# A conceptual typology for the population impacts of sea level rise *

**Mathew E. Hauer*** *Florida State University*
**R. Dean Hardy** *University of Maryland*
**Scott Kulp** *Climate Central*
**Valerie Mueller** *Arizona State University*
**David Wrathall** *Oregon State University*
**Bryan Jones** *City University of New York*
**Robert Kopp** *Rutgers University*
**Beth Fussell** *Brown University*
**Michael Oppenheimer** *Princeton University*
**Aimee Slangen** *NIOZ Royal Netherlands Institute for Sea Research*
**Carling Hay** *Boston College University*
**Elisabeth Gilmore** *Clark University*
**Peter Clark** *Oregon State University*
**Maia Call** *University of Maryland*
**Nicholas Magliocca** *University of Alabama*
**Glenn Milne** *University of Ottawa*
**Alex de Sherbinin** *Columbia University*
**Helen Adams** *Kings College London*
**Don Chambers** *University of South Florida*
**Andrew Bell** *New York University*
**Joyce Chen** *Ohio State University*

---

This paper provides a conceptual framework for assessments of the impacts of sea level rise on populations. Population impact assessments of sea level rise are common in the literature and such assessments directly influence our understanding of the societal effects of climate change and sea level rise. However, these assessments typically limit population exposure to inundation areas only. Drawing on increasingly sophisticated flood modeling, we propose a new typology for understanding population exposure risk to sea level rise based on a spatial envelope probability of exposure to tidal flooding approach. The typology identifies three types of exposure risk: direct, indirect, and tertiary. Implications and effects of sea level rise on each exposure risk typology is then discussed. Using Chatham County, Georgia as an example, we find that current assessments could grossly underestimate both the spatial and temporal dimensions of the societal impacts of sea level rise. The typology can be used to guide new research, assist with impact assessments, evaluate policy options, and provide more robust and holistic scenarios of sea level rise.

---

*Corresponding author. mehauer@fsu.edu p: 850-542-9369.

*All data and code that supports these conclusions are available as supplementary materials.

## Introduction

The societal impacts of climate change and sea level rise (SLR) are of utmost importance in the 21st century and climate assessments are an integral part of adaptation and risk management[1]. Research has long sought to identify the impact of sea level rise on society[2,3], with an increasing focus on estimation of at-risk populations associated with sea level rise[2,4]. With 40% of the US population living in a NOAA designated coastal community[5] and over one billion people living in coastal areas around the world[6], questions on the societal impacts of sea level rise continue to be asked.

One of the primary components of a climate assessments of the impacts of sea level rise involves calculating at-risk populations. A wide variety of definitions of 'at-risk' populations have been utilized including the populations in lower-elevation coastal zones[6,7], populations under the mean higher high water (MHHW) mark[8,4], and populations in the 100-year flood plain[9,10,11,12]. All three approaches conceptualize at-risk populations as binary outcomes, ie populations are either at-risk or not at-risk, located within specific geographies defined through each approaches' characterization schema and share shortcomings related to an equality of risk, an equality of temporal exposure, and an equality of exposure. First, these approaches presume an equality of risk within each geography assuming a homogeneous risk profile across heterogeneous terrain. For instance, in a flood plain based approach, all populations in the 100-year flood plain are implicitly assumed to have equal flood risk, despite certain populations living in the 10-year or 20-year flood plain. Second, these approaches presume an equality of temporal exposure. For populations living within 0.9m of the current MHHW mark, those living within 0.1-0.2m of the MHHW mark will surely experience effects of sea level rise sooner than those living in the 0.8-0.9m mark. And lastly, these approaches presume an equality of exposure. For populations living in a lower-elevation coastal zone, some will be exposed to sea level rise and others won't be exposed to sea level rise but could be exposed to other associated hazards such as storm surges and other livelihood impacts. These shortcomings combine to create a gross oversimplification of the extent, timing, exposure, and ultimately adaptation options for coastal communities.

In this paper, we compare and contrast these three theoretical, binary approaches and suggest a unified typology for investigating exposure to sea level rise using a probability spatial envelope typology. We characterize exposed populations into three main categories: directly impacted, indirectly impacted, and tertiary impacted. These categories combine the strengths of all three previous approaches into a single unified framework. We then examine the implications for this novel framework within the context of **insert case studies in the US here**.

