffetti, E., Rusca, M., Brandimarte, L., Mård, J., & Di Baldassarre, G. (2023). The wider the gap between rich and poor the higher the flood mortality. *Nature Sustainability*, 6(8), 995–1005. <https://doi.org/10.1038/s41893-023-01107-7>

- Linham, M. M., & Nicholls, R. J. (2015). Adaptation technologies for coastal erosion and flooding: A review. *Proceedings of the Institution of Civil Engineers - Maritime Engineering*. <https://doi.org/10.1680/maen.2011.29>
- Lloyd, S. J., Kovats, R. S., Chalabi, Z., Brown, S., & Nicholls, R. J. (2016). Modelling the influences of climate change-associated sea-level rise and socioeconomic development on future storm surge mortality. *Climatic Change*, *134*(3), 441–455. <https://doi.org/10.1007/s10584-015-1376-4>
- Marcos, M., Rohmer, J., Vousdoukas, M. I., Mentaschi, L., Le Cozannet, G., & Amores, A. (2019). Increased Extreme Coastal Water Levels Due to the Combined Action of Storm Surges and Wind Waves. *Geophysical Research Letters*, *46*(8), 4356–4364. <https://doi.org/10.1029/2019GL082599>
- Margulis, S., Hughes, G., Schneider, R., Pandey, K., Narain, U., & Kemeny, T. (2010). *Economics of adaptation to climate change: Synthesis report*.
- Mayo, T. L., & Lin, N. (2022). Climate change impacts to the coastal flood hazard in the northeastern United States. *Weather and Climate Extremes*, *36*, 100453. <https://doi.org/10.1016/j.wace.2022.100453>
- Mazhin, S. A., Farrokhi, M., Noroozi, M., Roudini, J., Hosseini, S. A., Motlagh, M. E., Kolivand, P., & Khankeh, H. (2021). Worldwide disaster loss and damage databases: A systematic review. *Journal of Education and Health Promotion*, *10*, 329. [https://doi.org/10.4103/jehp.jehp\\_1525\\_20](https://doi.org/10.4103/jehp.jehp_1525_20)
- McGranahan, G., Balk, D., & Anderson, B. (2007). The rising tide: Assessing the risks of climate change and human settlements in low elevation coastal zones.

*Environment and Urbanization*, 19(1), 17–37.

<https://doi.org/10.1177/0956247807076960>

McMichael, C., Dasgupta, S., Ayeb-Karlsson, S., & Kelman, I. (2020). A review of estimating population exposure to sea-level rise and the relevance for migration. *Environmental Research Letters*, 15(12), 123005. <https://doi.org/10.1088/1748-9326/abb398>

Milly, P. C. D., Wetherald, R. T., Dunne, K. A., & Delworth, T. L. (2002). Increasing risk of great floods in a changing climate. *Nature*, 415(6871), Article 6871.

<https://doi.org/10.1038/415514a>

Milne, G. A., Gehrels, W. R., Hughes, C. W., & Tamisiea, M. E. (2009). Identifying the causes of sea-level change. *Nature Geoscience*, 2(7), 471–478. <https://doi.org/10.1038/ngeo544>

Munich, R. (2011). *NatCatSERVICE: Natural catastrophe know-how for risk management and research*. Munich Re.

Neumann, B., Vafeidis, A. T., Zimmermann, J., & Nicholls, R. J. (2015). Future Coastal Population Growth and Exposure to Sea-Level Rise and Coastal Flooding—A Global Assessment. *PLOS ONE*, 10(3), e0118571. <https://doi.org/10.1371/journal.pone.0118571>

Nicholls, R. J. (2003). An expert assessment of storm surge “hotspots.” *Interim Re.*

Nicholls, R. J., & Cazenave, A. (2010). Sea-Level Rise and Its Impact on Coastal Zones.

*Science*, 328(5985), 1517–1520. <https://doi.org/10.1126/science.1185782>

Nicholls, R. J., Lincke, D., Hinkel, J., Brown, S., Vafeidis, A. T., Meysignac, B., Hanson, S. E., Merkens, J.-L., & Fang, J. (2021). A global analysis of subsidence, relative sea-level change and coastal flood exposure. *Nature Climate Change*, 11(4), 338–342.

<https://doi.org/10.1038/s41558-021-00993-z>

- Nishikawa, M. S. (2003). Global Unique Disaster IDentifier Number (GLIDE): For effective disaster information sharing and management. *Proceedings of the International Conference on Total Disaster Risk Management*.
- Patt, A. G., Tadross, M., Nussbaumer, P., Asante, K., Metzger, M., Rafael, J., Goujon, A., & Brundrit, G. (2010). Estimating least-developed countries' vulnerability to climate-related extreme events over the next 50 years. *Proceedings of the National Academy of Sciences*, *107*(4), 1333–1337. <https://doi.org/10.1073/pnas.0910253107>
- Peduzzi, P., & Herold, H. D. C. (2005). Mapping Disastrous Natural Hazards Using Global Datasets. *Natural Hazards*, *35*(2), 265–289. <https://doi.org/10.1007/s11069-004-5703-8>
- Pörtner, H.-O., Roberts, D. C., Masson-Delmotte, V., Zhai, P., Tignor, M., Poloczanska, E., Mintenbeck, K., Alegría, A., Nicolai, M., Okem, A., & others. (2019). IPCC special report on the ocean and cryosphere in a changing climate. *IPCC Intergovernmental Panel on Climate Change: Geneva, Switzerland*, *1*(3), 1–755.
- Reguero, B. G., Losada, I. J., Díaz-Simal, P., Méndez, F. J., & Beck, M. W. (2015). Effects of Climate Change on Exposure to Coastal Flooding in Latin America and the Caribbean. *PLOS ONE*, *10*(7), e0133409. <https://doi.org/10.1371/journal.pone.0133409>
- Reimann, L., Koks, E., de Moel, H., Ton, M. J., & Aerts, J. C. J. H. (2024). An Empirical Social Vulnerability Map for Flood Risk Assessment at Global Scale (“Globe-SoVI”). *Earth's Future*, *12*(3), e2023EF003895. <https://doi.org/10.1029/2023EF003895>
- Romanello, M., Napoli, C. D., Green, C., Kennard, H., Lampard, P., Scamman, D., Walawender, M., Ali, Z., Ameli, N., Ayeb-Karlsson, S., Beggs, P. J., Belesova, K., Berrang Ford, L., Bowen, K., Cai, W., Callaghan, M., Campbell-Lendrum, D., Chambers, J., Cross, T. J., ... Costello, A. (2023). The 2023 report of the Lancet Countdown on health and climate

- change: The imperative for a health-centred response in a world facing irreversible harms. *The Lancet*, 402(10419), 2346–2394. [https://doi.org/10.1016/S0140-6736\(23\)01859-7](https://doi.org/10.1016/S0140-6736(23)01859-7)
- Rosvold, E. L., & Buhaug, H. (2021). GDIS, a global dataset of geocoded disaster locations. *Scientific Data*, 8(1), 61. <https://doi.org/10.1038/s41597-021-00846-6>
- Shen, G., & Hwang, S. N. (2019). Spatial–Temporal snapshots of global natural disaster impacts Revealed from EM-DAT for 1900–2015. *Geomatics, Natural Hazards and Risk*, 10(1), 912–934. <https://doi.org/10.1080/19475705.2018.1552630>
- Taherkhani, M., Vitousek, S., Barnard, P. L., Frazer, N., Anderson, T. R., & Fletcher, C. H. (2020). Sea-level rise exponentially increases coastal flood frequency. *Scientific Reports*, 10(1), 6466. <https://doi.org/10.1038/s41598-020-62188-4>
- Tellman, B., Sullivan, J. A., Kuhn, C., Kettner, A. J., Doyle, C. S., Brakenridge, G. R., Erickson, T. A., & Slayback, D. A. (2021). Satellite imaging reveals increased proportion of population exposed to floods. *Nature*, 596(7870), 80–86. <https://doi.org/10.1038/s41586-021-03695-w>
- Tennant, E., & Gilmore, E. A. (2020). Government effectiveness and institutions as determinants of tropical cyclone mortality. *Proceedings of the National Academy of Sciences*, 117(46), 28692–28699. <https://doi.org/10.1073/pnas.2006213117>
- Vafeidis, A. T., Schuerch, M., Wolff, C., Spencer, T., Merkens, J. L., Hinkel, J., Lincke, D., Brown, S., & Nicholls, R. J. (2019). Water-level attenuation in global-scale assessments of exposure to coastal flooding: A sensitivity analysis. *Natural Hazards and Earth System Sciences*, 19(5), 973–984. <https://doi.org/10.5194/nhess-19-973-2019>

- Vitousek, S., Barnard, P. L., Fletcher, C. H., Frazer, N., Erikson, L., & Storlazzi, C. D. (2017). Doubling of coastal flooding frequency within decades due to sea-level rise. *Scientific Reports*, 7(1), 1399. <https://doi.org/10.1038/s41598-017-01362-7>
- Wahl, T., Haigh, I. D., Nicholls, R. J., Arns, A., Dangendorf, S., Hinkel, J., & Slangen, A. B. A. (2017). Understanding extreme sea levels for broad-scale coastal impact and adaptation analysis. *Nature Communications*, 8(1), Article 1. <https://doi.org/10.1038/ncomms16075>
- Wolff, C., Vafeidis, A. T., Lincke, D., Marasmi, C., & Hinkel, J. (2016). Effects of Scale and Input Data on Assessing the Future Impacts of Coastal Flooding: An Application of DIVA for the Emilia-Romagna Coast. *Frontiers in Marine Science*, 3. <https://doi.org/10.3389/fmars.2016.00041>
- Wong, P. P., Losada, I. J., Gattuso, J.-P., Hinkel, J., Khattabi, A., McInnes, K. L., Saito, Y., Sallenger, A., & others. (2014). Coastal systems and low-lying areas. *Climate Change*, 2104, 361–409.
- Woodruff, J. D., Irish, J. L., & Camargo, S. J. (2013). Coastal flooding by tropical cyclones and sea-level rise. *Nature*, 504(7478), Article 7478. <https://doi.org/10.1038/nature12855>
- Xu, H., Xu, K., Lian, J., & Ma, C. (2019). Compound effects of rainfall and storm tides on coastal flooding risk. *Stochastic Environmental Research and Risk Assessment*, 33(7), 1249–1261. <https://doi.org/10.1007/s00477-019-01695-x>

## **2. Chapter 2. Assessing the Global Threat of Coastal Flooding: A Mortality Risk Model**

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### **2.1. Abstract**

Coastal flooding, caused by sea level rise (SLR), storm surge, and tropical cyclones, is a growing threat. Previous studies have documented mortality associated with historical coastal flooding and developed predictions of mortality risk based on SLR and human development. This study updates those estimates and provides new forecasts by including new mortality data from events between 2010 and 2020. Primary data sources include the Emergency Events Database (EM-DAT) and the Sea Level Impacts Input Dataset by Elevation, Region, and Scenario (SLIIDERS) model. We first characterize trends in exposed populations and mortality associated with coastal flooding between 1990 and 2020. A mixed effect regression model estimates mortality associated with each coastal flooding event and investigates the influence of variables including Human Development Index (HDI), population, and event frequency. The frequency of recorded coastal flooding events between 1990 and 2020 has increased, while there was an overall decrease in recorded deaths associated with coastal flooding events. The association between mortality and coastal flood exposure is reduced in countries with higher populations. This result suggests countries with larger populations may buffer risks in exposed regions. Results showed

significant reduction in mortality risk, by approximately 34% (95% CI, 17-47%), associated with an increase of approximately 10 million in country-level population. Additionally, a 7% increase (95% CI, 3-11%) in mortality risk with each additional occurrence of a coastal flooding event was observed.

## **2.2. Introduction**

Sea level rise (SLR), subsidence, storm surges, and climatic cycles (e.g., El Niño Southern Oscillation (ENSO) events) all have a significant impact on coastal flooding (Hagen et al., 2022; Reguero et al., 2015; Wahl et al., 2017). Compiling estimates of deaths from several sources, Nicholls (2003) estimates approximately 2.9 million lives have been lost globally due to major hurricanes, cyclones, typhoons, and extra-tropical storms since 1700 (Nicholls, 2003). Climate change is causing more intense hurricanes with higher translational speed, which has a considerable impact on coastal flood risk (Camelo et al., 2020; Mayo & Lin, 2022). Flood risk is expected to further increase in many coastal locations due to SLR and intensified heavy rains (Milly et al., 2002; Woodruff et al., 2013; Xu et al., 2019). Meanwhile, the highest-risk areas are also seeing the most rapid population growth and inadequate preparation or adaptation (CRED 2015). With the escalation of climate driven SLR, the effects will become more evident, particularly in specific low-lying coastal areas, revealing heightened vulnerability in numerous nations across South, Southeast, and East Asia due to the prevalence of densely populated deltas linked to rapidly expanding urban centers (Ericson et al., 2006; Nicholls & Cazenave, 2010). SLR alone is expected to displace 1.16–2.25% of the global population by 2200, leading to substantial economic disruptions (Desmet et al. 2018) and outright annual losses of 0.3–9.3% of global gross domestic product (Hinkel et al. 2014).

Coastal flood damage and required adaptations deriving from a changing climate are likely to create significant costs, yet there is a paucity of comprehensive global studies evaluating the extent of this impact (Hinkel et al., 2014; Margulis et al., 2010). The Coastal Impact Assessment Model (CIAM) highlights the potential for coastal adaptation to significantly reduce the most severe projected effects of SLR on coastal resources, resulting in a reduction in global net present costs by a factor of 7 to below \$1.7 trillion until 2100 (Diaz, 2016). An updated version of CIAM (Depsky et al. 2023) estimates global SLR damages in 9,000 coastal segments accounting for local physical and socioeconomic characteristics, which is used in the U.S.EPA updated Social Cost of Carbon estimates (contributing \$2-3 of the \$190 per-tonne CO<sub>2</sub> estimate) (EPA 2023). The Framework for Evaluating Damages and Impacts (FrEDI) model projects the estimation of the total damage from high-tide flooding for the United States ranges from \$1.2 billion to \$1.134 trillion depending upon the adaptation scenario and Global Mean Sea Level (GMSL) conditions (EPA 2021).

