Coastal Impact and Adaptation Model (CIAM) Documentation[†]

1 Overview

The Coastal Impact and Adaptation Model (CIAM) is an optimization model that combines global scope with high spatial resolution to assess coastal impacts from sea level rise (SLR). CIAM's novel approach determines the least-cost adaptation strategy of over 12,000 coastal segments in the DIVA database (Vafeidis et al, 2008), and the model offers new estimates of the direct economic costs of SLR from the perspective of economic efficiency that complement the existing literature. These estimates can be flexibly aggregated at the city, country, regional, and global level. The motivation for this global scope is to inform the magnitude and sensitivity of potential coastal impacts, a major factor for decision-making and design of climate policy.

CIAM assesses coastal impacts by disaggregating the adaptation decision to the independent segment planner who chooses a public adaptation strategy based on local socioeconomic characteristics and the potential impacts of local SLR and uncertain storm surge damages. The objective of each coastal segment, as expressed in Equation 1, is to minimize the sum of adaptation costs (either protection or retreat) plus residual damages due to land inundation, wetland loss, and expected flood costs.[1] Adaptation strategies are evaluated according to the cost minimization problem

$$\min_{s} \sum_{t\in\Delta t} \Bigg(\frac{1}{(1+r)^t} \; (\text{ProtectionCost}_{s,t} + \text{RetreatCost}_{s,t} + \text{InundationCost}_{s,t} + \text{WetlandCost}_{s,t} + \text{FloodCost}_{s,t}) \Bigg) \tag{1}$$

where Δt is the decision-making planning period of annual time-steps t, r is the discount rate of 4%, and s is the adaptation strategy (i.e., protect, retreat, or do nothing and the extent, since extra adaptation can be pursued to minimize the expected cost of flood impacts). CIAM makes the simplifying assumption that the near-term extent of local SLR is known with perfect foresight for a given climate scenario.[2] Adaptation investments are made incrementally and modularly, and the chosen strategy is updated over time following an iterative process depicted in Figure 1(a).[3]

These strategies can be summarized diagrammatically. Figure 1(b) shows the counterfactual baseline case of no climate-driven SLR, against which all climate scenarios will be compared. Figures 1(c-e) show the cases corresponding to the three adaptation strategies: no adaptation, retreat, and protect.[4]

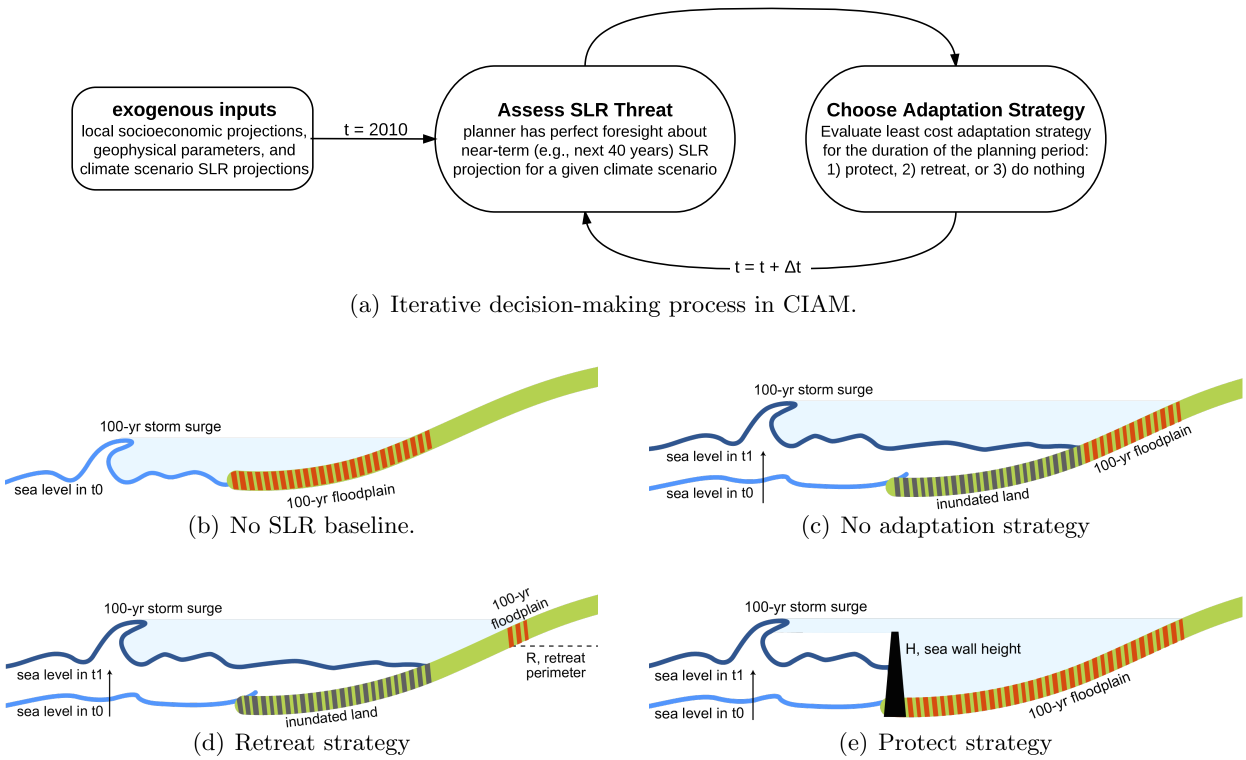
[†]Delavane B. Diaz, Department of Management Science and Engineering, Stanford University, Stanford, CA 94305; Phone: 650-646-5448; Email: delavane@stanford.edu.