## Conceptual Models in the Literature

The way populations exposed or at-risk to sea level rise are conceptualized drives the societal impacts from SLR. Assessments using lower-elevation coastal zones, for instance, use generalized risk allocations that can frame climate adaptation discussions across the widest possible area. It is not just simply SLR, but rather a combination of SLR, recurrent tidal flooding, and elevated risk of disastrous storm surges that comprise the full range of effects associated with sea level rise. However, more explicit spatiotemporal linkages to localized SLR hazards is clearly warranted. Adaptation strategies for those currently living under 1.8m of elevation, the "high" scenario of sea level rise expected in the 21st century[13], are inherently different from those living above 1.8m of elevation but still within the LECZ. Appropriate accounting of type of exposure to the hazards of sea level rise would improve upon our current frameworks.

Recent tidal events in the Atlantic Coast of the United States and elsewhere[14,15,16] have demonstrated that the impacts of rising sea levels are advancing further and faster than those indicated by inundation models that assess impacts at mean higher high water (MHHW). The increased frequency and magnitude of tidal flooding in coastal communities can be considered as the immediate impact of sea level rise (SLR). Perigean spring tide events cause regularly recurring water levels well above MHHW, and in many parts of the coast this causes significant flooding, sometimes referred to as nuisance flooding or recurring tidal flooding[17], particularly when these tidal events are supported by significant onshore winds from tropical cyclones or storms. Mean higher high water does not mark the highest extent of regularly occurring tide waters as the tide range will naturally exceed this level approximately half of the time, as its name suggests. Assessments using impacts from changes in MHHW inadvertently turn a blind eye to the potential impacts of sea level rise on areas above the MHHW mark. However, property just above the MMHW mark will be regularly flooded long before it transitions below the MHHW mark, thus individuals and properties would not be counted as impacted, despite being regularly flooded by tides that exceed MHHW with added SLR. This is especially important in areas with large variations in their tidal datums.

A more broad approach involves utilizing either lower-elevation coastal zones or the 100-year flood plain to characterize the populations exposed to hazards from sea level rise[11,6]. In this way, populations within these geographies are framed as having equal risk regardless of their location within the LECZ or the 100-year flood plain. This approach has a side effect of equalizing the temporal horizon of hazards associated with sea level rise. By characterizing all populations in the LECZ or the 100-year flood plain as being at-risk to the hazards associated with sea level rise, regardless of either the extent of sea level rise or the timing of the rise. In other words, both lower elevation coastal zones and 100-year flood plain approaches render any coastal population as exposed to sea level rise in any time period. This has an unintended consequence of inflating sea level rise hazards as all coastal populations are effectively "exposed" to sea level rise and makes it difficult to decompose the effect of sea level rise on typical coastal hazards. Shoreline populations in areas with tropical cyclone activity are already exposed to storm surges, for instance, regardless of sea level rise. Which additional populations will be exposed to storm surges due to a higher base water level becomes increasingly difficult with a LECZ or 100-year flood plain approach.