Mortality risks from coastal flooding events are the product of competing trends in population growth, population displacement, adaptation, event frequency, and event severity, complicating forecasts. The existing global population inhabiting low-elevation coastal zones is roughly 680 million, and this is expected to exceed one billion by 2050 (McMichael et al., 2020; Pörtner et al., 2019). Yet, more than 50 million people inhabiting the highest risk areas are estimated to be displaced by the end of this century in 84 developing countries under the scenario of 1-m sea level rise (Dasgupta, Laplante, Meisner, et al., 2009; Le & Awal, 2021). Meanwhile, even gradual SLR leads to significant increases in the magnitude and frequency of coastal flood events (Vitousek et al., 2017). Globally, population growth may be outpacing adaptation, with total flood fatalities rising even as risk of death among the exposed population falls (Hu et al., 2018;

Jonkman et al., 2024). Overall, mortality risks from coastal floods are concentrated in the most physically vulnerable (e.g., lowest lying) areas with highest population growth and comparatively low levels of economic development (Wong et al., 2014). Another evaluation of past events suggests mortality from storm surges is decreasing everywhere except Southeast Asia (Bouwer and Jonkman 2018).

Decreased risks observed in some regions may be attributable to adaptation. For example, a large literature suggests that countries with higher GDP per capita have lower climate-related mortality risk, possibly due to higher investment in activities and assets that mitigate risk both at an individual and collective level (Bakkensen & Mendelsohn, 2016; Hsiang & Narita, 2012; Neumann et al., 2015; Peduzzi & Herold, 2005; Tennant & Gilmore, 2020) . Patt et al. (2010) and Lloyd et al. (2016) express mortality risk as statistical functions of socio-economic variables like HDI, and characterize how mortality risk may evolve with changing socioeconomic conditions globally. Other studies have linked reductions in risk to improved storm and typhoon predictions and more successful warning and evacuation tactics. Hard coastal defense structures and beach nourishment techniques to control inundation risk due to storm surge might also be a reason for the decreasing trend in mortality risk, as these approaches continue to dominate coastal planning and management efforts globally (Harman et al., 2015). Planning for coastal risk adaptation is still in its early stages in many countries, with 48% of suggested initiatives predominantly existing as theoretical recommendations rather than implemented strategies (Le, 2020).

In the present work, we have created a model to assess the relationship between coastal flood events and mortality globally, and to identify trends in the relationship over the last 30 years and potential county-level sociodemographic modifiers of this relationship. We have updated

previous estimates of exposed populations used by Lloyd et al. (2016), through use of the DSCIM-SLIIDERS dataset calculating the populations at risk of coastal flooding. The study aims to fill the gap in research on storm surges by utilizing the latest EM-DAT dataset (EM-DAT, 2024) and estimated flood-exposed population to investigate the impact of a range of sociodemographic and exposure factors on storm surge-induced coastal flooding mortality risk.

## **2.3. Materials and Methods**

### **2.3.1. Global coastal flooding mortality data**

Currently, there are five databases that provide information on coastal flooding events at a global scale: the EM-DAT, NatCatSERVICE, Sigma, GLIDE, and BD CATNAT Global (Bevere & Weigel, 2021; Delforge et al., 2023; Jones et al., 2022; Mazhin et al., 2021; Munich, 2011; Nishikawa, 2003). In this study, we utilize the EM-DAT database as it is the most comprehensive publicly available database. EM-DAT records a natural disaster when at least one of the following conditions is met: A state of emergency is declared, at least 100 people are impacted, at least 10 people are killed, and a request for aid from abroad is made (CRED, 2015; Shen & Hwang, 2019). For our analysis, we filtered the EM-DAT dataset to include coastal flooding events categorized under three disaster subtypes: cyclones, tropical cyclones, and coastal flooding. Initially, there were 1736 EM-DAT coastal flooding events, from which events without recorded death counts (N=430) were excluded. We removed events in which there was no data on mortality available and have only included the events with death counts. After this filtering, a total of 1306 events with available death counts were used for further analysis.

Certain landlocked nations such as Laos, Zimbabwe, Bhutan, Switzerland, and Austria were listed in EM-DAT for events related to 20 coastal flooding events. The database we retained to calculate coastal populations (SLIIDERS, Section 2.3.2) lacked data on affected populations for

these countries, as it solely covers coastal areas. Consequently, events affecting these countries (N=20) were excluded from our analysis, resulting in a final dataset of 1286 events.

### **2.3.2. Estimation of coastal flood exposed population**

We derived the annual estimated exposed population at risk for coastal flooding from the DSCIM-SLIIDERS model (Depsky et al. 2022). Conceptually similar to the DIVA model, which includes 18 variables across 11980 coastal segments to estimate potentially exposed coastal populations, the SLIIDERS dataset builds from this previous work (Depsky et al., 2022). Details on data acquisition procedures from SLIIDERS are described in Supplementary File 1.

We use three variables from the SLIIDERS dataset: 1) population scale for each country  $i$ , a scaling factor used to calculate population changes relative to the year 2019 ( $K_i$ ); 2) the baseline population for 2019 for every segment  $j$  in a country  $i$ , decomposed by elevation  $l$  at 0.1-m intervals over the range 0–20m above sea level ( $P_{i,j,l,2019}$ ) and 3) 100-year surge height for every segment  $j$  in a country ( $M_j$ ). We calculate exposed population based on the number of people living within a 1-in-100-year surge height for consistency with other investigations (Hanson et al., 2011; Neumann et al., 2015, Depsky et al. 2022).

SLIIDERS calculates elevation-specific population data ( $P_{i,j,l,2019}$ ) by cross-referencing elevation data from CoastalDEM (1-arc-second resolution) with population distribution data from Land Scan 2019. Similarly, surge height ( $R_j$ ) is acquired from CoDec v1 which uses Global Tide and Surge Model (GTSM) and ERA5 reanalysis product using present climate change scenarios. We calculate exposed population for every segment ( $j$ ) for 2019 ( $P_{i,j,2019}$ ) by summing the populations in every elevation level  $l$  up to the elevation level that corresponds to the 100-year surge height relevant to that segment ( $R_j$ ), according to Equation 1 below. Because 100-year

surge heights ( $R_j$ ) do not correspond precisely to the 0.1-m resolution of population levels  $l$ , linear interpolation is used to calculate  $P_{i,j,l,2019}$  at  $l = R_j$ .

$$P_{i,j,2019} = \sum_{l=0}^{l=R_j} P_{i,j,l,2019} \quad \text{Eq. 1}$$

SLIDERS reports a scaling factor ( $K_{i,t}$ ) for each country  $i$  for years  $t \in [2000,2100] \wedge t \neq 2019$  (i.e., for all years between 2000 and 2100 excluding 2019) to calculate population change over time relative to the 2019 baseline. For years 1990 to 1999, we calculate scaling factor ( $K_{i,t}$ ) using data from the World Bank (World Bank, 2024) . For the period of 2000–2020, all segments in a country  $i$  are assigned the population scaling factor reported by SLIDERS for a given year. This is expressed formally in Equation 2. SLIDERS bases scaling factors for future years (relative to 2019) on two GDP projections (International Institute for Applied Systems Analysis (IIASA) and Organization for Economic Co-operation and Development (OECD)) and five SSP projections (SSP1- SSP5). For the present analysis, we applied SSP2 and IIASA GDP projections as followed by Depsky et al. (2022).

$$K_{i,t} = \frac{P_{i,t}}{P_{i,2019}} \quad \text{Eq. 2}$$

Where,  $P_{i,t}$  is the population of the country  $i$  from 1990-1999 from World Bank and  $P_{i,2019}$  is the population of country  $i$  at baseline year 2019.

As described above, a major source of uncertainty in previous analyses of trends in mortality risk from coastal hazards has been identification of a relevant “exposed” population. In general, more expansive definitions of “exposed” populations (e.g., total coastal population of an affected country) are associated with higher certainty that events are correctly matched to populations but may underestimate risk estimates for countries with large coastal populations far from the

location of the hazard. Conversely, restrictive definitions of exposed populations may not be possible to apply uniformly to historical events where spatial data for populations and event occurrence is incomplete; these definitions may require events to be discarded from the analysis or may require excessive modeler judgment.

Here, we consider two alternative definitions of exposed population: the total coastal population of the country where an event occurs (Section 2.3.2.1) and the population in the most relevant Administration Level 1 region (e.g., state or province) (Section 2.3.2.2). We evaluate the influence that alternative definitions have on findings for trends and projections in mortality risk.

### **2.3.2.1 Country level coastal population**

Equation 3 describes how the coastal population was calculated for all countries  $i$  for all years  $t \in [1990, 2100] \wedge t \neq 2019$  (i.e., for all years between 1990 and 2100 excluding 2019) ( $P_{i,t}$ ): yearly populations were calculated for each segment by applying the scaling factor the coastal segment population described in Equation 1 ( $P_{i,j,2019}$ ).  $P_{i,t}$  was calculated for all countries  $i$  and all years  $t$ : the 2019 populations of coastal segments  $j$  (up to the elevation corresponding to the 100-year surge height, as described above) were multiplied by the country- and year-specific scaling factor ( $K_{i,t}$ ) and then summed over all segments  $j$  in a country  $i$ .

$$P_{i,t} = \sum_j P_{i,j,2019} \times K_{i,t} \quad \text{Eq. 3}$$

### **2.3.2.2 Administrative level 1 population**

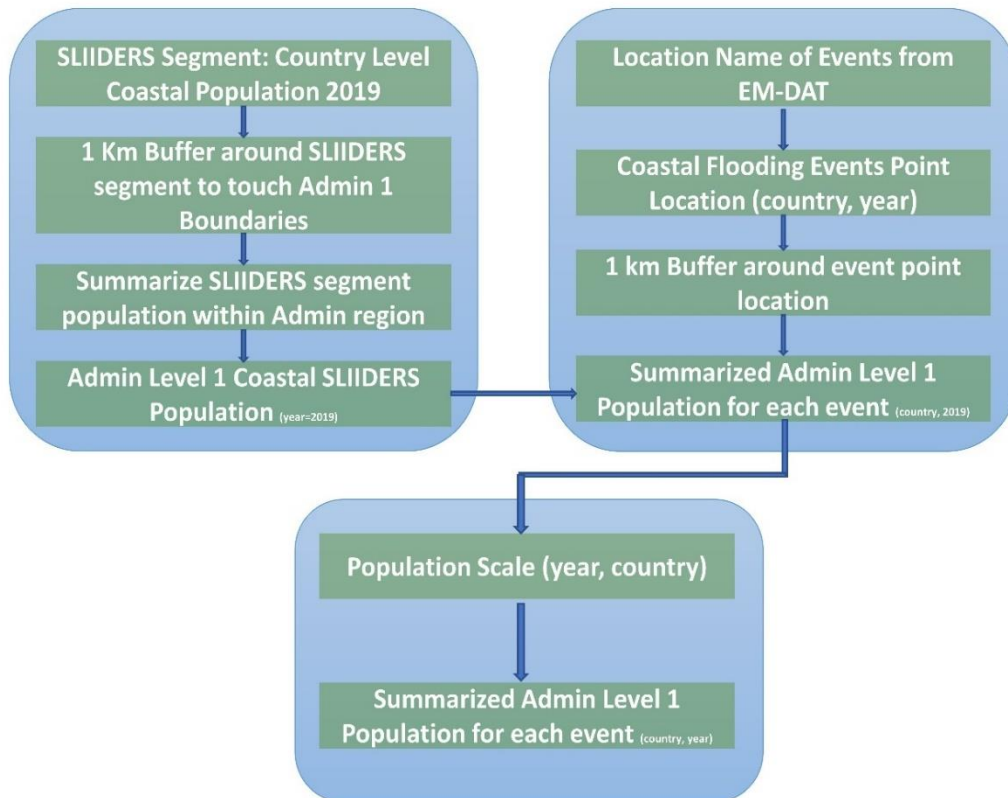
Equation 4 describes an alternative measure for exposed population, which captures the coastal population within the administrative level 1 region (e.g., state or province) affected by an event.

This population is specific to year ( $t$ ) and event ( $q$ ) rather than to year and country ( $i$ ) as in Section 2.2.1. In Equation 4,  $P_{q,j,2019}$  is the coastal population from SLIIDERS in the administrative level 1 region affected by an event  $q$ .

$$P_{q,t} = \sum_J P_{q,j,2019} \times K_{i,t} \quad \text{Eq. 4}$$

The location data for coastal flooding events was derived from EM-DAT using the event names as identifiers. Utilizing GeoAPI in Python, precise point locations for each coastal flooding event were obtained. Each recorded disaster in EM-DAT is uniquely identified by a disaster number, formulated from the country, year, and four distinct digits. The SLIIDERS geodatabase, as described by Depsky et al. (2023), was acquired, containing point locations for individual SLIIDERS segments along with their respective baseline populations for 2019. These datasets were combined by joining the SLIIDERS point location shapefile with the SLIIDERS segment population. To estimate the population at administrative level 1, shapefiles delineating Admin Level 1 boundaries were sourced from Database of Global Administrative Areas (GADM, 2024). Given that several SLIIDERS segment centroids were not directly adjacent to coastal areas, a 2-km buffer radius was applied around each segment to ensure the inclusion of the coastal population. The geoprocessing tool "Summarize Within" in ArcGIS Pro was employed to aggregate population data from SLIIDERS segments to the administrative level 1 polygons. This involved summing the populations of all SLIIDERS segments lying within each respective administrative boundary, thereby obtaining the population estimate for the corresponding administrative region. All of these estimated coastal admin level 1 populations is for baseline year 2019. These population estimates were then adjusted to reflect the original year of the events, accounting for temporal changes in population distribution. Population estimates for coastal flooding events were scaled back to their original year to ensure temporal accuracy. This

adjustment accounted for population dynamics in coastal regions over time, providing a more accurate representation of the population affected in admin level 1 by each coastal event. The general flow chart of obtaining the admin level affected population for each coastal flooding event is shown in Fig.1.