[1]CIAM models public adaptation and assumes the entire coastal segment acts in unison (as if it was enforced by policy), rather than account for heterogeneity in adaptation strategy (e.g., sorting behavior). Furthermore, the decision of one segment is assumed to have no bearing on neighboring segments.

[2]The relatively smooth, incremental rise due to thermal inertia allows this simplified construction of SLR 'learning', whereas other climate changes are likely to be more abrupt or difficult to detect (e.g., thermohaline circulation Keller et al, 2008).

[3]The adaptation planning period (Δt) is assumed to be 40 years; however, I conduct a sensitivity analysis of 100 years given major coastal defense structures may be planned for a longer duration.

[4]In reality, a much broader set of adaptation measures will be deployed in response to SLR, including intermediate



(a) Iterative decision-making process in CIAM.

(b) No SLR baseline.

(c) No adaptation strategy.

(d) Retreat strategy.

(e) Protect strategy.

Figure 1: Diagrams of CIAM algorithm and adaptation strategies. (a) Each segment follows an iterative decision-making process, choosing the least-cost adaptation strategy for the current planning period; this process repeats over the model time horizon. (b) No SLR. Baseline floodplain for an illustrative 100-year extreme sea level height (shown in red); this may drive some initial level of adaptation prior to SLR. (c) No adaptation. SLR causes incremental loss of inundated land (shown in gray), incurring reactive retreat costs. The new 100-year floodplain exposes new land depending on the coastal topography. This may be the least-cost strategy in some undeveloped areas. (d) Retreat. SLR causes the loss of inundated land and incurs planned relocation costs below the retreat perimeter R. Expected flood damage is limited to extremes that penetrate the retreat perimeter (e.g., $\geq R$). (e) Protect. Land is protected from SLR damages by the sea wall with height H. In addition to protection costs, overtopping extremes (e.g., $\geq H$) incur an expected flood cost. The impact of SLR on wetlands is not depicted in the diagram.

1.1 CIAM parameters and cost functions

Here I describe the geophysical and socioeconomic parameters that determine the potential magnitude of coastal impacts and adaptation costs.

The unit of analysis in CIAM is the individual coastal segment, as described by the DIVA database, which partitions the world's coasts into 12,148 distinct segments of similar physical characteristics, with a median length of 18 km.[5] The DIVA parameters used in CIAM are coastline

steps like accommodation as well as hybrid approaches. However, this analysis only considers the three benchmark cases of no adaptation, retreat, and protect.