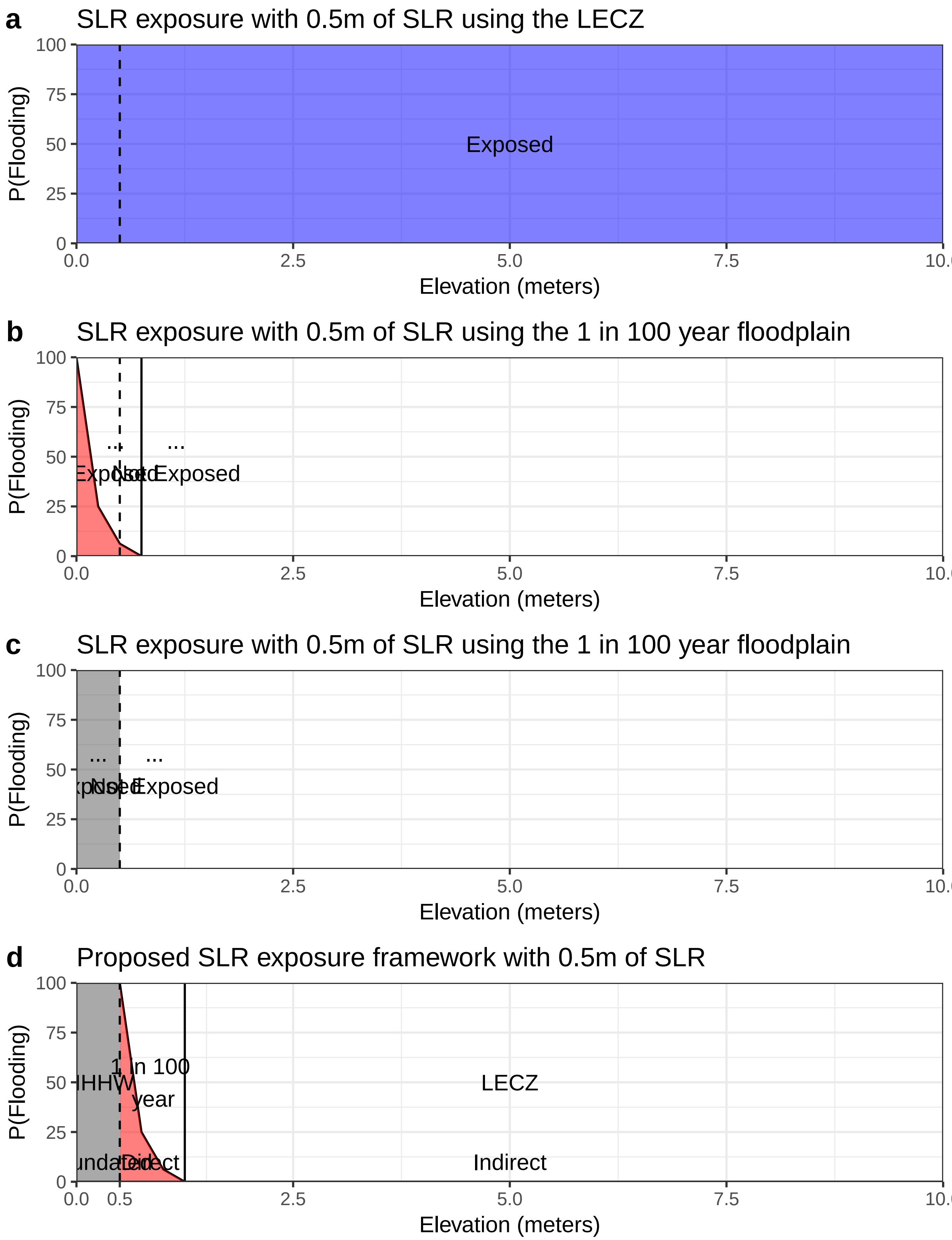


Figure 1: **SLR typology outline.** The vertical dashed line represents 0.5m of SLR, the solid vertical line represents the exposed population using a floodplain approach.

Figure 1 summarize the current conceptual models for examining the impacts of sea level rise. Panels a, b, and c in Figure 1 demonstrate conceptually who is at risk of SLR assuming 0.5m of SLR. Using a LECZ conceptualization (a), all persons within the LECZ are assumed to be exposed to SLR. Using the 1 in 100 year floodplain conceptualization (b), all persons below a given elevation are assumed to be at risk despite reduced flood risks at higher elevations. Using a MHHW conceptualization (c), only those persons who have exactly 100% probability of flooding are considered at risk.

**Add table 1 here showing typical studies and their approaches**

## A Unified Conceptual Model

When taken together, these three models capture all possible hazards associated with sea level rise but are plagued by issues on an individual conceptual basis. We propose a new model, unifying the MHHW, LECZ, and 100-year floodplain approaches into a more conceptually sound framework based on a spatial envelope, probability of exposure model. In a departure from the other three models' characterizations of at-risk and not at-risk, we characterize exposure to sea level rise as **inundated**, **direct**, and **indirect** based on a location's probability of flooding within spatial envelopes. A three tiered exposure approach allows for a pliable examination of both hazard exposure and adaptive options.