**Fig. 1.** Methodology of estimating Admin Level 1 exposed population from SLIIDERS for coastal flooding events.

In our efforts to estimate the exposed population at risk of coastal flooding at administrative level 1, we faced a significant challenge. For 438 events, we were unable to access the necessary administrative level 1 coastal population data. This was primarily due to inconsistent recording practices regarding event locations in the EM-DAT database. Despite the provision of separate

columns for administrative levels, these locations were not consistently documented. Moreover, 91 out of 1306 coastal flooding events in the EM-DAT database lacked any location data whatsoever.

### **2.3.3. Comparison of EM-DAT and National Oceanic and Atmospheric Administration (NOAA) billion-dollar disaster database**

To investigate coastal flooding events at the national level, particularly concerning the coverage and concurrence of such events in national disaster databases, we conducted a comparative analysis between EM-DAT and the National Oceanic and Atmospheric Administration (NOAA) Billion-Dollar Disaster database. The NOAA database is recognized as a prominent repository for disaster data within the United States (NOAA, 2024). Focusing on events with damages exceeding one billion dollars, in this study we specifically targeted coastal flooding incidents, including tropical cyclones and coastal floods, within the United States in both databases from 1990 to 2020. We only selected coastal flood related events in the USA causing at least of one billion dollars of damage from EM-DAT database in this comparison analysis.

### **2.3.4. Trend analysis**

EM-DAT trends in coastal flood induced mortality, coastal-flooding exposed population and coastal flooding frequency were evaluated using Modified Mann Kendall (MMK) trend test method. The MMK approach is a non-parametric test utilized to identify monotonic trends, operating independently of the need for normal distribution assumptions (Hu et al., 2018). We used ggplot2 library to create a time series plot for flooding deaths and coastal flooding frequency, including a natural spline fit to illustrate temporal trends. Similarly, for trend analysis of exposed population, we merged EM-DAT event date with estimated yearly admin 1 exposed population data from SLIDERS.

### **2.3.5. Data processing of socioeconomic variables**

During the data processing phase for our model, we encountered 96 events lacking Human Development Index (HDI) values. EM-DAT provided separate country codes for territories, which were then converted to the corresponding governing country codes to enhance event count accuracy. For South Korea and Somalia, HDI data was absent from the UNDP csv dataset and was manually inputted. Similarly, for countries such as Madagascar, Solomon Islands, Dominica, Bahamas, Antigua and Barbuda, Vanuatu, Saint Kitts and Nevis, and Saint Vincent and the Grenadines, certain historical HDI values were unavailable. In these instances, we opted to utilize the latest available HDI data from the UNDP dataset for historical events occurring in these nations.

### 2.3.6. Mortality risk model

We employed a negative binomial regression model as shown in Equation 5 to assess how economic and social variables affect the association between coastal flooding events and mortality. Equation 5a represents the version of the model where exposed population is the total coastal population of a country affected by a coastal event (described in Section 2.3.2.1), and Equation 5b represents the version where exposed population is only the population in the administrative level 1 region (described in Section 2.3.2.2).

$$\widehat{M}_a = (\beta_1 + b_i) + \beta_2 \times E_i + \beta_3 \times \ln(N_{i,t}) + \beta_4 \times H_{i,t} + \beta_5 \times T + \beta_6 \times \log(P_{i,t}) \quad \text{Eq. 5a}$$

$$\widehat{M}_b = (\beta_1 + b_i) + \beta_2 \times E_i + \beta_3 \times \ln(N_{i,t}) + \beta_4 \times H_{i,t} + \beta_5 \times T + \beta_6 \times \log(P_{q,t}) \quad \text{Eq. 5b}$$

$\widehat{M}$  is estimated mortality for an event (number of fatalities);  $E_i$  is the count of coastal flooding events in the five previous years from EM-DAT,  $N_{i,t}$  is the yearly country population estimate for the country in which the event occurs from the World Bank (World Bank, 2024);  $H_{i,t}$  is the human development index (HDI) for the country and year of the event (UNDP, 2024);  $T$  is the year of the event;  $P_{i,t}$  (Eq. 5a) is the coastal population in the country affected and  $P_{q,t}$  (Eq. 5b)

is the coastal population in the administrative level 1 region affected.  $\beta_1$  is the global fitted intercept;  $b_i$  is a country-specific fitted intercept; and  $\beta_2, \beta_3, \beta_4, \beta_5$ , and  $\beta_6$  are fitted intercepts for the respective variables described above.

In this analysis, the UNDP HDI classification was adapted by combining the "Very High" and "High" categories into a single "High" category, while retaining the "Medium" and "Low" categories as defined in UNDP classification. In stratified analyses, we subset the dataset based on World Bank country income groups: low, lower-middle, upper-middle, and high, determined by Gross National Income (GNI) expressed in US dollars, derived using the Atlas Method (World Bank, 2024).

### **2.3.7. Comparison with the latest model**

Lindersson et al. (2023) developed a model to estimate death counts, incorporating a more finely resolved dataset of exposed populations compared to SLIDERS. They focused on flooding events recorded in EM-DAT from 1990 to 2018, specifically including Geocoded Disasters (GDIS) events (Rosvold & Buhaug, 2021). In our study, we adopted their analytical framework, modifying the flooding criteria to encompass tropical cyclones, coastal flooding, and extratropical storms while excluding riverine and flash flooding, since we are interested in developing a model to estimate mortality from SLR due to climate change. To compare our analysis, we used a subset of their data, focusing on coastal flood-related events matching GDIS IDs. We conducted two generalized mixed-effect models using different exposed population data as offset variables while maintaining consistency in other predictor variables. Our primary hypothesis posits that the model incorporating the finer-resolution exposed population data from Lindersson et al. (2023) at admin level 2 and 3, will yield more accurate predictions compared to the model utilizing SLIDERS exposed population data with coarser resolution, thus this

comparison will allow us to assess consistency with our main model, which includes more events, yet at reduced spatial resolution. The HDI classification was simplified to high and low due to a limited sample size. In this context, the medium and low categories specified by UNDP were consolidated into the low category, while the high and very high categories outlined by UNDP were merged into the high category. For the purpose of this specific analysis, the high category serves as the reference HDI.

## 2.4. Results

### 2.4.1. Coastal flooding trend

Table 2 illustrates a decreasing trend in deaths per event attributable to coastal flooding over time, contrasted with an increasing trend in annual flooding frequency and annual exposed population, although the trend in exposed population was not significant. Fig. S2 presents a scatter plot illustrating coastal flooding related deaths reported in EM-DAT between 1990 to 2020. A decreasing trend over time is estimated, along with two notable outliers occurring in the years 1991 and 2008. In 1991, Tropical Cyclone "Gorky" caused 138,388 deaths. In 2008, Cyclone "Nargis" resulted in 138,366 deaths.

**Table 2 |Regional annual trends of coastal flooding deaths, coastal flood-affected population and coastal flooding frequency**

| Region            | Variables                  | Tau value | p-Value        | Sen's Slope |
|-------------------|----------------------------|-----------|----------------|-------------|
| <b>Global</b>     | Deaths                     | -0.117    | < <b>0.001</b> | -0.005      |
|                   | Affected Population        | -0.067    | 0.928          | -662630.221 |
|                   | Annual Affected Population | 0.415     | < <b>0.001</b> | 152379.200  |
|                   | Annual Flooding Frequency  | 0.228     | < <b>0.001</b> | 0.429       |
| <b>Low Income</b> | Deaths                     | -0.159    | < <b>0.001</b> | -0.171      |

|                     |                            |        |                |            |
|---------------------|----------------------------|--------|----------------|------------|
|                     | Population Affected        | -0.169 | < <b>0.001</b> | -164.669   |
|                     | Annual Affected Population | -0.406 | < <b>0.001</b> | -48638.129 |
|                     | Annual Flooding Frequency  | -0.434 | < <b>0.001</b> | -0.250     |
| <b>Lower Middle</b> | Deaths                     | -0.04  | <b>0.020</b>   | -0.008     |
| <b>Income</b>       | Population Affected        | 0.088  | 0.090          | 37.669     |
|                     | Annual Affected Population | 0.699  | < <b>0.001</b> | 149804.244 |
|                     | Annual Flooding Frequency  | 0.426  | < <b>0.001</b> | 0.333      |
| <b>Upper Middle</b> | Deaths                     | -0.572 | 0.567          | 0.000      |
| <b>Income</b>       | Population Affected        | 0.207  | <b>0.007</b>   | 26.957     |
|                     | Annual Affected Population | 0.606  | < <b>0.001</b> | 11106.5    |
|                     | Annual Flooding Frequency  | 0.537  | < <b>0.001</b> | 0.314      |
| <b>High Income</b>  | Deaths                     | -0.109 | < <b>0.001</b> | -0.014     |
|                     | Population Affected        | 0.0823 | < <b>0.001</b> | 20.669     |
|                     | Annual Affected Population | 0.317  | < <b>0.001</b> | 11617.744  |
|                     | Annual Flooding Frequency  | 0.278  | < <b>0.001</b> | 0.163      |

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*Note.* Tau value denotes Mann Kendall Tau value. Tau >0 denotes increasing trend. Tau <0 denotes decreasing trend. Sen's slope provides the magnitude of the trend. A total of 1286 coastal flooding events were considered for analysis, utilizing SLIDERS Admin affected population data. "Death" denotes the number of deaths per coastal flooding event, while "Affected population" refers to the SLIDERS affected population corresponding to each coastal flooding event. Annual values for affected population and flooding frequency were calculated by aggregating their respective sums on a yearly basis.

Similarly, in Fig. S3, we can see the time series of coastal flood exposed populations from 1990 to 2020. In Fig. S4, we can observe the gradual increasing trend in coastal flood events between 1990 to 2020.

We have divided countries into four World Bank defined income ranges: Low Income, Lower Middle Income, Upper Middle Income and High-Income. Table 1 shows the MMK trend

analysis result for different income categories. Coastal flooding related deaths per event is decreasing in every category except for upper middle-income, where no statistically significant trend is seen. The estimated population affected is decreasing significantly in low-income countries, while in other categories except lower middle income it is increasing. We can visually observe the trend of Coastal Flooding Deaths from coastal flooding in different income categories in Fig. S5.

#### **2.4.2. Comparison of EM-DAT database and NOAA billion-dollar disaster database**

Both the NOAA Billion-Dollar disaster database and the Emergency Events Database (EM-DAT) offer vital information about the frequency of coastal flooding events. We compared Tropical Cyclone events and coastal flooding events in the United States recorded in each dataset between 1990 and 2020. The NOAA database has 46 coastal flooding related events and EM-DAT billion-dollar filter has 40 events. From 1990 to 2020, a total of 78 incidents were documented in the EM-DAT database for USA, prior to any filtration based on billion-dollar income damage. Around 98% of total events found in the EM-DAT database are also found in the NOAA database and the overall trends in mortality are similar (Fig. S1.) Similarly, 98% total events found in NOAA database are also found in EM-DAT database. The common recorded events had differences in the recorded deaths in 33 events (72%). Hurricanes Bob, Katrina, Mathew, Irma, Florence, Michael, Dorian, Imelda, Isaias, Zeta and Eta have matching death records. Hurricane Lili, Hurricane Isidore, Hurricane Dolly, Hurricane Lee and Hurricane Hanna are recorded in NOAA billion-dollar disaster database but not in EM-DAT records. Conversely, Hurricane Joaquin is recorded in EM-DAT but not in NOAA database. When filtering the EM-DAT database by the monetary damages to only include those that record \$ 1 billion or higher in

damages, 87% of EM-DAT billion-dollar disaster events matched with NOAA billion-dollar disaster database.

### 2.4.3. Assessment of Mortality Risk Model

In this study, we have developed a mixed effect negative binomial regression model using data from all coastal countries to assess the association between country-level population, HDI, and frequency of coastal flooding events and mortality from coastal flooding.