[5]Descriptions of the database and the integrated model can be found in Hinkel and Klein (2009); Vafeidis et al (2008). The CIAM framework presented here has been independently developed based on the DIVA database v1.5.5 (DINAS COAST Consortium, 2006), using a copy obtained while the database was publicly-released. The database is no longer supported and subsequent versions (e.g., v1.8) have not been made public.

length, inundation surface area by elevation, storm surge frequencies, wetland extent, and initial population density for each segment. I integrate a variety of additional socioeconomic characteristics described below in order to evaluate adaptation costs and residual damages. With the exception of initial population density, the DIVA database does not provide the socioeconomic characteristics that are needed to evaluate adaptation costs and residual damages in CIAM. I integrate a variety of additional data sources, described in Table SM 1 and depicted in Figure SM 2.

Table 1: Data sources for model inputs.

Data	**Source**
Coastal segment physical attributes	DIVA database v1.5.5 (Vafeidis et al, 2008)
Population and income projections	UN (2012); IMF (2011); Penn World Table (2011)
Global protection cost	Hillen et al (2010)
Construction cost index	World Bank International Comparison Program (2011)
Land value	FUND (Anthoff and Tol, 2014);
	GTAP v8.1 (Baldos and Hertel, 2012)
Wetland value	Brander et al (2006)

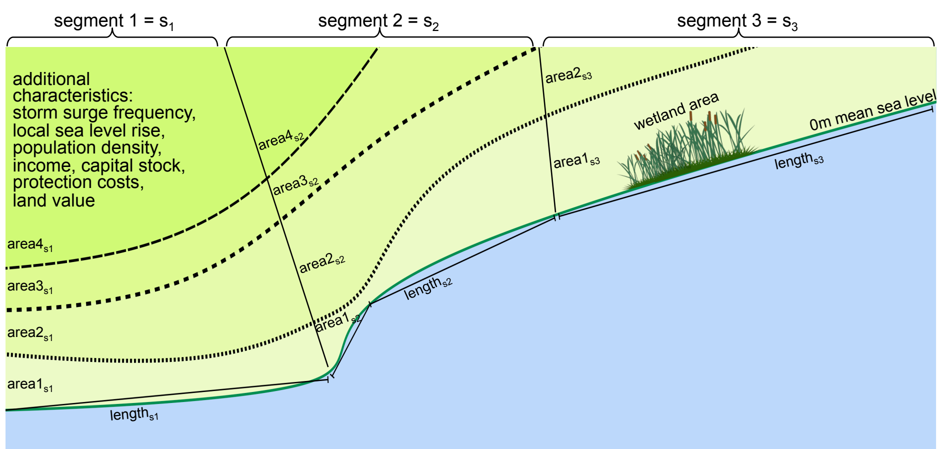


Figure 2: Diagram of three illustrative coastline segments, annotated with inundation zone areas (i.e., areaN = the area between N and N-1 m of elevation (sq km), where N denotes the elevation in meters) and segment coastline length. Additional characteristics include storm surge frequency, population density, income, capital stock, land value, and protection costs and are assumed to be uniform throughout the segment.

I now describe these parameters in more detail, grouped by their role in determining the coastal impacts, residual damages, and adaptation costs for each coastal segment.

Inundation zones The DIVA database provides the inundation zones, defined in 1 m increments of vertical elevation, for each coastal segment. The land surface area of inundation zones is based on the Global Land One-kilometer Base Elevation (GLOBE) data set, a gridded, global Digital Elevation Model (DEM) with 30 arc-second (1 km) resolution. Zones were computed within DIVA using ArcInfo geographic information system (GIS) assuming that inundation occurs if elevation is below the projected sea level rise. CIAM computes inundation surface area as the piece-wise linear interpolation between 1 m increments of vertical elevation e, hereafter indicated by the area operator $area(e)$.

Population and income CIAM projects coastal population density and income growth over time.

National population growth rate projections to 2100 are based on the United Nations World Population Prospects (2012). These growth rates are applied to the initial population density for a country's coastal segment as reported in DIVA, which is based on the Gridded Population of the World (GPW) version 2 dataset (1995). CIAM's assumption of the country-level growth rate may underestimate future population levels because developed coastal areas often exhibit faster growth; however, it is not clear whether or not this trend will continue given the threat of SLR, so the national average is a reasonable assumption.