We characterize those who are **inundated** as those people living below the future MHHW mark. These are the populations who will be the most adversely affected, will experience impacts from sea level rise the soonest, and who are directly threatened by inundation if adaptive measures are not undertaken. Inundation exposure is analogous to the population's risk understood through the MHHW approach discussed above. Eventually, these populations will experience water levels above their elevation 50%+ of the time. These areas are typically discussed in conversations concerning managed retreats[18,19]. Such areas will be directly affected as soon as 2045 under some of the most aggressive sea level rise curves[20]; @[13].

We characterize those who are **directly** exposed to sea level rise as those people who are living above the future MHHW mark, but below the spatial extent of future flooding from sea level extremes or tidal flooding. These are the populations exposed to recurrent or nuisance flooding[21,16] and will experience water levels above their elevation less than 50% of the time. These areas are typically not discussed in the context of managed retreats, but are frequently discussed regarding adaptive measures such as elevating roads[22], coastal armoring[23], or other near-term adaptations.

Finally, we characterize those who are **indirectly** exposed to sea level rise as living in areas above both the MMHW mark and the extent of future tidal flooding, but in neighborhoods that are directly or semi-directly at risk to sea level rise. Here, we conceptualize the rest of the areas located in a LECZ or 100-year floodplain or other coastal geography. While these areas are not likely to see their properties exposed to elevated sea levels, the people in these areas will likely drive on flooded roads, go to workplaces in flooded areas, and could see their property values depressed[24].

Our framework bases SLR exposure on both flood exposure, expressed here as probability of flooding, and geographic location. We can also see the presence of indirectly impacted populations under current conditions (\autoref{figure1). Sea level rise is typically imagined as a hazard typified by long range time horizons up to 2,000 years into the future[4], but related impacts from sea level rise, specifically manifested as coastal flooding, are occurring today in parts of the Atlantic Coast of the United States and Venice, Italy, for instance.

## Methods and Materials

*Population projections*

**TO BE REWRITTEN. This is just stand in text**

We project populations in **our case study locations or the whole US** by producing spatio-temporally contiguous population estimates by using a modified Hammer Method[25,8] in a three-step process to produce estimates by census block groups (CBG) for the period

1940-2100. We first estimate historic housing units in CBGs for the period 1940-2010, we then rake these estimates using the Housing Unit Method to convert estimates of housing units to estimates of population, and finally we project the growth rates in CBGs, controlling output population totals to county-level projections produced by Hauer.

Equation 1 demonstrates the modified Hammer Method for estimating the number of housing units in CBGs.

$$\hat{H}_{ij}^{v} = \left( \frac{C_j^v}{\sum_{i=1}^{n} \sum_{t=1939}^{v-1} H_{ijt}^{v}} \right) \cdot \sum_{t=1939}^{v-1} H_{ijt}^{v} \tag{1}$$

where:

$C_j^v$ is the number of HUs in county $j$ counted in census taken in time $v$

$H_{ij}^v$ is the number of HUs in block group $i$ in county $j$ based on the "year structure built" question in the U.S. Census American Community Survey (ACS)

$v$ is the set of time periods $v \in \{1940, 1950, 1960, 1970, 1980, 1990, 2000, 2010\}$

Thus, to estimate the number of housing units in block group $i$ in county $j$ for the year 1970, for example, the number counted in county $j$ according to the 1970 census ($C_j^{1970}$) is divided by the number of HUs in county $j$, as estimated in the ACS, for the period 1939-1969 ($\sum_{i=1939}^{1969} H_j^{1970}$) and multiplied by the number of HUs estimated in the ACS in block group $i$ for the same period ($\sum_{i=1939}^{1969} H_{ij}^{1970}$). This is repeated for each decade until the most recent time period. These estimates of HUs for each CBG provide the key input needed to convert an estimate of HUs into an estimate of total population.

Data for historically estimating the housing units come from two main sources. First, the ACS 2008-2012 estimates provide the "year structure built" data as well as the 2010 boundaries for the CBGs. Second, the actual historical count of populations and housing units for each county come from digitized records available on the Census Bureau's website.[1]

[1] For 1940 to 1990, data can be found at http://www.census.gov/prod/cen1990/cph2/cph-2-1-1.pdf. Census 2000 data can be downloaded through American FactFinder.