**Table 3 | Negative binomial mixed regression model results**

| <i>Covariate variables</i> | <b>Model 1</b>        |                  | <b>Model 2</b>        |                  | <b>Model 3</b>        |                  |
|----------------------------|-----------------------|------------------|-----------------------|------------------|-----------------------|------------------|
|                            | <i>Risk ratios</i>    | <i>p</i>         | <i>Risk ratios</i>    | <i>p</i>         | <i>Risk ratios</i>    | <i>p</i>         |
| LnP                        | 0.44<br>(0.37 – 0.52) | <b>&lt;0.001</b> | 0.69<br>(0.55 – 0.85) | <b>0.001</b>     | 0.66<br>(0.53 – 0.83) | <b>&lt;0.001</b> |
| Cumulative Event Count     | 1.03<br>(1.01 – 1.05) | <b>0.001</b>     | 1.07<br>(1.03 – 1.11) | <b>&lt;0.001</b> | 1.07<br>(1.03 – 1.10) | <b>&lt;0.001</b> |
| HDI Class [Low]            | 2.80<br>(1.73 – 4.54) | <b>&lt;0.001</b> | 1.63<br>(0.83 – 3.23) | 0.158            | 2.03<br>(1.06 – 3.89) | <b>0.032</b>     |
| HDI Class [High]           | 0.43<br>(0.31 – 0.60) | <b>&lt;0.001</b> | 0.47<br>(0.30 – 0.73) | <b>0.001</b>     | 0.36<br>(0.23 – 0.56) | <b>&lt;0.001</b> |
| Year                       | 0.96<br>(0.95 – 0.97) | <b>&lt;0.001</b> | 0.93<br>(0.91 – 0.95) | <b>&lt;0.001</b> | 0.96<br>(0.94 – 0.98) | <b>&lt;0.001</b> |
| <b>Random Effects</b>      |                       |                  |                       |                  |                       |                  |
| $\sigma^2$                 | 8.74                  |                  | 4.70                  |                  | 5.63                  |                  |
| $\tau_{00}$                | 2.43 Country_Code     |                  | 2.69 Country_Code     |                  | 3.76 Country_Code     |                  |
| ICC                        | 0.22                  |                  | 0.36                  |                  | 0.40                  |                  |
| N                          | 82 Country_Code       |                  | 65 Country_Code       |                  | 82 Country_Code       |                  |
| Observations               | 1286                  |                  | 848                   |                  | 1286                  |                  |
| AIC                        | 12060.342             |                  | 8719.490              |                  | 13454.961             |                  |
| log-Likelihood             | -6022.171             |                  | -4351.745             |                  | -6719.480             |                  |

*Note.* The outcome variable in all models is mortality risk (death per affected population), Models (1) – (3) takes random intercepts at country level. Risk ratios (RRs), representing

exponentiated model estimates, were calculated along with various other statistical measures including residual variance ( $\sigma^2$ ), between-group variance ( $\tau_{00}$ ), intra-class correlation coefficient (ICC), number of groups (N), Akaike information criterion (AIC), and Log-Likelihood. Parentheses were used to denote 95% confidence intervals (CIs), and significance ( $p \leq 0.05$ ) was indicated by bold letters. We used maximum likelihood estimation, facilitated by the R-package 'glmmTMB', to fit the models.

In Table 3, we can see the result of the three variations of the mortality risk model: Model 1 uses country level SLIDERS exposed population estimates, model 2 contains only events (N=848) in which admin level 1 SLIDERS exposed population is available, and model 3 is a combined model, using admin level 1 exposed population for 848 events and country level exposed population estimated for the remaining 438 events. We can see a similar negative association between mortality rate and population. A10 million increase in population is associated with a reduction in mortality risk of 56% (this is the Risk ratio), 31% and 34% in model 1, 2 and 3 respectively. Similarly, for each additional coastal flooding event experienced in the previous five years the mortality risk increases by 3% in model 1 and 7% in model 2 and 3. Compared to medium HDI category, the mortality risk in Low HDI category is significantly higher in model 1 and model 3 but is not significant in model 2 using the higher spatially resolved (admin 1) exposed population estimates. Similarly, comparing High HDI it suggests reduced mortality risk in all models and is significant.

Figure 2 illustrates the global representation of annual predicted mortality rate based on model 3.

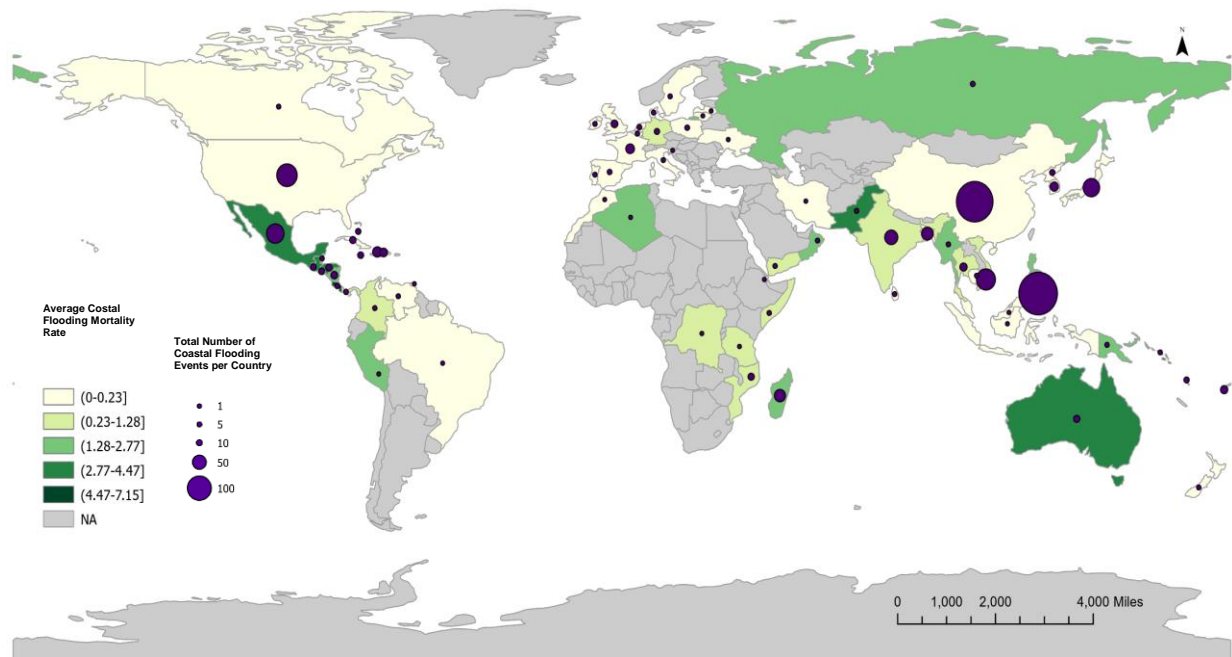
**Table 4 | Negative binomial mixed regression model results stratified by country income category**

| Income Category | Low                   |              | Lower Middle          |              | Upper Middle          |              | High                  |          |
|-----------------|-----------------------|--------------|-----------------------|--------------|-----------------------|--------------|-----------------------|----------|
|                 | Risk ratios           | <i>p</i>     | Risk ratios           | <i>p</i>     | Risk ratios           | <i>p</i>     | Risk ratios           | <i>p</i> |
| LnP             | 0.62<br>(0.39 – 0.97) | <b>0.038</b> | 0.66<br>(0.49 – 0.90) | <b>0.007</b> | 0.58<br>(0.39 – 0.88) | <b>0.010</b> | 0.82<br>(0.47 – 1.44) | 0.495    |

|                        |                       |              |                       |                  |                       |                  |                       |       |
|------------------------|-----------------------|--------------|-----------------------|------------------|-----------------------|------------------|-----------------------|-------|
| Cumulative Event Count | 0.97<br>(0.91 – 1.04) | 0.405        | 1.11<br>(1.06 – 1.16) | <b>&lt;0.001</b> | 1.03<br>(0.95 – 1.13) | 0.474            | 0.94<br>(0.87 – 1.02) | 0.154 |
| Year                   | 0.93<br>(0.89 – 0.98) | <b>0.004</b> | 0.95<br>(0.91 – 0.98) | <b>0.007</b>     | 0.90<br>(0.86 – 0.95) | <b>&lt;0.001</b> | 1.00<br>(0.95 – 1.04) | 0.835 |
| <b>Random Effects</b>  |                       |              |                       |                  |                       |                  |                       |       |
| $\sigma^2$             | 4.73                  |              | 5.21                  |                  | 5.79                  |                  | 7.97                  |       |
| $\tau_{00}$            | 1.32 Country_Code     |              | 3.32 Country_Code     |                  | 5.31 Country_Code     |                  | 7.17 Country          |       |
| ICC                    | 0.22                  |              | 0.39                  |                  | 0.48                  |                  | 0.47                  |       |
| N                      | 18 Country_Code       |              | 44 Country_Code       |                  | 29 Country_Code       |                  | 43 Country            |       |
| Observations           | 282                   |              | 475                   |                  | 222                   |                  | 307                   |       |
| AIC                    | 3495.525              |              | 5204.251              |                  | 1977.346              |                  | 2777.602              |       |
| log-Likelihood         | -1741.763             |              | -2596.126             |                  | -982.673              |                  | -1382.801             |       |

*Note.* The outcome variable in all income model is mortality risk (death per affected population), All income region model takes random intercepts at country level. Risk ratios (RRs), representing exponentiated model estimates, were calculated along with various other statistical measures including residual variance ( $\sigma^2$ ), between-group variance ( $\tau_{00}$ ), intra-class correlation coefficient (ICC), number of groups (N), Akaike information criterion (AIC), and Log-Likelihood. Parentheses were used to denote 95% confidence intervals (CIs), and significance ( $p \leq 0.05$ ) was indicated by bold letters. We used maximum likelihood estimation, facilitated by the R-package 'glmmTMB', to fit the models.

We also evaluated associations within income categories: Low Income, Lower Middle-Income, Upper Middle-Income, and High Income. The results are summarized in Table 4. The results are similar to the results of the global scale. We found a significant consistent negative association between population and mortality risk in all income categories except high income. While RR estimate of cumulative coastal flooding event counts of the previous 5 years is only significant in lower middle-income countries.



**Fig. 2.** Predicted mortality rate from negative binomial regression model 3.

#### 2.4.4. Comparison with latest study

We assessed the performance of our model against the findings of Lindersson et al. (2023) by incorporating their calculated exposed population derived from Google Earth Engine (GEE). The outcomes are summarized in Table 5. Model 4 applies the estimated exposed population from Lindersson et al. (2023), while Model 5 utilizes the SLIIDERS exposed population at the administrative level 1, and Model 6 incorporates both administrative-level 1 and total exposed populations at country level from SLIIDERS. Our comparative analysis reveals a notable escalation in the estimated mortality risk by 13% for each occurrence of coastal flooding events within the preceding 5 years, as observed specifically in Model 5.

**Table 5 | Negative binomial mixed regression model results for model comparisons with finer resolution exposed population**

| Covariate variables       | Mortality Risk<br>Model 4    |                  | Mortality Risk<br>Model 5      |                  | Mortality Risk<br>Model 6    |                  |
|---------------------------|------------------------------|------------------|--------------------------------|------------------|------------------------------|------------------|
|                           | Risk ratios                  | <i>p</i>         | Risk ratios                    | <i>p</i>         | Risk ratios                  | <i>p</i>         |
| LnP                       | 1.35<br>(0.87 – 2.10)        | 0.179            | 0.72<br>(0.37 – 1.41)          | 0.339            | 0.66<br>(0.41 – 1.06)        | 0.083            |
| Cumulative Event<br>Count | 0.99<br>(0.91 – 1.08)        | 0.847            | 1.13<br>(1.03 – 1.25)          | <b>0.013</b>     | 0.96<br>(0.89 – 1.03)        | 0.267            |
| Low HDI                   | 4.37<br>(0.86 – 22.20)       | 0.076            | 3.17<br>(0.52 – 19.40)         | 0.212            | 3.52<br>(0.84 – 14.83)       | 0.086            |
| Year                      | 0.78<br>(0.73 – 0.83)        | <b>&lt;0.001</b> | 0.84<br>(0.78 – 0.91)          | <b>&lt;0.001</b> | 0.90<br>(0.85 – 0.96)        | <b>&lt;0.001</b> |
| $\sigma^2$                | 8.04                         |                  | 4.29                           |                  | 10.40                        |                  |
| $\tau_{00}$               | 2.14 <sub>Country_Code</sub> |                  | 3.03 <sub>Country_Code.x</sub> |                  | 3.33 <sub>Country_Code</sub> |                  |
| ICC                       | 0.21                         |                  | 0.41                           |                  | 0.24                         |                  |
| N                         | 29 <sub>Country_Code</sub>   |                  | 24 <sub>Country_Code.x</sub>   |                  | 29 <sub>Country_Code</sub>   |                  |
| <b>Observations</b>       | <b>147</b>                   |                  | <b>111</b>                     |                  | <b>147</b>                   |                  |
| Deviance                  | 164.556                      |                  | 124.578                        |                  | 156.187                      |                  |
| AIC                       | 1387.340                     |                  | 1110.305                       |                  | 1353.696                     |                  |
| log-Likelihood            | -686.670                     |                  | -548.152                       |                  | -669.848                     |                  |

*Note.* The outcome variable in all models is mortality risk (death per affected population), Models (4) – (6) takes random intercepts at country level. Risk ratios (RRs), representing exponentiated model estimates, were calculated along with various other statistical measures including residual variance ( $\sigma^2$ ), between-group variance ( $\tau_{00}$ ), intra-class correlation coefficient (ICC), number of groups (N), Akaike information criterion (AIC), and Log-Likelihood. Parentheses were used to denote 95% confidence intervals (CIs), and significance ( $p \leq 0.05$ ) was indicated by bold letters. We used maximum likelihood estimation, facilitated by the R-package 'glmmTMB', to fit the models.

## 2.5. Discussion

Our model suggests country population is associated with a lower mortality rate due to coastal flooding, consistent with previous results by Lloyd et al. 2016. The impacts of coastal flooding may be more buffered in countries with a higher inland population, potentially leading to more resources available to protect coastal populations. Inconsistent with the previous results of Lloyd et al 2016, we estimate that the number of coastal flooding events experienced in each country is positively associated with mortality during coastal flooding. If flooding occurs frequently in populous areas, local governments and communities may have created efficient risk-reduction measures, such as enhanced building rules, early warning systems, and community education initiatives.

High income nations have employed more coastal flooding adaptation technologies compared to low and middle income countries (Linham & Nicholls, 2015). With this context it is reasonable to conclude that countries with higher HDI have better coastal flood adaptation, retreat and protection measures and thus will have lower mortality risk than countries with lower HDI, consistent with our results. Similarly, Romanello et al. (2023) also found the average fatalities from floods and storms decreased in high HDI countries, going from 86 deaths to 16 deaths per event, and in very high HDI countries from 11 deaths to 8 deaths between 1990–1999 and 2013–2022 respectively, exhibiting a noticeable decline. The considerable decline in overall coastal flooding-related deaths could be a result of better early warning systems, better coastal management techniques, or successful public health initiatives. Planning and development of coastal infrastructure have intensified due to population growth in coastal areas and SLR (Bulleri & Chapman, 2010).

