

1 Article

2 Climate impacts on capital accumulation in a small 3 island developing state

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10

11 **Abstract:** This paper constructs a model of climate-related damage for small island developing
12 states (SIDS). We focus on the loss of private productive capital stocks through extreme climate
13 events. In contrast to most economic analyses of climate impacts, which assume temperature-
14 dependent damage functions, we draw on the engineering literature to allow for a greater or lesser
15 degree of anticipation of climate change when designing capital stocks and balancing current
16 adaptation expenditure against future loss & damage. We apply the model to tropical storm damage
17 in the small island developing state of Barbados and show how anticipatory behavior changes the
18 damage to infrastructure for the same degree of climate change. Thus, in the model, damage
19 depends on behavior as well as climate variables.

20 **Keywords:** climate change; adaptation; loss & damage; damage function; return period; tropical
21 cyclone

22 **JEL codes:** O11; Q01

23

24 1. Introduction

25 Small island developing states (SIDS) are expected to be among the most heavily impacted by
26 climate change [1], including from sea level rise, cyclones, rising temperatures, and changing rainfall
27 patterns [2]. While many small island economies perform comparatively well [3], arguably because
28 they must be open to trade due to their narrow resource and export bases [4], their reliance on exports
29 contributes to fluctuations in growth and recurrent high debt levels [5]. The combination of economic
30 and climate vulnerability suggests that understanding climate-economy interactions is particularly
31 important for SIDS. Yet, because of the limited data for most small islands, there have been few
32 studies, particularly those that treat the economy as a whole (the recent study by Moore et al. [6]
33 being a rare exception).

34 Most economic analysis of climate impacts is carried out with global integrated assessment
35 models (IAMs) that combine greenhouse gas emissions from economic activity with a representation
36 of the climate system. Some IAMs, such as DICE [7, 8] and FUND [9] include feedback from the
37 climate system to the economy. Both DICE and FUND implement a cost-benefit analysis and compute
38 optimal emissions trajectories, given their assumptions about social preferences (an optimization
39 mode). Other IAMs, such as GCAM [10, 11], can also be run in a simulation mode for exploring
40 alternative non-optimal scenarios. IAMs that compute climate damage assume a “damage function”
41 that depends on global mean temperature [12]. While most are aggregate, the FUND model takes a
42 disaggregated approach, with separate damage functions for different kinds of climate impacts [13,
43 14]. Each damage function depends on global climate (either global temperature or greenhouse gas
44 concentration) and average income.

45 This paper develops a sub-global simulation model. It is applied to national scale but could also
46 be applied at regional scale. The goal is to represent damage from climate change, in particular the
47 loss of productive capital¹ through extreme climate events. We depart from both FUND and DICE
48 by proposing a behaviorally-motivated model for climate damage, rather than a parameterized
49 model. This is useful for simulation, because it allows for a richer set of alternative scenarios and
50 policy options by targeting specific behavioral rules. We further differ from FUND and DICE by
51 representing climate damage to capital stocks rather than as a loss in GDP. Both the inclusion of
52 adaptive behaviors and loss of physical capital also distinguishes the study from that of Moore et al.
53 [6], who applied RICE, the regional version of the DICE model, to a study of climate impacts in the
54 Caribbean. Moore et al. employed a general equilibrium analysis, which contrasts both with partial
55 equilibrium analyses, such as that of Strobl [15], and with the dynamic macroeconomic analysis
56 carried out in this paper.

57 Loss of productive capital is admittedly one of many ways in which natural disasters affect
58 societies and economic performance. There are humanitarian impacts, loss of inventory, disrupted
59 supply chains, and damage to public infrastructure. Moreover, these impacts are unequally
60 distributed, with particularly strong effects on poorer households, and are thereby likely to
61 exacerbate poverty [16]. Nevertheless, damage to productive capital stocks (“capital stock shocks”:
62 see [17]) do occur, can be expected to affect long-term performance, and should be accounted for in
63 growth models [18]. Moreover, under climate change, events that were rare under historical climate
64 conditions are becoming more frequent, and can be expected to become even more common as the
65 climate continues to change [19, 20].