To estimate the population at time $t$ ($P_t$), Equation 2 is applied to convert an estimate of HUs to an estimate of population.

$$P_t = H \cdot PPHU \tag{2}$$

Where $H$ is the number of housing units and $PPHU$ is the persons per housing unit. The two variables required to calculate the $PPHU$ are known only for each historical census at the county level, thus the $PPHU$ for each CBG must be estimated. Keeping in the same tradition as Hammer, we utilize the known variability in current decadal CBG geography for $PPHU$ to backcast $PPHU$ for prior decades based on this variability using a double-rake proportional fitting algorithm**?** . The first rake occurs by proportionally adjusting each CBG's $PPHU$ value and the second rake occurs by ensuring the sum of the CBG populations equal the county's historical count of population.

Equation 3 demonstrates the historical calculations of population for each CBG for any given time period.

$$P_{ij}^{\prime v} = \frac{P_j^v}{\sum\left[\left(\frac{PPHU_{ij}^{2010}}{PPHU_j^{2010}} \cdot PPHU_j^v\right) \cdot \hat{H}_{ij}^v\right]} \cdot \hat{P}_{ij}^v \tag{3}$$

The $PPHU$ in CBG $i$ in county $j$ in 2010 is denoted as $PPHU_{ij}^{2010}$ while the $PPHU$ observed in county $j$ in historical time $v$ is denoted as $PPHU_j^v$. The initial $PPHU$ estimate for each CBG is computed as the ratio of the PPHU in CBG $i$ in county $j$ in 2010 to the PPHU in county $j$ in 2010 multiplied by the observed PPHU in county $j$ in historical time period $v$. This initial estimate of historical PPHUs are then multiplied by the estimated number of Housing Units as estimated from Equation 1 ($\hat{H}_{ij}^v$) in historical time $v$ to create an initial estimate of population. These are then summed to the county level and proportionally adjusted based on the observed population of a county from historical time period $v$. By simply dividing the estimated population by the estimated number of housing units, we will generate $PPHU$ for any given time period ($P_{ij}^{\prime v}/\hat{H}_{ij}^v$). This provides us with variable $PPHU$

estimates for each CBG for each time period in any given county. This makes it possible to produce a historical time series of population and housing units at the CBG geography with consistent boundaries for a period of 1940-2010 and with unique $PPHU$ values for each time period.

To estimate the historical population in block group $i$ in county $j$ in time 1970, for example, one would first divide $PPHU_{ij}^{2010}$ by $PPHU_{j}^{2010}$ and then multiply by the PPHU in county $j$ in historical time $v$ ($PPHU_{j}^{1970}$). In essence, this creates a raked $PPHU$ value in historical time $v$. This raked $PPHU$ value is then multiplied by the output from the Equation 1 ($\hat{H}_{ij}^{1970}$), and summed to county $j$. This creates an estimated population in time $v$ that is raked a second time ($P_{j}^{1970}/\hat{P}_{j}^{1970}$) and multiplied by the estimated population in each member block group ($\hat{P}_{ij}^{1970}$).

*Limitations*

There are several limitations in using these approaches that we acknowledge. These limitations include (i) assumptions that the relative distribution of housing in each year-built period (ie, 1939-1970) represents the actual proportional allocation of housing in that period. For example, if block group $i$ contains 10% of the housing units built between 1939 and 1970 in county $j$, as observed in the ACS, Hammer's method assumes that block group contains 10% of the counted housing units from Census 1970. And (ii) the methods rely heavily on the accuracy of the reported age distribution (year structure built) of the housing stock. Errors due to misreporting or age heaping can significantly impact the results. Additionally, the method we ouline above relies on relatively low "churn" of the housing stock. Any homes that are destroyed and rebuilt will bias estimates toward more recently built structures.