One novel component of our study is the incorporation of the DSCIM SLIDERS model for estimating the exposed population which takes mean sea level rise into account, allowing us to

develop predictions based on projections of SLR and population change. The surge height variable in the SLIDERS is the estimated sea level from ERA5 reanalysis which incorporates present climate scenario of Global Tide and Surge Model (GTSM). DSCIM SLIDERS estimates were used from 2000 forward, however we had to adjust the method to estimate the potentially exposed population between 1990 and 1999. Also, the potentially exposed population estimates from SLIDERS are at admin level 1, so spatial resolution for specific events would improve accuracy of this variable, which we were able to evaluate in our comparison to coastal flooding events characterized by Lindersson et al. 2023.

When comparing our trend analysis (MMK trend analysis method) of coastal flooding with all-cause flooding and Hu et al.'s (2018) research, we observed similar decreasing trends in coastal flooding deaths but increasing trends in coastal flooding events. Similarly, Franzke and Sentelles (2020) also carried out a trend analysis using quantile regression and tested the significance by non-parametric Mann Kendall method and found global storm-related mortality is decreasing. Although the number of deaths due to coastal flooding is decreasing over time, the frequency of event occurrence is increasing. So, these findings underscore the importance of understanding and addressing complex dynamics of coastal flooding to mitigate its impact on coastal communities.

One limitation of this study is the presence of missing data in the EM-DAT database.

Approximately 25% of coastal flooding incidents reported to EM-DAT in this study did not include death count estimates. The absence of established guidelines for handling missing data in disaster databases has led to an oversight of this issue in previous literature (Jones et al., 2022). If EM-DAT resolves this issue regarding missing data or establishes proper guidelines for handling

missing data in disaster databases, it would be beneficial for future studies utilizing these databases.

When comparing our model results to a subset of Lindersson and co-authors' model, socio-demographic variables were not significant. Initially, their study encompassed 584 all-cause flooding events, but after filtering out coastal flooding and tropical cyclone-related incidents, events reduced to 147. Their study provided finer exposed population data at administrative levels 2 and 3 from the Global Human Settlement products compared to our exposed population at administrative level 1 from SLIDERS population data our models have shown that increasing year is significant.. One possible explanation for this lack of significance of sociodemographic variables in this smaller subset could be the limited number of coastal flooding events. In the future, improvements in the GDIS database sourced from EM-DAT could enhance the precision of disaster location at administrative levels 1, 2, and 3. This, in turn, will increase the spatial resolution of flooding events, improving the accuracy of estimated exposed populations in future studies, leading to a better understanding of the relationship between mortality risk and socio-economic co-variates.

Franzke and Sentelles (2020) employed a probabilistic model approach to explore the relationship between extreme event fatalities and covariates such as climate variability factors and socio-economic indicators. In their analysis, they identified an association with climate covariates but did not find significance in predicting fatalities with socio-economic parameters. In contrast, both our study and the study by Lloyd et al. (2016), which employed regression model approaches, found a significant relationship with socio-economic variables such as HDI. In future studies, exploring regression statistical approaches could offer insights into the association between coastal flood-related mortality and climate covariates.

Zhang et. al (2021) conducted a study on global mortality risk from riverine flooding under various climate scenarios, utilizing Eleven Atmosphere Ocean Global Circulation Models (AOGCMs) and projecting death tolls. They utilized historical death data at the country level from the EM-DAT disaster database, incorporating inundation depth across different climate scenarios, socio-economic pathways, and three distinct timescales: 1986-2005, 2016-2035, and 2046-2065. Furthermore, SLIIDERS has the capability to integrate different sea level rise scenarios. For future studies, researchers can adopt various sea level rise scenarios from DSCIM-SLIIDERS and py-CIAM to estimate coastal flooding mortality risk and future exposed populations across different socio-economic pathways.

## **2.6. Conclusion**

The analysis of temporal trends reveals a noteworthy pattern: a decline in coastal flooding mortality, concomitant with an increase in the frequency of coastal flooding incidents. Our model suggests a significant relationship between coastal flooding mortality risk, HDI, population and cumulative coastal flooding occurrence. We suggest more research on filling missing death count in EM-DAT to increase the sample size for future research in coastal flooding and extreme weather-related disaster.

## **References**

- Adnan, M. S. G., Haque, A., & Hall, J. W. (2019). Have coastal embankments reduced flooding in Bangladesh? *Science of The Total Environment*, 682, 405–416.  
<https://doi.org/10.1016/j.scitotenv.2019.05.048>

- Azevedo de Almeida, B., & Mostafavi, A. (2016). Resilience of Infrastructure Systems to Sea-Level Rise in Coastal Areas: Impacts, Adaptation Measures, and Implementation Challenges. *Sustainability*, 8(11), Article 11. <https://doi.org/10.3390/su8111115>
- Bakkensen, L. A., & Mendelsohn, R. O. (2016). Risk and Adaptation: Evidence from Global Hurricane Damages and Fatalities. *Journal of the Association of Environmental and Resource Economists*, 3(3), 555–587. <https://doi.org/10.1086/685908>
- Barredo, J. I. (2007). Major flood disasters in Europe: 1950–2005. *Natural Hazards*, 42(1), 125–148. <https://doi.org/10.1007/s11069-006-9065-2>
- Bevere, L., & Weigel, A. (2021). Natural catastrophes in 2020. *Swiss RE Sigma*.
- Bulleri, F., & Chapman, M. G. (2010). The introduction of coastal infrastructure as a driver of change in marine environments. *Journal of Applied Ecology*, 47(1), 26–35. <https://doi.org/10.1111/j.1365-2664.2009.01751.x>
- Camelo, J., Mayo, T. L., & Gutmann, E. D. (2020). Projected Climate Change Impacts on Hurricane Storm Surge Inundation in the Coastal United States. *Frontiers in Built Environment*, 6. <https://www.frontiersin.org/articles/10.3389/fbuil.2020.588049>
- CRED, U. (2015). The human cost of natural disasters: A global perspective. *Centre for Research on the Epidemiology of Disaster (CRED), Brussels*.
- Dasgupta, S., Laplante, B., Meisner, C., Wheeler, D., & Yan, J. (2009). The impact of sea level rise on developing countries: A comparative analysis. *Climatic Change*, 93(3), 379–388. <https://doi.org/10.1007/s10584-008-9499-5>
- Dasgupta, S., Laplante, B., Murray, S., & Wheeler, D. (2009). *Climate Change and the Future Impacts of Storm-Surge Disasters in Developing Countries* (SSRN Scholarly Paper 1479650). <https://doi.org/10.2139/ssrn.1479650>

- Dedekorkut-Howes, A., Torabi, E., & Howes, M. (2020). When the tide gets high: A review of adaptive responses to sea level rise and coastal flooding. *Journal of Environmental Planning and Management*, 63(12), 2102–2143.  
<https://doi.org/10.1080/09640568.2019.1708709>
- Delforge, D., Wathelet, V., Below, R., Sofia, C. L., Tonnelier, M., van Loenhout, J., & Speybroeck, N. (2023). *EM-DAT: the Emergency Events Database*.
- Depsky, N., Bolliger, I., Allen, D., Choi, J. H., Delgado, M., Greenstone, M., Hamidi, A., Houser, T., Kopp, R. E., & Hsiang, S. (2022). DSCIM-Coastal v1.0: An Open-Source Modeling Platform for Global Impacts of Sea Level Rise. *EGUsphere*, 1–47.  
<https://doi.org/10.5194/egusphere-2022-198>
- Diaz, D. B. (2016). Estimating global damages from sea level rise with the Coastal Impact and Adaptation Model (CIAM). *Climatic Change*, 137(1–2), 143–156.  
<https://doi.org/10.1007/s10584-016-1675-4>
- Em-DAT, C. / Ucl. (2024). *EM-DAT* [dataset]. [www.emdat.be](http://www.emdat.be)
- Ericson, J. P., Vörösmarty, C. J., Dingman, S. L., Ward, L. G., & Meybeck, M. (2006). Effective sea-level rise and deltas: Causes of change and human dimension implications. *Global and Planetary Change*, 50(1), 63–82. <https://doi.org/10.1016/j.gloplacha.2005.07.004>
- Fang, J., Lincke, D., Brown, S., Nicholls, R. J., Wolff, C., Merkens, J.-L., Hinkel, J., Vafeidis, A. T., Shi, P., & Liu, M. (2020). Coastal flood risks in China through the 21st century – An application of DIVA. *Science of The Total Environment*, 704, 135311.  
<https://doi.org/10.1016/j.scitotenv.2019.135311>

- Fauzi, D. (2021). Coastal Flood Responses in Manila Bay, the Philippines: Understanding Social Contract in the Policy-Making Processes. *Case Studies in the Environment*, 5(1), 1438458. <https://doi.org/10.1525/cse.2021.1438458>
- Franzke, C. L. E., & Torelló I Sentelles, H. (2020). Risk of extreme high fatalities due to weather and climate hazards and its connection to large-scale climate variability. *Climatic Change*, 162(2), 507–525. <https://doi.org/10.1007/s10584-020-02825-z>
- Hagen, I., Huggel, C., Ramajo, L., Chacón, N., Ometto, J. P., Postigo, J. C., & Castellanos, E. J. (2022). Climate change-related risks and adaptation potential in Central and South America during the 21st century. *Environmental Research Letters*, 17(3), 033002. <https://doi.org/10.1088/1748-9326/ac5271>
- Hallegatte, S., Green, C., Nicholls, R. J., & Corfee-Morlot, J. (2013). Future flood losses in major coastal cities. *Nature Climate Change*, 3(9), 802–806. <https://doi.org/10.1038/nclimate1979>
- Harman, B. P., Heyenga, S., Taylor, B. M., & Fletcher, C. S. (2015). Global Lessons for Adapting Coastal Communities to Protect against Storm Surge Inundation. *Journal of Coastal Research*, 31(4), 790–801. <https://doi.org/10.2112/JCOASTRES-D-13-00095.1>
- Hinkel, J., & Klein, R. J. T. (2009). Integrating knowledge to assess coastal vulnerability to sea-level rise: The development of the DIVA tool. *Global Environmental Change*, 19(3), 384–395. <https://doi.org/10.1016/j.gloenvcha.2009.03.002>
- Hinkel, J., Lincke, D., Vafeidis, A. T., Perrette, M., Nicholls, R. J., Tol, R. S. J., Marzeion, B., Fettweis, X., Ionescu, C., & Levermann, A. (2014). Coastal flood damage and adaptation costs under 21st century sea-level rise. *Proceedings of the National Academy of Sciences*, 111(9), 3292–3297. <https://doi.org/10.1073/pnas.1222469111>

- Hsiang, S. M., & Narita, D. (2012). Adaptation to cyclone risk: Evidence from the global cross-section. *Climate Change Economics*, *03*(02), 1250011.  
<https://doi.org/10.1142/S201000781250011X>
- Hu, P., Zhang, Q., Shi, P., Chen, B., & Fang, J. (2018). Flood-induced mortality across the globe: Spatiotemporal pattern and influencing factors. *Science of The Total Environment*, *643*, 171–182. <https://doi.org/10.1016/j.scitotenv.2018.06.197>
- Jones, R. L., Guha-Sapir, D., & Tubeuf, S. (2022). Human and economic impacts of natural disasters: Can we trust the global data? *Scientific Data*, *9*(1), 572.  
<https://doi.org/10.1038/s41597-022-01667-x>
- Jonkman, S. N. (2005). Global Perspectives on Loss of Human Life Caused by Floods. *Natural Hazards*, *34*(2), 151–175. <https://doi.org/10.1007/s11069-004-8891-3>
- Jonkman, S. N., Curran, A., & Bouwer, L. M. (2024). Floods have become less deadly: An analysis of global flood fatalities 1975–2022. *Natural Hazards*.  
<https://doi.org/10.1007/s11069-024-06444-0>
- Kirezci, E., Young, I. R., Ranasinghe, R., Lincke, D., & Hinkel, J. (2023). Global-scale analysis of socioeconomic impacts of coastal flooding over the 21st century. *Frontiers in Marine Science*, *9*. <https://doi.org/10.3389/fmars.2022.1024111>
- Kron, W. (2013). Coasts: The high-risk areas of the world. *Natural Hazards*, *66*(3), 1363–1382.  
<https://doi.org/10.1007/s11069-012-0215-4>
- Le, T. D. N. (2020). Climate change adaptation in coastal cities of developing countries: Characterizing types of vulnerability and adaptation options. *Mitigation and Adaptation Strategies for Global Change*, *25*(5), 739–761. <https://doi.org/10.1007/s11027-019-09888-z>