National income levels are based on Penn World Table (2011) with IMF World Economic Outlook (2011) projections to 2100. Some per capita income levels within a country are modestly adjusted to reflect the fact that highly urban coastal areas are likely to have elevated income levels relative to those areas with the national average coastal population density. Specifically, CIAM assumes that income per capita increases in population density (σ_L):

$$ypc_{t,seg} = ypc_{t,country} \max\left\{1, \left(\frac{\sigma_{Lt,seg}}{\overline{\sigma_L}}\right)^{0.05}\right\} \tag{2}$$

where $\overline{\sigma_L}$ is the division between rural and urban population density at 250 people per square kilometer. The elasticity of 0.05 is based on the regression of Lagerlöf and Basher (2006). The majority of segments are assigned a scaling factor of 1 or 1.1, with the highest factor being 1.25 for the top 1% of densely populated cities.

Population and income density are assumed to be uniform within the segment. The current analysis does not consider alternative socioeconomic projections, although Hinkel et al (2014) have shown such drivers can have a bearing on coastal impacts over time.

Capital stocks Local capital stocks are estimated using a capital-output ratio to overcome the lack of geospatial data on capital. Capital-output ratios tend to be in the range of 2.5–5, and CIAM assumes a value of 3.[6] This accommodates the fact that capital stocks will grow over time based on the potential investment available. Thus, capital density for each segment is given $\sigma_{Kt} = 3\ ypc_t\ \sigma_{Lt}$ and is assumed to be uniform within the segment. Although capital formation and production functions may change in a warming world, and these shifts would have significant implications for impact assessments, this is beyond the scope of this analysis.

Adaptation cost: Protection CIAM assumes a reference cost of constructing generic coastal protection, generalized as a sea wall, regardless of the specific defense installed (e.g., dike, revetment,

[6] Nordhaus (2010) uses a value of 3.67 in the G-Econ dataset and notes "nominal national capital output ratios have changed little over the 1929-2004 period".

floodgate, etc.) or whether soft measures (e.g., beach nourishment) would better suit the location.

The reference cost is based on the average cost for dikes and sea walls reported in a review of international coastal adaptation costs by Hillen et al (2010). This gives a reference cost of \$6.02 million per kilometer of coastline per vertical meter of protection. Because construction costs are likely to vary by region, the reference cost is adjusted in CIAM with a national construction cost index that accounts for differences in the cost and availability of construction materials and labor for civil engineering construction projects (World Bank International Comparison Program, 2011). These costs are held constant over time, in absence of better information – increased global demand for concrete and rising wages in developing countries could cause costs to increase over time, while innovation could drive down protection costs.

Protection construction costs are assumed to be linear in coastline length l and quadratic in sea wall height H, the latter reflecting the fact that higher protection requires proportionally more structural foundation:

$$\text{ConstructionCost}_t = l \cdot pc \cdot ({H_t}^2 + mcH_t) \tag{3}$$

where pc is the country-specific protection construction cost and mc is the annual average maintenance cost, reported by Hillen et al as 2% of the baseline cost.

In addition to the cost of constructing the protection, there is an opportunity cost to the land occupied by the dike given by the current land value lv_t. CIAM assumes a 60° slope on each side of the dike, which implies that the dike width is 1.7 times the height. Thus, the total costs of protection are

$$\text{ProtectionCost}_t = \text{ConstructionCost}_t + l \cdot lv_t \cdot 1.7H_t \tag{4}$$

CIAM makes the simplifying assumption that all protection is constructed to be 100% reliable and without delay. In addition to omitting potential damages resulting from this residual vulnerability, protection may have negative externalities such as inhibiting public shore access and increased erosion (Kriesel and Friedman, 2003; Nicholls, 2011); these costs are not accounted for in the current model.

It is possible that protection costs may decline over time due to innovation as the world responds to the threat of rising seas. In this way, coastal protection would benefit from 'learning-by-doing', the process by which accumulated experience brings about incremental improvements to production methods, allowing firms to lower costs (Arrow, 1962). Nemet (2006) represents this relationship in the learning curve equation

$$C_t = C_0 \left(\frac{q_t}{q_0}\right)^{-b} \text{ where } LR = 1 - 2^{-b} \tag{5}$$

where C is the technology cost in year 0 or t, q is cumulative output quantity in year 0 or t, b is the learning coefficient, and LR is the learning rate. For example, a modest learning rate of 5% would reflect the mature nature of most coastal protection, and protection costs would be reduced by 5% with each doubling of protection installed. This feature is not used in the current analysis; CIAM assumes no learning rate for protection costs.