Despite these limitations, previous research supports our methodological approach. First, regarding the appropriateness of proportional fitting to small-area demographic analysis – limitation (i) – scholars have successfully employed proportional fitting methods to sub-county and sub-county geographies with great success for a number of years[26] with Wong[27] even encouraging their use for small area geographic analysis. Evaluations of the errors associated with proportional fit estimates of Census Tracts and CBGs demonstrate consistently low errors[27,26,28,29] giving us confidence in the quality of our own sub-county proportionally fit historical estimates. The more recent evaluations of sub-county and sub-county proportional fitting utilize ACS data – the same data source we use – finding acceptably low errors. Second, regarding low "churn" of the housing stock – limitation (ii) – it is possible that the devestating hurricanes that hit the US over the past few decades could cause our estimates to be biased toward more recently built structures. However, the proportional fitting approach ensures that sub-county housing unit estimates always sum to the observed housing units in the historical period. Thus, only if the "churn" occurs in a significantly uneven geographic pattern should this be a concern. While this is possible, we believe it unlikely in light of the stability and accuracy of our out-of-sample validation.

*Flooding*

**SCOTT -> Can you fill in how you developed the flood plain approach?**

## RESULTS

**TO BE EDITED. This is a stand-in for our results section**

To demonstrate the differences in impacts under our proposed model compared to previous frameworks, we use an empirical example of Chatham County, Georgia (Figure 2). Chatham County is an ideal platform for demonstrating the various populations exposed to sea level rise in our conceptual model. It is a coastal county with a Census 2010 population of approximately 266,000, making it a medium-sized area, and it is typified by its coastal marsh ecosystem and very large astronomical tides. It has also been identified as having approximately 10% of its population at risk to sea level rise using a MHHW approach[8].

We use the National Oceanographic and Atmospheric Administration's (NOAA) sea level rise database that simulate expected changes in the mean higher high water (MHHW) mark

Table 1: My caption

| | |
|---|---|
| Inundated | $PR_j^s = P_j \ \cdot \ \frac{A_j^s}{A_j^0}$ |
| Directly | $PR_j^s = P_j \ \cdot \ \frac{A_j^{s+}}{A_j^0}$ |
| Indirectly | $\frac{A_j^{s+}}{A_j^0} > 0, \ Indirectly = P_j$ |

on areas that are hydrologically connected to coastal areas for the 0ft through 5ft datasets. These datasets does not take into account additional land loss caused by other natural factors such as erosion, subsidence, or future construction and NOAA provides these data "as is" without warranty to their performance. Land lost due to sea level rise is calculated with a spatial overlay workflow in ArcGIS 10.1 as one minus the percentage of land lost under the 0ft base layer of sea level rise, ie 1ft divided by 0ft, 2ft divided by 0ft, etc. The first step in the analysis was to utilize a base, 0ft Mean Higher High Water (MHHW) layer, which was derived from NOAA's 0ft scenario, and used as the initial condition to calculate a base of dry land area contained within the geographies of 2010 Census Block Groups. The resulting calculation is therefore a total area of dry land currently available for human habitation within each Census Block Group geography.

We used an area based approach to classify populations as inundated, directly, or indirectly impacted using Census Block Group geographies through the following sets of equations in Table X. All populations reported come from Census 2010.

Where the population at risk of being impacted ($PR_j^s$) under scenario $s$ in census block group $j$ is equal to the population ($P$) in census block group $j$ multiplied by the ratio of dry land area ($A_j^s$) in census block group $j$ under sea level rise scenario $s$ to the dry land area under 0ft of sea level rise ($A_j^0$). For indirectly and tertiary impacted areas, we use $s+$ to denote the dry land area under sea level rise scenario $s$ plus the highest astronomical tide. For Chatham County, this is roughly equivalent to approximately 2ft above the MHHW mark.