- Le, T. D. N., & Awal, R. (2021). Chapter 9—Adaptation to climate extremes and sea level rise in coastal cities of developing countries. In A. Fares (Ed.), *Climate Change and Extreme Events* (pp. 145–170). Elsevier. <https://doi.org/10.1016/B978-0-12-822700-8.00003-2>
- Lindersson, S., Raffetti, E., Rusca, M., Brandimarte, L., Mård, J., & Di Baldassarre, G. (2023). The wider the gap between rich and poor the higher the flood mortality. *Nature Sustainability*, *6*(8), 995–1005. <https://doi.org/10.1038/s41893-023-01107-7>
- Linham, M. M., & Nicholls, R. J. (2015). Adaptation technologies for coastal erosion and flooding: A review. *Proceedings of the Institution of Civil Engineers - Maritime Engineering*. <https://doi.org/10.1680/maen.2011.29>
- Lloyd, S. J., Kovats, R. S., Chalabi, Z., Brown, S., & Nicholls, R. J. (2016). Modelling the influences of climate change-associated sea-level rise and socioeconomic development on future storm surge mortality. *Climatic Change*, *134*(3), 441–455. <https://doi.org/10.1007/s10584-015-1376-4>
- Marcos, M., Rohmer, J., Vousdoukas, M. I., Mentaschi, L., Le Cozannet, G., & Amores, A. (2019). Increased Extreme Coastal Water Levels Due to the Combined Action of Storm Surges and Wind Waves. *Geophysical Research Letters*, *46*(8), 4356–4364. <https://doi.org/10.1029/2019GL082599>
- Margulis, S., Hughes, G., Schneider, R., Pandey, K., Narain, U., & Kemeny, T. (2010). *Economics of adaptation to climate change: Synthesis report*.
- Mayo, T. L., & Lin, N. (2022). Climate change impacts to the coastal flood hazard in the northeastern United States. *Weather and Climate Extremes*, *36*, 100453. <https://doi.org/10.1016/j.wace.2022.100453>

- Mazhin, S. A., Farrokhi, M., Noroozi, M., Roudini, J., Hosseini, S. A., Motlagh, M. E., Kolivand, P., & Khankeh, H. (2021). Worldwide disaster loss and damage databases: A systematic review. *Journal of Education and Health Promotion, 10*, 329.  
[https://doi.org/10.4103/jehp.jehp\\_1525\\_20](https://doi.org/10.4103/jehp.jehp_1525_20)
- McGranahan, G., Balk, D., & Anderson, B. (2007). The rising tide: Assessing the risks of climate change and human settlements in low elevation coastal zones. *Environment and Urbanization, 19*(1), 17–37.  
<https://doi.org/10.1177/0956247807076960>
- McMichael, C., Dasgupta, S., Ayeb-Karlsson, S., & Kelman, I. (2020). A review of estimating population exposure to sea-level rise and the relevance for migration. *Environmental Research Letters, 15*(12), 123005. <https://doi.org/10.1088/1748-9326/abb398>
- Milly, P. C. D., Wetherald, R. T., Dunne, K. A., & Delworth, T. L. (2002). Increasing risk of great floods in a changing climate. *Nature, 415*(6871), Article 6871.  
<https://doi.org/10.1038/415514a>
- Milne, G. A., Gehrels, W. R., Hughes, C. W., & Tamisiea, M. E. (2009). Identifying the causes of sea-level change. *Nature Geoscience, 2*(7), 471–478. <https://doi.org/10.1038/ngeo544>
- Munich, R. (2011). *NatCatSERVICE: Natural catastrophe know-how for risk management and research*. Munich Re.
- Neumann, B., Vafeidis, A. T., Zimmermann, J., & Nicholls, R. J. (2015). Future Coastal Population Growth and Exposure to Sea-Level Rise and Coastal Flooding—A Global Assessment. *PLOS ONE, 10*(3), e0118571. <https://doi.org/10.1371/journal.pone.0118571>
- Nicholls, R. J. (2003). An expert assessment of storm surge “hotspots.” *Interim Re.*

- Nicholls, R. J., & Cazenave, A. (2010). Sea-Level Rise and Its Impact on Coastal Zones. *Science*, 328(5985), 1517–1520. <https://doi.org/10.1126/science.1185782>
- Nicholls, R. J., Lincke, D., Hinkel, J., Brown, S., Vafeidis, A. T., Meysignac, B., Hanson, S. E., Merkens, J.-L., & Fang, J. (2021). A global analysis of subsidence, relative sea-level change and coastal flood exposure. *Nature Climate Change*, 11(4), 338–342. <https://doi.org/10.1038/s41558-021-00993-z>
- Nishikawa, M. S. (2003). Global Unique Disaster IDentifier Number (GLIDE): For effective disaster information sharing and management. *Proceedings of the International Conference on Total Disaster Risk Management*.
- Patt, A. G., Tadross, M., Nussbaumer, P., Asante, K., Metzger, M., Rafael, J., Goujon, A., & Brundrit, G. (2010). Estimating least-developed countries' vulnerability to climate-related extreme events over the next 50 years. *Proceedings of the National Academy of Sciences*, 107(4), 1333–1337. <https://doi.org/10.1073/pnas.0910253107>
- Peduzzi, P., & Herold, H. D. C. (2005). Mapping Disastrous Natural Hazards Using Global Datasets. *Natural Hazards*, 35(2), 265–289. <https://doi.org/10.1007/s11069-004-5703-8>
- Pörtner, H.-O., Roberts, D. C., Masson-Delmotte, V., Zhai, P., Tignor, M., Poloczanska, E., Mintenbeck, K., Alegría, A., Nicolai, M., Okem, A., & others. (2019). IPCC special report on the ocean and cryosphere in a changing climate. *IPCC Intergovernmental Panel on Climate Change: Geneva, Switzerland*, 1(3), 1–755.
- Reguero, B. G., Losada, I. J., Díaz-Simal, P., Méndez, F. J., & Beck, M. W. (2015). Effects of Climate Change on Exposure to Coastal Flooding in Latin America and the Caribbean. *PLOS ONE*, 10(7), e0133409. <https://doi.org/10.1371/journal.pone.0133409>

- Reimann, L., Koks, E., de Moel, H., Ton, M. J., & Aerts, J. C. J. H. (2024). An Empirical Social Vulnerability Map for Flood Risk Assessment at Global Scale (“GlobE-SoVI”). *Earth’s Future*, 12(3), e2023EF003895. <https://doi.org/10.1029/2023EF003895>
- Romanello, M., Napoli, C. D., Green, C., Kennard, H., Lampard, P., Scamman, D., Walawender, M., Ali, Z., Ameli, N., Ayeb-Karlsson, S., Beggs, P. J., Belesova, K., Berrang Ford, L., Bowen, K., Cai, W., Callaghan, M., Campbell-Lendrum, D., Chambers, J., Cross, T. J., ... Costello, A. (2023). The 2023 report of the Lancet Countdown on health and climate change: The imperative for a health-centred response in a world facing irreversible harms. *The Lancet*, 402(10419), 2346–2394. [https://doi.org/10.1016/S0140-6736\(23\)01859-7](https://doi.org/10.1016/S0140-6736(23)01859-7)
- Rosvold, E. L., & Buhaug, H. (2021). GDIS, a global dataset of geocoded disaster locations. *Scientific Data*, 8(1), 61. <https://doi.org/10.1038/s41597-021-00846-6>
- Shen, G., & Hwang, S. N. (2019). Spatial–Temporal snapshots of global natural disaster impacts Revealed from EM-DAT for 1900-2015. *Geomatics, Natural Hazards and Risk*, 10(1), 912–934. <https://doi.org/10.1080/19475705.2018.1552630>
- Taherkhani, M., Vitousek, S., Barnard, P. L., Frazer, N., Anderson, T. R., & Fletcher, C. H. (2020). Sea-level rise exponentially increases coastal flood frequency. *Scientific Reports*, 10(1), 6466. <https://doi.org/10.1038/s41598-020-62188-4>
- Tellman, B., Sullivan, J. A., Kuhn, C., Kettner, A. J., Doyle, C. S., Brakenridge, G. R., Erickson, T. A., & Slayback, D. A. (2021). Satellite imaging reveals increased proportion of population exposed to floods. *Nature*, 596(7870), 80–86. <https://doi.org/10.1038/s41586-021-03695-w>

- Tennant, E., & Gilmore, E. A. (2020). Government effectiveness and institutions as determinants of tropical cyclone mortality. *Proceedings of the National Academy of Sciences*, *117*(46), 28692–28699. <https://doi.org/10.1073/pnas.2006213117>
- Vafeidis, A. T., Schuerch, M., Wolff, C., Spencer, T., Merkens, J. L., Hinkel, J., Lincke, D., Brown, S., & Nicholls, R. J. (2019). Water-level attenuation in global-scale assessments of exposure to coastal flooding: A sensitivity analysis. *Natural Hazards and Earth System Sciences*, *19*(5), 973–984. <https://doi.org/10.5194/nhess-19-973-2019>
- Vitousek, S., Barnard, P. L., Fletcher, C. H., Frazer, N., Erikson, L., & Storlazzi, C. D. (2017). Doubling of coastal flooding frequency within decades due to sea-level rise. *Scientific Reports*, *7*(1), 1399. <https://doi.org/10.1038/s41598-017-01362-7>
- Wahl, T., Haigh, I. D., Nicholls, R. J., Arns, A., Dangendorf, S., Hinkel, J., & Slangen, A. B. A. (2017). Understanding extreme sea levels for broad-scale coastal impact and adaptation analysis. *Nature Communications*, *8*(1), Article 1. <https://doi.org/10.1038/ncomms16075>
- Wolff, C., Vafeidis, A. T., Lincke, D., Marasmi, C., & Hinkel, J. (2016). Effects of Scale and Input Data on Assessing the Future Impacts of Coastal Flooding: An Application of DIVA for the Emilia-Romagna Coast. *Frontiers in Marine Science*, *3*. <https://doi.org/10.3389/fmars.2016.00041>
- Wong, P. P., Losada, I. J., Gattuso, J.-P., Hinkel, J., Khattabi, A., McInnes, K. L., Saito, Y., Sallenger, A., & others. (2014). Coastal systems and low-lying areas. *Climate Change*, *2104*, 361–409.
- Woodruff, J. D., Irish, J. L., & Camargo, S. J. (2013). Coastal flooding by tropical cyclones and sea-level rise. *Nature*, *504*(7478), Article 7478. <https://doi.org/10.1038/nature12855>

Xu, H., Xu, K., Lian, J., & Ma, C. (2019). Compound effects of rainfall and storm tides on coastal flooding risk. *Stochastic Environmental Research and Risk Assessment*, *33*(7), 1249–1261. <https://doi.org/10.1007/s00477-019-01695-x>

### **3. Chapter 3. Conclusions**

#### **3.1. Conclusions**

Performing the trend analysis spanning the past three decades, we observed a significant decline in coastal flooding mortality in global scale and across all income regions. However, during the same period, the frequency of coastal flooding events increased, except in low-income countries. Similarly, the annual population affected by coastal flooding exhibited a decreasing trend globally and in low-income nations, while displaying an increasing trend in lower middle, upper middle and higher-income regions.

With a sample size of 1286 coastal flooding events, we found significant associations between mortality rate and socio-economic variables. We found that mortality risk increases by 7% (95% CI, 3-10%) for each additional coastal flooding events in the previous five years. For every 61 million increment in population the mortality risk decreases by 34% (95% CI, 17-47%). There is a notable increase in mortality risk observed in low HDI regions compared to medium HDI regions. Conversely, high HDI regions exhibit a significant decrease in mortality risk based on the findings of Model 3.

For instance, in the case of the Philippines, the population has been steadily increasing over time. It is noteworthy that the country has experienced the highest number of coastal flooding events, totaling 186 as shown in Table S1 between 1990 and 2020. Despite this, mortality rates due to such events are declining. This trend can be attributed to the implementation of government policies, such as the construction of sea dikes, which have provided immediate protection (Fauzi, 2021). Similarly, in China with second highest occurrence of coastal flooding events from 1990-2020, population and average annual events are increasing, yet mortality is decreasing over time. From these two countries with the highest number of recorded events, the population at the

national level is increasing in both cases, while mortality rates are decreasing. These trends are consistent with the findings of our model. Comparatively, Bangladesh has seen a decrease in the number of coastal flooding events over time, yet the population exposed to such events is on the rise. Despite this, mortality rates are decreasing. This can be attributed to the advancement of early warning systems, which are now more effective than in previous years (Adnan et al., 2019). For instance, due to the absence of adequate early warning systems, the devastating Cyclone Gorky struck Bangladesh in 1991, claiming around 139,000 lives. These observed trends align with the predictions of our model. The reason for this declining trend could be due to improvement in early warning systems, infrastructure development like sea dikes construction, flood barrier construction, community preparedness awareness and improved healthcare and emergency response (Azevedo de Almeida & Mostafavi, 2016).

### **3.2. Recommendations for future work**

For future studies, it would be beneficial to utilize models such as SLIDERS and pyCIAM if they are made more user-friendly and accompanied by clear instructions for extracting data on the coastal flooding exposed population. These models have incorporated 23 sea level rise scenarios and adaptation measures, thus providing a comprehensive framework for coastal flooding analysis.

One limitation of this study is the loss of coastal flooding events due to unavailable death records from EM-DAT, resulting in the exclusion of nearly 25% of events. Addressing this issue in future research would significantly enhance the sample size available for analysis.