Adaptation cost: Retreat There are two costs incurred with the decision to retreat incrementally to a perimeter R_t from R_{t-1}, where R is the level of retreat in terms of vertical elevation e. One is the damage cost from inundation, the permanent loss of land and immobile capital; these costs will be discussed in the next heading.

The other is the adaptation cost associated with redeveloping and relocating the affected people and infrastructure further inland. The adaptation cost of retreat is a function of the affected mobile capital K and population L:

$$\text{RetreatCost}_t = \theta_L^{retreat}\ \sigma_{Lt}\ area(R_t - R_{t-1}) + (\theta_K^{retreat} + dc)\ \sigma_{Kt}\ area(R_t - R_{t-1}) \qquad (6)$$

where $\theta_L^{retreat}$ and $\theta_K^{retreat}$ are the cost coefficients of retreat per unit of population and mobile capital (applying a stylized assumption that one-fourth of the capital stock is mobile), respectively, and the quantity of affected L and K depend on the density σ of each and the incremental area of retreat.

The cost coefficient $\theta_L^{retreat}$ is intended to reflect observed domestic migration costs. CIAM applies a value of 1, opting for a middle ground between 3, used in the FUND model (Anthoff and Tol, 2014), and 0.5 (R. Mendelsohn, personal communication). $\theta_K^{retreat}$ is assumed to be one-tenth of the asset value of mobile capital. Additionally, there is a demolition cost dc for abandoned immobile capital, arbitrarily assumed to be 5% of its value. Finally, a reactive retreat in the case of a do nothing strategy (No Adaptation) is assumed to be five times as costly due to the lack of advance planning. It should be emphasized that many parameters lack an empirical basis and the choices made here are speculative. These assumptions can be adjusted by interested users. Furthermore, these factors indicate areas where additional research is needed.

CIAM treats each coastal segment as a single low-lying zone. When people or capital relocate, they do so to the outer extent of the development and are assumed to be out of harm's way with full productivity. Although a detailed treatment of capital is essential to any local assessment of coastal impacts, the requisite geospatial capital stock data are not available on a global basis. Thus, capital dynamics are beyond the scope of this model.

Damage cost: Inundation Unprotected land will be incrementally inundated by rising seas. These damage costs are based on the extent of land endowment lost and national land values. Moreover, immobile capital (e.g., infrastructure and transportation networks, assumed to be 75% of the total capital stock) will be abandoned upon inundation. Sufficient foresight about inundation can avoid real capital losses, so damages depend on the type of adaptation. If retreat is planned in advance, true economic depreciation is the efficient market response: affected fixed capital assets will be fully depreciated by the time of retreat (see Yohe et al, 1995).

Accordingly, CIAM assumes that with advance notice of SLR and the decision to make a planned retreat, coastal structures will be depreciated over the IRS structure lifetime of 30 years such that at the point that land is lost, the capital has no value. In contrast, the No Adaptation strategy assumes no advance notice of SLR, so the entire asset value is lost in a reactive retreat.

Damage costs from inundation are incurred when local SLR $lslr$ exceeds the current level of adaptation:

$$\text{InundationCost}_t = lv_t\, area(\cdot) + (1-\delta)\, \sigma_{K\,t}\, area(\cdot) \tag{7}$$

$$\text{where } area(\cdot) = \begin{cases} area(lslr_t) - area(lslr_{t-1}) & \text{if No Adaptation} \\ area(lslr_t) - area(R_{t-1}) & \text{if Retreat} \\ 0 & \text{if Protect} \end{cases}$$

and where lv_t is the current interior land value, the affected capital stock is given by the density σ_K times the exposed area, and the period depreciation rate δ can be between 1 or 0, denoting full or no advance depreciation, respectively.

The value of the coastal land endowment lost to inundation corresponds to the value of interior land, as argued in Yohe (1989).[7] Interior national land value is derived from average rents for agricultural land from Global Trade Analysis Project (GTAP) (Baldos and Hertel, 2012). An alternate assumption about interior land values is based on the current FUND model, which derives national land values relative to the average OECD land value depending on income density (Anthoff and Tol, 2014). FUND land values tend to be an order of magnitude higher than the GTAP values; the importance of this assumption is explored as a sensitivity analysis. Land values are assumed to appreciate over time, depending on demand and willingness to pay. Because it is unclear how land values and their appreciation patterns will change in response to the SLR threat, no major change to property value appreciation is assumed. CIAM follows the regression undertaken by Abraham and Hendershott (Yohe et al, 1999), such that land values rise as a function of growth in income and population density, with elasticities of 0.5 and 0.03 respectively.