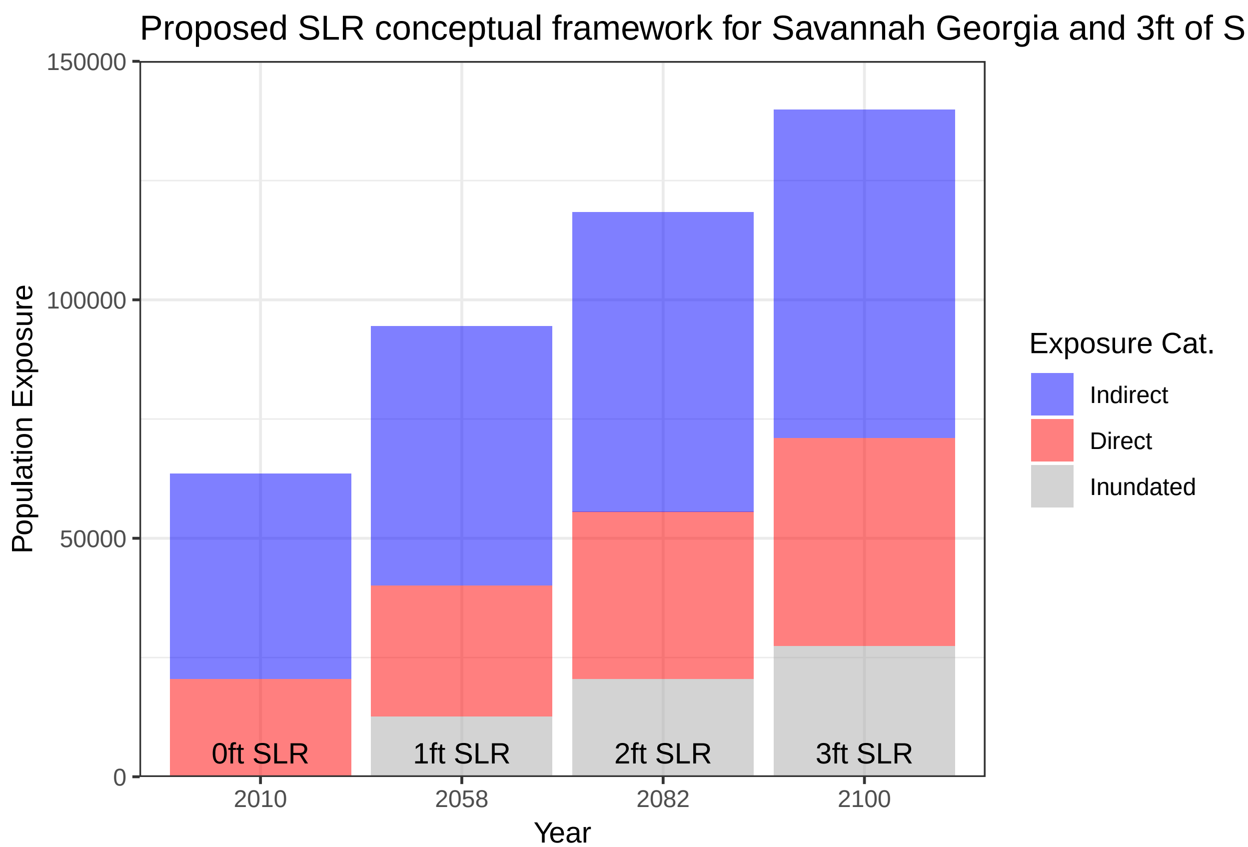


Figure 2: **Proposed SLR typology effect in Chatham County, GA** The vertical dashed line represents 0.5m of SLR, the solid vertical line represents the exposed population using a floodplain approach.

Figure 2 shows the results for all three at-risk classifications under current conditions (0ft) through 3ft of SLR. We can see that the narrowest interpretation of exposure to sea level rise (**inundated**), roughly corresponds to those who will be inundated by MHHW, represents the smallest exposed population. Approximately 12,000 people could be directly exposed with 1ft of SLR, growing to approximately 27,000 with 3ft of SLR. Those who could be exposed to coastal flooding, or **directly exposed**, currently sits at approximately 21,000 people under a 0ft, baseline sea level rise scenario representing current conditions. This nearly doubles to approximately 43,000 people with 3ft of SLR. Lastly, we see that those who live in neighborhoods that will experience flooding is currently approximately 63,000 but grows to nearly 140,000 with just 3ft of SLR.

## DISCUSSION

### *Relation to Adaptation*

**DAVID COULD YOU WRITE 3-4 paragraphs here? Conclusion to be written**

## References

1. Howden, M. and Jacobs, K. L. *Climatic change* **135**(1), 157–171 (2016).

2. Curtis, K. J. and Schneider, A. *Population and Environment* **33**(1), 28–54 (2011).

3. Wu, S.-Y., Yarnal, B., and Fisher, A. *Climate Research* **22**(3), 255–270 (2002).

4. Strauss, B. H., Kulp, S., and Levermann, A. *Proceedings of the National Academy of Sciences* **112**(44), 13508–13513 (2015).