66 Our approach can be seen as an extension of the temperature-dependent depreciation rate
67 introduced by Fankhauser and Tol [21]. We ultimately derive a (sea-surface) temperature-dependent
68 depreciation rate, but we start by considering the return period of tropical cyclones, rather than
69 temperature, as the relevant climate variable. Return periods for certain types of events are calculable
70 from climate model outputs [19, 22, 23], and are a conventional input into the design practices of civil
71 engineers, particularly hydrologists concerned with flooding and storm damage [24, 25]. Thus, our
72 approach connects economic analysis under climate change to engineering practice.

73 In engineering design and risk assessment there is a need to relate the magnitude of an extreme
74 event to its frequency. With public investment, this relationship enables engineers and planners to
75 design infrastructure to efficiently utilize resources in a way that reflects societal values [24]. For
76 commercial projects, it allows engineers to balance potential damage to productive capital (loss &
77 damage) against adaptation costs.

78 *1.1. Tropical storm impacts in the Caribbean and in Barbados*

79 Tropical cyclones, more commonly known in the Caribbean as hurricanes and tropical storms,
80 have caused tens of thousands of deaths since records became available in the late 1880s. They have
81 affected millions of lives and destroyed billions of dollars in property. Since the 1930s, storm intensity
82 has not subsided and populations have increased. Casualty rates have decreased due to increasingly
83 effective mitigation measures and improved preparedness activities, yet property damage has risen,
84 highlighting weaknesses in structural mitigation and adaptation measures [26].

85 Since 1995, there has been an increase in the intensity and distribution of hurricanes in the
86 Caribbean. Increases in global temperature are expected to further intensify and increase the
87 frequency of category 3-5 hurricanes. This poses a direct threat to small Caribbean states, which are
88 mainly coastal communities [27]. From 1950-2014 the Caribbean has been impacted by a total of 581
89 tropical cyclones (298 tropical storms, and 283 hurricanes) that either made landfall or passed within
90 69 miles of Caribbean islands [28]. The 2017 Atlantic hurricane season was the third worst in history.

¹ By “productive capital” we mean physical stocks (typically buildings and machinery) used to produce goods and services for sale. We distinguish it from non-commercial capital (such as housing), non-productive commercial capital (such as protective structures), and public infrastructure (such as roads).

91 Hurricanes Maria and Irma caused an estimated total economic damage of US\$220 billion² and
 92 affected many of the Caribbean islands including Dominica, Antigua and Barbuda, St. Maarten,
 93 Anguilla, the British Virgin Islands and Puerto Rico. The value of infrastructure, buildings, and other
 94 capital stocks exceeds GDP, and in some instances the loss of GDP in island states was over 100%; for
 95 example, Hurricane Maria damage loss totaled 224% of Dominica's GDP [29] and Hurricane Irma left
 96 the island of Barbuda uninhabitable for days.

97 Most tropical cyclones that pass through the Caribbean miss Barbados, which lies on the
 98 southern fringe of the hurricane belt. Nevertheless, Barbados is periodically affected by tropical
 99 storms and hurricanes. Since 2010, the island has been impacted by four tropical storm events and
 100 one trough system. The sovereign insurance payouts under the Caribbean Catastrophe Risk
 101 Insurance Facility (CCRIF) for these event total US\$18 million with highest payouts occurring in 2018
 102 due to tropical storm Kirk (5.8 million USD), and in 2010 tropical cyclone Tomas (8.5 million USD).
 103 Loss & damage is affected by the degree of preparation in anticipation of a storm. Barbados expected
 104 modest impacts from tropical cyclone Tomas in 2010 and preparations were correspondingly modest.
 105 The impacts were much worse than anticipated, and resulted in the country's largest payout to date
 106 under CCRIF.