Damage cost: Wetland loss DIVA reports total wetland area within a coastal segment, given by the combined extent of wetlands, based on a global survey of 4,315 wetland sites (Hoozemans, 1993), and mangroves, based on the World Mangrove Atlas (Spalding, 1997). Of the 12,148 coastal segments in DIVA, 3,119 of them have wetland area. Wetlands have the ability to migrate naturally inland if space is available, although the potential for such wetland accretion is limited by the rate of SLR.

CIAM applies a simple, rate-based rule to determine the impact to wetlands of SLR. This current treatment stands to be improved to account for key factors related to tidal range, sediment supply, wetland sensitivity, and migration space (as done with DIVA in McFadden et al, 2007). In the absence of greater representation of wetland characteristics and physical processes, CIAM assumes a generalized wetland type with suspended sediment concentrations above 20 mg/L and tidal ranges over 1m that can tolerate up to 10 mm of SLR per year (Kirwan et al, 2010).[8]

However, if a coastal segment chooses to protect, all wetland services are lost due to coastal squeeze, as the coastal protection consumes the available migration space (McFadden et al, 2007).

[7] Early analyses of coastal impacts assumed that the value of inundated land was equal to the value of the coastal land that was physically lost to inundation. As hedonic property studies consistently show that coastal land is valued higher than the average due to water-related amenities (Earnhart, 2001; Kriesel and Friedman, 2003), this approach led to higher overall inundation costs.

[8] Kirwan et al (2010) report that these sediment and tidal conditions are typical of many estuaries in western Europe and the southeastern United States.

Thus, annual wetland costs are given

$$\text{WetlandCost}_t = \begin{cases} wv_t \cdot area(\cdot) \left(\frac{\frac{\mathrm{d}SLR}{\mathrm{d}t}}{\lambda_{cr}} \right)^2 & \text{if Retreat or No Adaptation and } \frac{\mathrm{d}SLR}{\mathrm{d}t} < \lambda_{cr} \\ wv_t \cdot area(\cdot) & \text{if Protect or } \frac{\mathrm{d}SLR}{\mathrm{d}t} \geq \lambda_{cr} \end{cases} \tag{8}$$

$$\text{where } area(\cdot) = \min \{ area(lslr_t),\ \text{wetland extent} \}$$

and where wv_t is the annual value of wetland services, $\frac{\mathrm{d}SLR}{\mathrm{d}t}$ is the rate of SLR in m per year, and λ_{cr} is the critical threshold of wetland migration of 0.01.

Wetland value is based on the annual value of ecosystem services, calibrated to the meta-analysis of Brander et al (2006). This formulation assumes that wetland value increases as a function of growth in income and population density, with elasticities of 1.16 and 0.47 respectively.

Damage cost: Flooding DIVA reports the 1, 10, 100, and 1000-year and maximum surge height, calculated from tidal level data, barometric pressure, wind speeds, and sea bed slopes as described in Vafeidis et al (2008). The frequency of local sea level extremes is approximated by a generalized extreme value (GEV) distribution (as in Lempert et al, 2012). I use this local surge frequency data from DIVA in order to calibrate a probability density function to represent uncertain sea level extremes as a random variable s. The probability density function of the GEV distribution is

$$f(s) = \frac{1}{\sigma} t(s)^{\xi+1} \mathrm{e}^{-t(s)}, \text{ where } t(s) = \left(1 + \left(\frac{s-\mu}{\sigma} \right) \xi \right)^{\frac{-1}{\xi}} \tag{9}$$

GEV parameters σ, ξ, and μ are calibrated for each of the 12,148 segments by fitting the nonlinear cumulative distribution function to the surge frequencies.