5. Ache, B. W., Crossett, K. M., Pacheco, P. A., Adkins, J. E., and Wiley, P. C. *Estuaries and coasts* **38**(1), 151–155 (2015).

6. Neumann, B., Vafeidis, A. T., Zimmermann, J., and Nicholls, R. J. *PloS one* **10**(3), e0118571 (2015).

7. McGranahan, G., Balk, D., and Anderson, B. *Environment and urbanization* **19**(1), 17–37 (2007).

8. Hauer, M. E., Evans, J. M., and Mishra, D. R. *Nature Climate Change* **6**(7), 691 (2016).

9. Nicholls, R. J. and Cazenave, A. *science* **328**(5985), 1517–1520 (2010).

10. Brown, S., Nicholls, R., Goodwin, P., Haigh, I., Lincke, D., Vafeidis, A., and Hinkel, J. *Earth's Future* .

11. Hallegatte, S., Ranger, N., Mestre, O., Dumas, P., Corfee-Morlot, J., Herweijer, C., and Wood, R. M. *Climatic change* **104**(1), 113–137 (2011).

12. Heberger, M., Cooley, H., Herrera, P., Gleick, P. H., and Moore, E. *Climatic Change* **109**(1), 229–249 (2011).

13. Sweet, W. V., Kopp, R. E., Weaver, C. P., Obeysekera, J., Horton, R. M., Thieler, E. R., and Zervas, C. (2017).

14. Carbognin, L., Teatini, P., Tomasin, A., and Tosi, L. *Climate Dynamics* **35**(6), 1039–1047 (2010).

15. Spanger-Siegfried, E., Fitzpatrick, M., and Dahl, K. (2014).

16. Dahl, K. A., Fitzpatrick, M. F., and Spanger-Siegfried, E. *PloS one* **12**(2), e0170949 (2017).

17. Fennessey, L. A., Hamlett, J. M., Aron, G., and LaSota, D. *Journal of Hydrologic Engineering* **6**(4), 317–327 (2001).

18. Huntington, H. P., Goodstein, E., and Euskirchen, E. *Ambio* **41**(1), 66–74 (2012).

19. Hino, M., Field, C. B., and Mach, K. J. *Nature Climate Change* **7**(5), 364 (2017).

20. DeConto, R. M. and Pollard, D. *Nature* **531**(7596), 591 (2016).

21. Chang, H., Lafrenz, M., Jung, I.-W., Figliozzi, M., Platman, D., and Pederson, C. *Annals of the Association of American Geographers* **100**(4), 938–952 (2010).

22. Titus, J. G., Hudgens, D. E., Trescott, D. L., Craghan, M., Nuckols, W. H., Hershner, C. H., Kassakian, J., Linn, C. J., Merritt, P. G., McCue, T., et al. *Environmental Research Letters* **4**(4), 044008 (2009).

23. Jin, D., Hoagland, P., Au, D. K., and Qiu, J. *Ocean & Coastal Management* **114**, 185–193 (2015).

24. Neumann, J. E., Emanuel, K., Ravela, S., Ludwig, L., Kirshen, P., Bosma, K., and Martinich, J. *Climatic Change* **129**(1-2), 337–349 (2015).

25. Hammer, R. B., Stewart, S. I., Winkler, R. L., Radeloff, V. C., and Voss, P. R. *Landscape and Urban Planning* **69**(2), 183–199 (2004).

26. Beckman, R. J., Baggerly, K. A., and McKay, M. D. *Transportation Research Part A: Policy and Practice* **30**(6), 415–429 (1996).

27. Wong, D. W. *The Professional Geographer* **44**(3), 340–348 (1992).

28. Choupani, A.-A. and Mamdoohi, A. R. *Transportation Research Procedia* **17**, 223–233 (2016).

29. Rose, A. N. and Nagle, N. N. *Computers, Environment and Urban Systems* **63**, 38–49 (2017).