## References

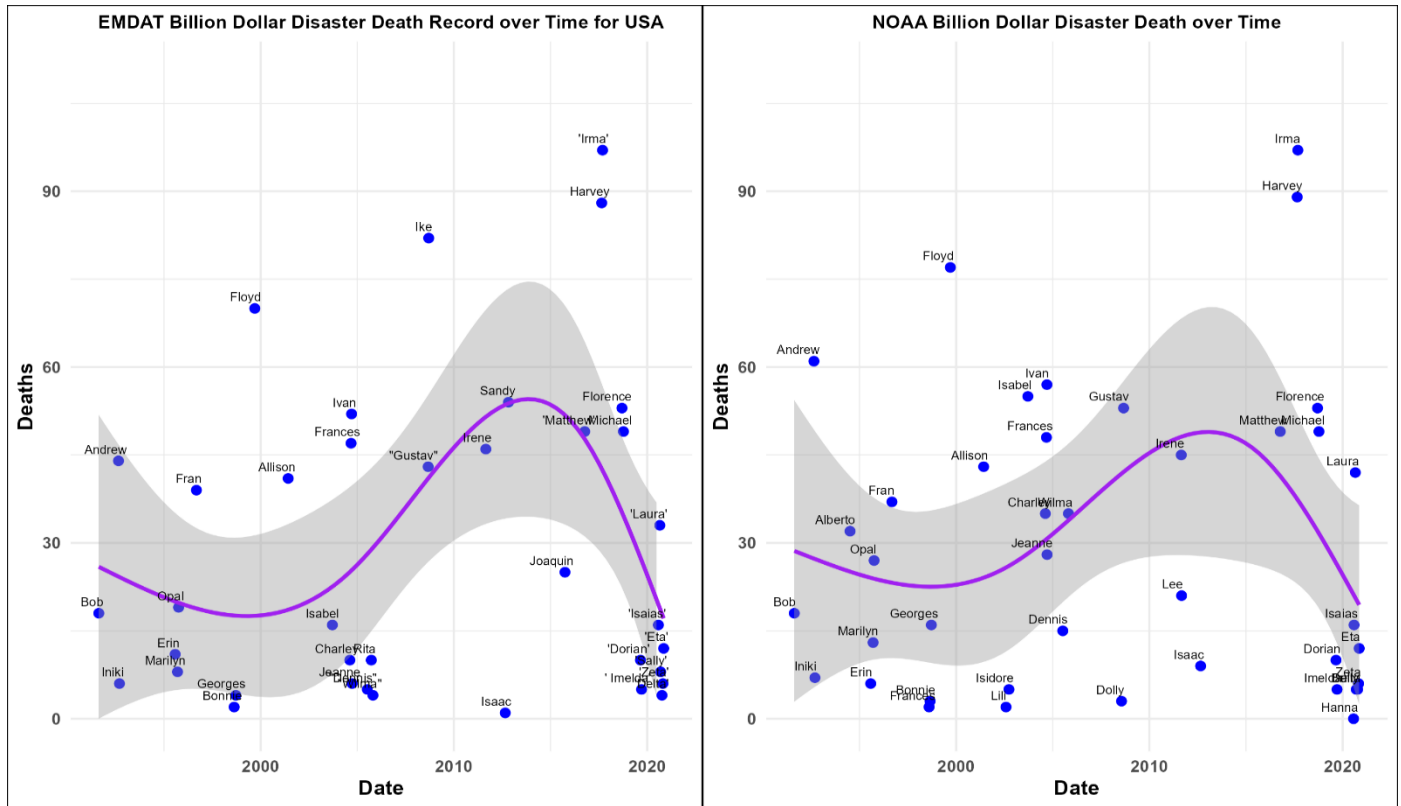
- Adnan, M. S. G., Haque, A., & Hall, J. W. (2019). Have coastal embankments reduced flooding in Bangladesh? *Science of The Total Environment*, 682, 405–416.  
<https://doi.org/10.1016/j.scitotenv.2019.05.048>
- Azevedo de Almeida, B., & Mostafavi, A. (2016). Resilience of Infrastructure Systems to Sea-Level Rise in Coastal Areas: Impacts, Adaptation Measures, and Implementation Challenges. *Sustainability*, 8(11), Article 11. <https://doi.org/10.3390/su8111115>
- Fauzi, D. (2021). Coastal Flood Responses in Manila Bay, the Philippines: Understanding Social Contract in the Policy-Making Processes. *Case Studies in the Environment*, 5(1), 1438458. <https://doi.org/10.1525/cse.2021.1438458>

## Appendix A. DSCIM SLLIDERS Accessibility

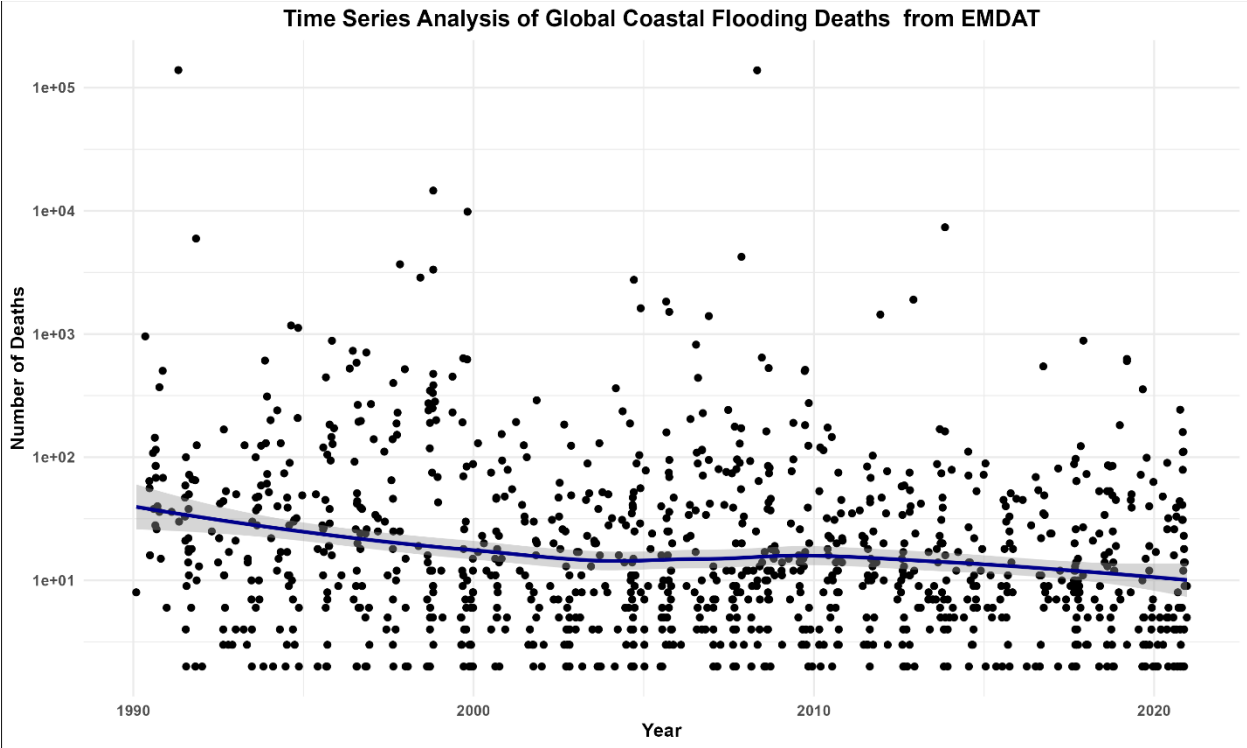
There are two methods for acquiring the DSCIM SLLIDERS input dataset. The SLLIDERS output is directly accessible via a download link (accessible at <https://zenodo.org/record/7693868>), however an alternate option requires compiling the SLLIDERS from the original source code (<https://zenodo.org/record/6456115>), which is also available. The output variables from the SLLIDERS-ECON results are stored in ZARR files, a format that is compatible with xarray files, retrieved using the Python programming language.

Supplemental Tables

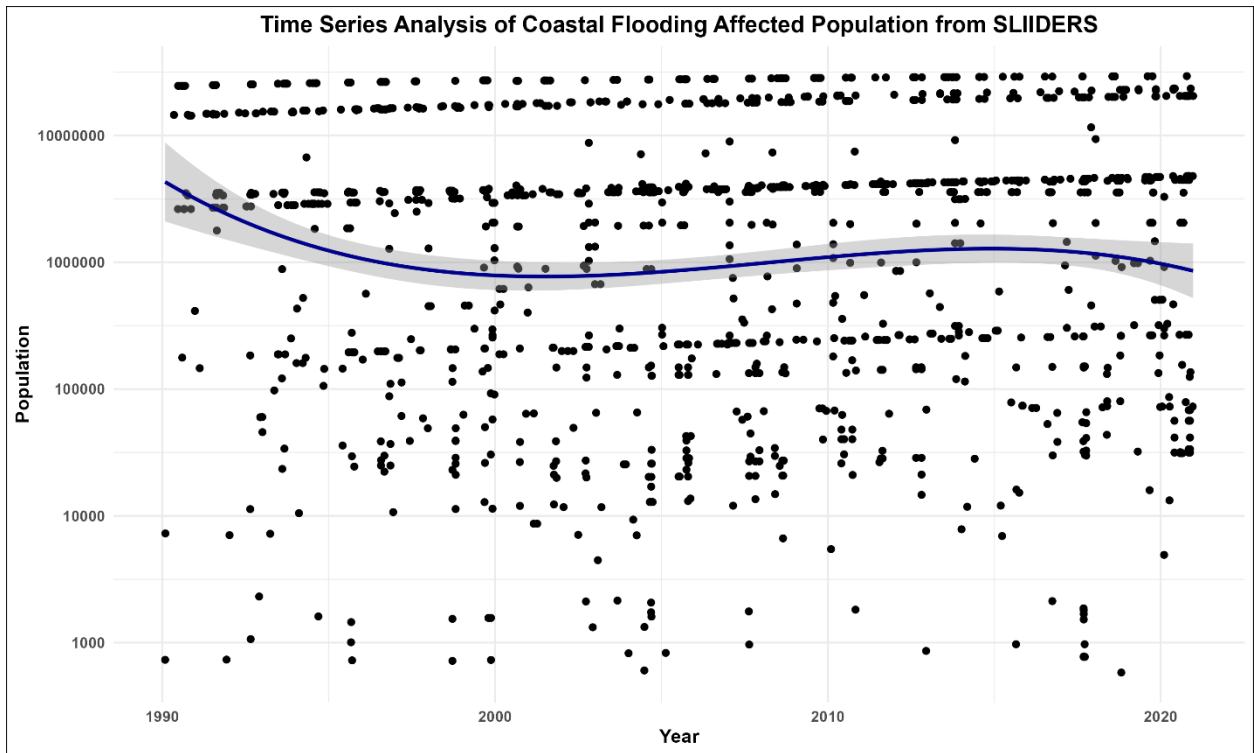
## Appendix B. Supplemental Figures



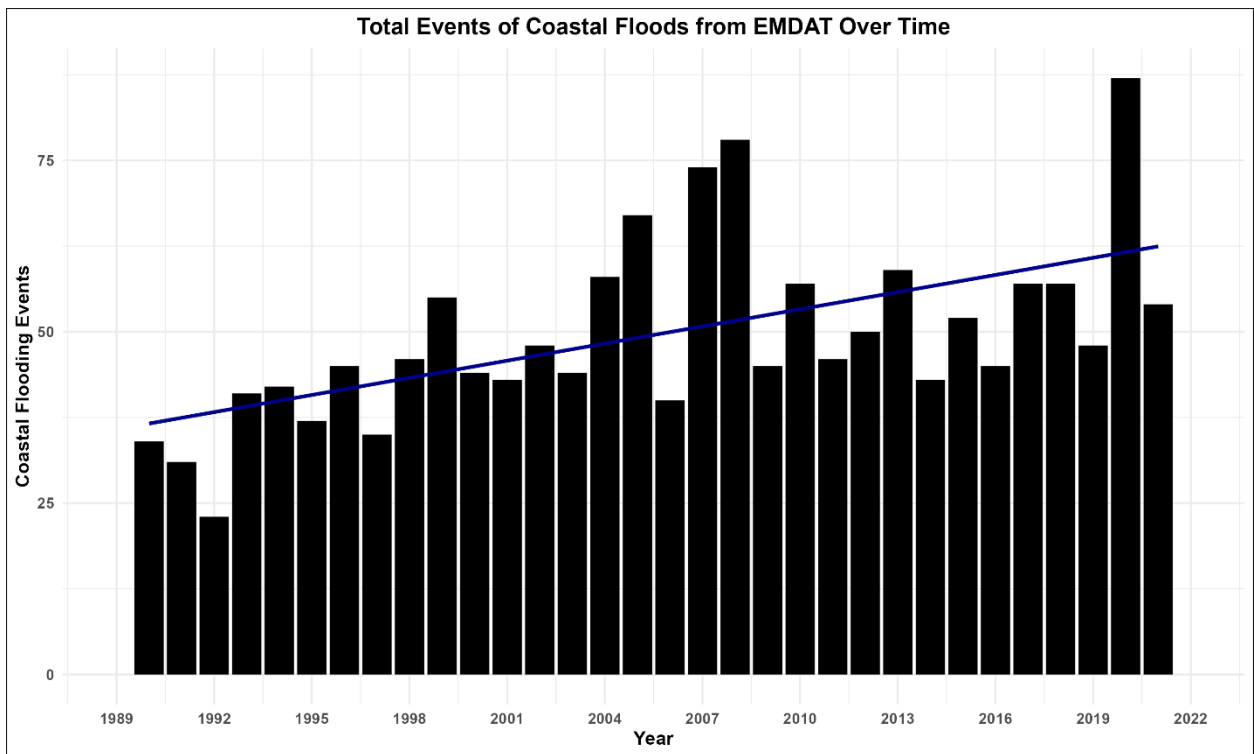
**Fig.S1.:** Comparative analysis of NOAA billion-dollar disaster and United States events in EM-DAT from 1990-2020. (40 events in EM-DAT and 46 Events in NOAA billion-dollar disaster, loess regression method is used in fitting the line with 95% confidence interval).