CIAM estimates flood costs based on the expected damage given uncertain sea level extremes s, $\mathbb{E}[\text{Damage}(s)]$, which can be thought of as the actuarially fair cost of insurance. This is computed as the integral over all possible sea level extremes s (i.e., exceeding the current adaptation level A and up to s_{max}, the maximum for a given segment), multiplying the probability density $f(s)$ of a given height, times the resulting damage from extreme sea level s:

$$\mathbb{E}[\text{Damage}(s)] = \int_A^{s_{max}} f(s) \text{Damage}(s) \mathrm{d}s \tag{10}$$

Flood damage for extreme sea level s is given

$$\text{Damage}(s) = (1-\rho) \int_{e_{min}}^{lslr+s} area'(e) \cdot (\sigma_K \ \phi(h(e)) + \sigma_L \ \mu \ VSL) \ \mathrm{d}e \tag{11}$$

Conceptually, the total land affected by extreme sea level s can be discretized into vertical sections of elevation e exposed to a given flood water height h, and for each location the loss of affected capital stocks and people can be computed. Specifically, for a given elevation, the damage to capital stocks is calculated by multiplying the exposed area by the capital density σ_K scaled by the flood depth-damage function $\phi(h)$; the damage to people is calculated by multiplying the exposed area by the population density σ_L scaled by a flood mortality factor μ of 0.01 (Jonkman and Vrijling, 2008) times the national value of statistical life, VSL.

Thus, total damage is computed by integrating the continuous equivalent (i.e., Equation 11) over the exposed landform from a lower bound elevation of e_{min} (which depends on the adaptation decision as given in Equation 12) to the upper bound of $lslr + s$, and then adjusted based on a national resilience index ρ. These terms will be explained in turn. $area(e)$ gives the total land area lying below elevation e.

The flood depth-damage function for capital damage $\phi(h) = \frac{h}{1+h}$ is a logistic function increasing in the location's flood water height h, and follows from Hinkel et al (2014). Note that the flood water height h at a given location can be written in terms of the total extent of local SLR and sea level extreme less the location's elevation, according to the definitional identity $h = lslr + s - e$.

National VSL is linked to the current US government value of \$9.1M,[9] and varies by country and over time with a per capita income elasticity of 0.5 following Viscusi and Aldy (2003).

Importantly, the extent of flood exposure depends the type of adaptation chosen: a protect strategy floods the entire area trapped behind the sea wall, while a retreat strategy exposes much less settled land to the surge. Thus, e_{min} gives the lower bound of exposure in terms of elevation:

$$e_{min} = \begin{cases} 0 & \text{if Protect} \\ R_t & \text{if Retreat} \\ lslr & \text{if No Adaptation} \end{cases} \tag{12}$$

Finally, estimated damages are adjusted based on a national resilience index, where $\rho = \frac{ypc}{ypc_{2010,USA}+ypc}$, a logistic function increasing in national per capita income ypc to reflect resilience from safety measures and building codes (Fankhauser and McDermott, 2014), and defined such that a factor of 0.5 corresponds to current US income levels.

The present study assumes stationarity in the distribution of sea level extremes (i.e., the current distribution persists despite climate change), such that the effect of SLR is linear and additive. It is not fully understood whether the tail of the distribution will be further influenced by climate change (Grinsted et al, 2013) or other factors such as SLR, bathymetry, water depth, or wetland effects (Cayan et al, 2008; Smith et al, 2010).

Initial adaptation state Before evaluating coastal impacts under any climate scenarios, CIAM is first used to assess the counterfactual baseline case of no climate-driven SLR. As part of this assessment, an initial level of adaptation for a given location is taken as an exogenous input. (If the initial state were instead assumed to be zero adaptation, the segment would face the full extent of expected flood damage, i.e., Equation 10, where adaptation level $A = 0$.)

In order to overcome the lack of data on existing adaptation levels at the segment level, the CIAM baseline assumes an initial state of efficient present-day adaptation. Specifically, this is determined by running the model with zero adaptation, and then using the resulting efficient

[9]The US government VSL is 216 times per capita income in CIAM, which is on par with the FUND assumption of 200 times per capita income following Cline (1992).

adaptation response as the initial state. CIAM has also explored alternatives to this internal calibration exercise; for example, assuming all segments above a threshold population density are initially adapted to level of the 100-year floodplain. Additionally, the DIVA database includes its own existing sea dike height that has been used for comparison. A subsequent paper is planned to discuss the role of the initial adaptation state, given evidence that society is currently under-adapted to present-day sea levels and surge, and the sensitivity of costs to the assumed initial state. To the extent that coastal zones are under-adapted, there will be additional transition costs not captured here.

Not included in the model Coastal impacts in CIAM do not include all known damages to coastal zones. Some of these omitted impacts from SLR and climate change more generally include erosion, saltwater intrusion, ocean acidification, changes in coastal tourism and recreation, the potential cost of international migration, and interactions with other impact sectors such as agriculture. The CIAM framework could be extended to account for many of these localized impacts and the special treatment of vulnerable areas such as low-lying islands and ports, as well as introducing more diverse adaptation options like accommodation. In addition, the treatment of uncertain extreme surge and the resulting damages would benefit from exploring different attitudes towards risk, as well sensitivity analysis around the potential for nonstationarity in the storm surge distribution, should warming increase the likelihood of sea level extremes; furthermore, cyclones often combine flooding with wind damage, which is currently omitted.

1.2 CIAM Numerical Process and Model Code

CIAM is programmed in GAMS (Brooke et al, 1988).[10] The model solves each segment independently, looping over 12,148 segments for a given climate scenario. Each adaptation planning period is solved sequentially. The current model time horizon runs from 2000 to 2100. Once all segments have been solved, results can be aggregated at various levels.

Data and code are publicly available at the web repository `https://github.com/delavane/CIAM`.

The CIAM framework presented in this paper represents an initial effort rather than a final answer. Making the model openly available to the integrated assessment community is intended to facilitate improvements to the formulation as well as a broad range of future collaborations.

2 Implementation of SLR Scenarios

The SLR scenarios correspond to the local sea level projections published in Kopp et al (2014), which are used as an exogenous and deterministic input to CIAM. Kopp et al develop site-specific probability distributions for 1,091 locations across the global network of tide-gauge sites for each representative concentration pathway (RCP) (Meinshausen et al, 2011). This is done using 10,000 Latin hypercube samples from time-dependent probability distributions of cumulative contributions from thermal expansion, glaciers, ice sheets, and land water storage based on process model

[10] Development of a version in R is underway.

projections and expert assessments, as well as a Gaussian process model for non-climatic factors. Each CIAM segment is mapped to the nearest tide-gauge site, such that the site-specific projections can be used to determine coastal impacts that reflect the spatial variability of SLR. CIAM also evaluates a baseline case with no climate change for comparison; in this scenario there is no climate-driven SLR, but each segment continues to experience non-climatic vertical land movement due to glacio-isostatic adjustment, tectonics, and subsidence, following the local background rate reported in Kopp et al.

I use the 10,000 Monte Carlo samples for each tide-gauge site to develop summary quantiles for local SLR corresponding to a particular RCP.[11] Specifically, I determine the median, 5th and 95th percentile of each site's SLR projection and apply these as a global scenario (i.e., assume that the site-specific 5th/50th/95th percentile projection is experienced by every segment and at all points in time). It is important to note that this scenario approach is not internally coherent and also overly extreme – e.g., each site realizing its 95th percentile of sea level rise is likely to be more pessimistic than the 95th percentile globally. Nevertheless, this is a necessary simplification for implementation because it would not be feasible to run each of the Monte Carlo samples produced by Kopp et al for the 12,148 segments in CIAM such that summary quantiles could be reported over the final CIAM results. Thus, the figure error bars should be interpreted with the understanding that they are the aggregation of every segment's percentile range, and therefore are more divergent than a comparable global scenario would suggest.

These projections are specified as SLR since 2000, which does not include 0.15 m of global mean SLR since 1900 (Church and Clark, 2013). Because CIAM assesses coastal impacts relative to the current baseline, the extent to which floodplains have expanded due to prior SLR prior and the initial state is therefore under-adapted is not captured. This topic remains for a future analysis.

In the current model configuration, CIAM assumes that the planner has perfect foresight about the near-term SLR projection. However, in the future I plan to incorporate uncertainty about SLR in order to explore the role of hedging on adaptation decisions. This stochastic framework can take advantage of the rich probabilistic results of Kopp et al.

[11] Code and data file were obtained from `https://github.com/bobkopp/LocalizeSL/releases`.

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