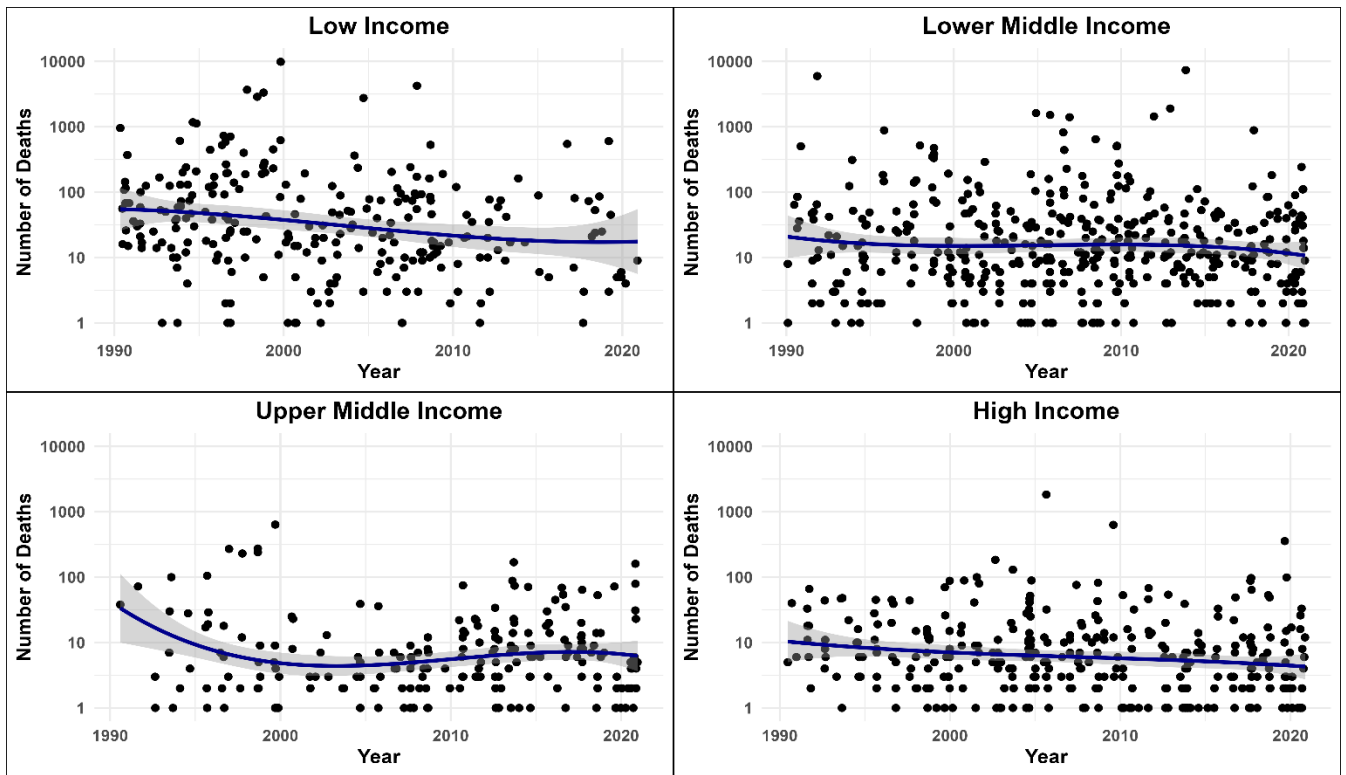
**Fig. S2.** Scatter Plot of Time Series Analysis of Annual Coastal Flooding Deaths from EM-DAT from 1286 coastal flooding events (1990-2020)



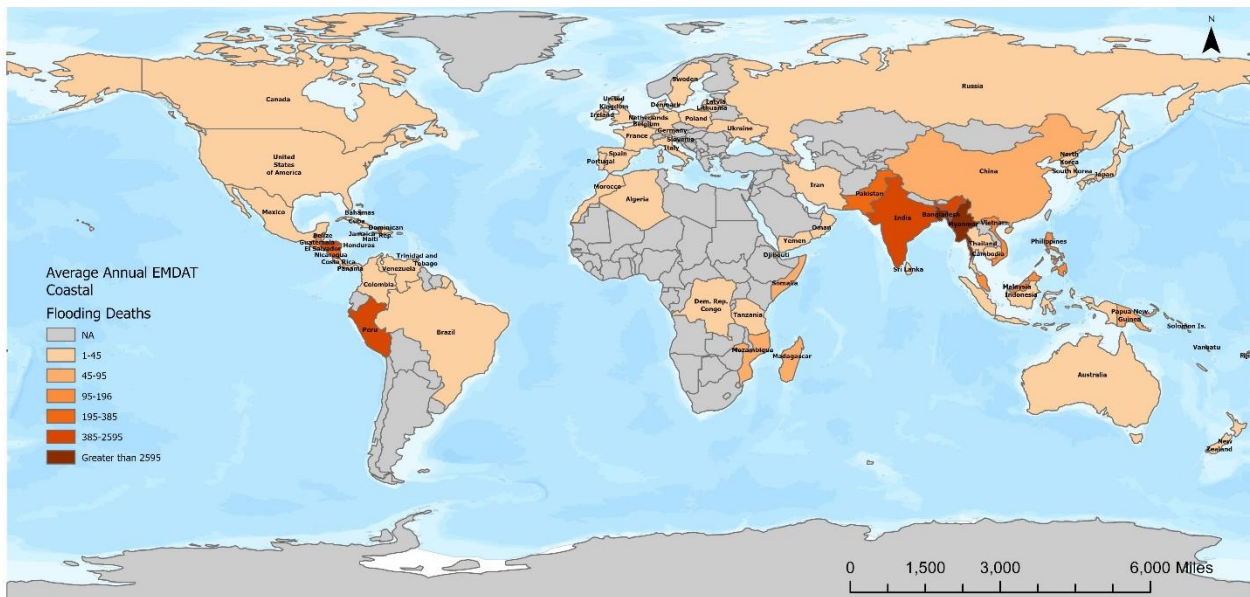
**Fig. S3.** Scatter Plot of Time Series Analysis of Population Affected by Coastal Flooding from SLIDERS (1990-2020)



**Fig. S4.** Total Annual Events of Coastal Floods from EM-DAT over time. (Coastal flooding events in EM-DAT are grouped by year )



**Fig. S5.** Scatter plot time series of coastal flooding deaths from EM-DAT for different income regions



**Fig S6.** Global Average Coastal Flooding Death estimated by averaging the death tolls of events per year based on country from EM-DAT

**Table S1 |Average used country level variables and predicted variable from model**

| Country Code | Events Counts | Deaths  | Exposed Population | Predicted Deaths | Predicted Mortality Rate (%) |
|--------------|---------------|---------|--------------------|------------------|------------------------------|
| ATG          | 5             | 1.40    | 1255.49            | 4.20             | 0.31                         |
| AUS          | 14            | 4.93    | 63195.19           | 2986.47          | 3.54                         |
| BEL          | 5             | 2.20    | 458994.39          | 30.37            | 0.01                         |
| BGD          | 42            | 3476.50 | 6586350.50         | 4813.34          | 0.07                         |
| BHS          | 10            | 40.90   | 8271.85            | 453.63           | 5.36                         |
| BLZ          | 5             | 12.60   | 3231.11            | 78.50            | 2.12                         |
| BRA          | 2             | 3.50    | 3709448.16         | 743.32           | 0.02                         |
| BRB          | 2             | 1.00    | 2677.38            | 8.37             | 0.26                         |
| CAN          | 3             | 1.67    | 93426.36           | 85.97            | 0.07                         |
| CHN          | 176           | 51.15   | 11733851.78        | 9697.02          | 0.08                         |
| COD          | 1             | 17.00   | 4466.94            | 67.59            | 1.51                         |
| COL          | 4             | 9.75    | 45120.13           | 384.71           | 0.67                         |
| COM          | 1             | 8.00    | 32137.50           | 258.78           | 0.81                         |
| CPV          | 1             | 9.00    | 9702.23            | 44.11            | 0.45                         |
| CRI          | 6             | 14.33   | 11949.82           | 678.42           | 3.76                         |
| CUB          | 15            | 5.67    | 39076.06           | 31.99            | 0.06                         |
| DEU          | 10            | 6.80    | 1062717.39         | 5284.29          | 0.45                         |
| DJI          | 1             | 2.00    | 43607.76           | 495.73           | 1.14                         |
| DMA          | 4             | 24.50   | 726.13             | 40.88            | 5.37                         |
| DNK          | 4             | 3.25    | 173440.69          | 11.85            | 0.01                         |
| DOM          | 22            | 28.32   | 13964.71           | 127.09           | 0.91                         |
| DZA          | 1             | 12.00   | 145.39             | 2.77             | 1.90                         |
| ESP          | 6             | 8.00    | 77634.64           | 175.80           | 0.11                         |
| FJI          | 20            | 8.70    | 10082.58           | 79.63            | 0.69                         |
| FRA          | 27            | 8.81    | 603743.18          | 1358.73          | 0.20                         |
| FSM          | 3             | 17.67   | 7012.62            | 53.71            | 0.76                         |
| GBR          | 17            | 5.59    | 3048820.22         | 9.51             | 0.00                         |
| GRD          | 1             | 39.00   | 1803.44            | 28.99            | 1.61                         |
| GTM          | 12            | 190.00  | 9094.83            | 350.20           | 3.36                         |
| HND          | 15            | 992.53  | 15614.52           | 817.04           | 4.02                         |
| HTI          | 29            | 195.90  | 53117.97           | 1072.02          | 2.23                         |
| IDN          | 1             | 11.00   | 11599594.55        | 3189.86          | 0.03                         |
| IND          | 51            | 386.96  | 5785306.88         | 25846.92         | 0.53                         |
| IRL          | 3             | 3.67    | 82520.73           | 21.18            | 0.02                         |
| IRN          | 1             | 12.00   | 354230.12          | 166.86           | 0.05                         |
| ITA          | 3             | 5.33    | 670387.29          | 41.31            | 0.01                         |
| JAM          | 13            | 4.69    | 13603.88           | 7.77             | 0.06                         |
| JPN          | 68            | 15.18   | 1048050.47         | 2073.67          | 0.18                         |
| KHM          | 4             | 22.00   | 55614.12           | 234.82           | 0.39                         |
| KNA          | 1             | 5.00    | 718.53             | 9.46             | 1.32                         |

|     |     |          |            |          |      |
|-----|-----|----------|------------|----------|------|
| KOR | 26  | 26.31    | 1520758.87 | 327.11   | 0.02 |
| LCA | 3   | 6.33     | 730.79     | 29.25    | 3.18 |
| LKA | 5   | 10.40    | 40303.95   | 17.15    | 0.05 |
| LTU | 1   | 2.00     | 11381.03   | 17.95    | 0.16 |
| LVA | 1   | 6.00     | 57564.05   | 105.90   | 0.18 |
| MAR | 1   | 1.00     | 174582.23  | 490.35   | 0.28 |
| MDG | 40  | 50.33    | 17956.93   | 394.43   | 3.04 |
| MEX | 75  | 30.97    | 51497.78   | 2184.45  | 4.57 |
| MMR | 5   | 27739.60 | 556772.36  | 13626.30 | 2.30 |
| MOZ | 15  | 71.33    | 129906.77  | 826.90   | 1.34 |
| MUS | 4   | 2.50     | 5774.93    | 40.26    | 0.68 |
| MYS | 2   | 136.00   | 115887.72  | 287.95   | 0.25 |
| NIC | 17  | 218.71   | 11932.27   | 270.40   | 2.24 |
| NLD | 6   | 3.67     | 4053458.82 | 47.87    | 0.00 |
| NZL | 3   | 7.00     | 127900.42  | 34.26    | 0.03 |
| OMN | 5   | 23.80    | 26594.93   | 289.59   | 1.49 |
| PAK | 4   | 276.25   | 4477.87    | 193.20   | 4.39 |
| PAN | 6   | 16.83    | 20370.19   | 225.45   | 0.64 |
| PER | 1   | 518.00   | 7424.80    | 160.10   | 2.16 |
| PHL | 186 | 157.04   | 750797.69  | 12714.23 | 1.85 |
| PNG | 3   | 73.00    | 39358.27   | 1532.56  | 3.79 |
| POL | 6   | 3.50     | 111586.12  | 14.74    | 0.01 |
| PRK | 8   | 29.38    | 853559.47  | 348.38   | 0.04 |
| PRT | 4   | 2.00     | 62566.91   | 14.43    | 0.02 |
| RUS | 6   | 7.83     | 590641.91  | 10747.43 | 1.91 |
| SLB | 3   | 20.33    | 27569.27   | 911.75   | 4.89 |
| SLV | 12  | 74.67    | 20785.53   | 219.62   | 1.00 |
| SOM | 5   | 52.00    | 46091.45   | 744.13   | 1.57 |
| SVN | 1   | 1.00     | 4923.32    | 1.81     | 0.04 |
| SWE | 4   | 4.50     | 127536.25  | 22.07    | 0.01 |
| THA | 20  | 21.15    | 2160837.96 | 12776.47 | 0.57 |
| TON | 2   | 1.00     | 4988.88    | 39.08    | 0.63 |
| TTO | 1   | 1.00     | 2871.01    | 6.24     | 0.22 |
| TZA | 1   | 4.00     | 176515.32  | 4098.59  | 2.32 |
| UKR | 1   | 11.00    | 247468.41  | 272.83   | 0.11 |
| USA | 89  | 36.21    | 2633081.75 | 4658.40  | 0.17 |
| VCT | 3   | 2.67     | 885.12     | 22.86    | 1.80 |
| VEN | 4   | 29.50    | 145237.05  | 59.01    | 0.04 |
| VNM | 81  | 99.86    | 2398793.11 | 8839.77  | 0.39 |
| VUT | 8   | 4.50     | 2816.78    | 81.73    | 2.67 |
| WSM | 5   | 8.60     | 1492.67    | 43.73    | 4.04 |
| YEM | 4   | 18.75    | 40703.53   | 483.87   | 1.11 |

*Note* "Country Code" refers to the three-digit ISO code of the country. "Event count" represents the total number of coastal flooding events that occurred from 1990 to 2020, as recorded in EM-DAT. "Deaths" indicates the average total deaths due to coastal flooding during the same period. "Exposed population"

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refers to the average administrative level 1 exposed population from SLIDERS corresponding to the respective coastal events for each country from 1990 to 2020. "Predicted Deaths" represents the predicted deaths from Model 3. "Predicted Mortality" is the average ratio of Predicted Deaths to the exposed population for each respective country from 1990 to 2020.