107 1.2. Model probability distributions

108 In this paper we focus on hydro-meteorological factors, specifically storms. Two approaches for
 109 modeling such events are generally used: annual maximum series (AMS) and peaks-over-threshold
 110 (POT) analyses [30]. In the AMS approach, a probability distribution is fit to the series of maximum
 111 events (*e.g.*, flood or wind speed) in each year of the record. In the POT approach, only the
 112 magnitudes and arrivals of events exceeding a threshold are modeled using probability distributions.
 113 POT methods capture the reality that multiple events of interest may occur in a single year, whereas
 114 no events of interest may occur in other years. POT methods do, however, typically require more
 115 data for calibration. In this paper we apply an AMS model, leaving the more complex POT analysis
 116 for future work.

117 The magnitude-frequency relationship is most often expressed in terms of the quantiles of the
 118 probability distribution assumed to approximate the behavior of a particular disaster type,

$$F_X(x_p) = p, \quad (1)$$

119 where F_X is the cumulative distribution function (CDF) of random variable X , and x_p is the p^{th} quantile
 120 of X , where $0 \leq p \leq 1$ is the non-exceedance probability of magnitude x_p over a particular time period,
 121 normally taken to be a year. This information is very often communicated in terms of the return
 122 period of an event of magnitude x_p , where the return period T is defined as the inverse of the
 123 exceedance probability,

$$T = \frac{1}{1-p} = \frac{1}{1-F_X(x_p)}. \quad (2)$$

124 If the distribution of the disaster magnitude is not changing, the return period can be interpreted
 125 in two ways: 1) if F_X describes the distribution of maximum observed event in a time period (say the
 126 maximum annual flood), then over T periods one expects (in the statistical sense of "expectation")
 127 for x_p to be exceeded exactly once; 2) if the realizations of X are independent from one time period to
 128 the next, then the return period is also the average waiting time to observe an event exceeding x_p .

129 1.3. Stationarity and non-stationarity

130 A crucial assumption behind the use of the return period is stationarity, meaning that the
 131 probability distribution of events remains unchanged over time. Stationarity has never held exactly

² Matt Sheehan, *Reinsurance News*, April 5, 2018, <https://www.reinsurancene.ws/hurricanes-harvey-irma-maria-cost-re-insurers-80bn-impact-forecasting/>.

132 in reality. Even in a stationary climate, land use change from human activity (e.g., de/afforestation,
 133 urbanization, agricultural practices, etc.) can affect flood distributions in complex ways [31]. Yet, even
 134 when it is justified, the concept of a return period can be challenging for non-specialists to
 135 understand. As non-stationarity accelerates and amplifies due to climate change [32]³, the meaning
 136 of the return period becomes problematic even for specialists [33–36]. Nevertheless, the return period
 137 remains a popular means of communicating the frequency-magnitude relationship of extreme events,
 138 and it was adopted in the IPCC special report on extreme events [19].

139 In this paper we allow for forward-looking design in that an engineer is assumed to choose the
 140 least-cost design given anticipated changes in the frequency of extreme events.

141 1.4. The perpetual inventory model with climate damage

142 In the model developed in this paper, gross domestic output (GDP), which we denote by Y , is
 143 given by a capital productivity κ multiplied by the total capital stock,

$$Y_t = \kappa K_t. \quad (3)$$

144 The change in the value of capital stock, K , is given by the value of gross investment, I , net of
 145 depreciation, D . The capital stock in period $t+1$ is then calculated as

$$K_{t+1} = K_t + I_t - D_t. \quad (4)$$

146 This “perpetual inventory” method of accounting for capital stock is a common approach (e.g., it was
 147 used for the Penn World Tables: [37]). It can be implemented in a straightforward way using data
 148 from national accounts, with the initial level of the capital stock as the only free parameter.

149 Depreciation can be expressed as a rate δ per unit of capital stock multiplied by the value of the
 150 capital stock. In practice, depreciation rates vary over time. However, in this paper we assume it to
 151 be constant, in which case we can write equation (4) as

$$K_{t+1} = (1 - \delta) K_t + I_t. \quad (5)$$

152 Our assumption of a constant depreciation rate is consistent with an assumption that climate change
 153 affects capital stocks only through extreme events. More gradual changes, such as rising sea levels
 154 leading to quicker erosion of sea defenses, are not considered in this model.

155 Extreme climate events can lead to loss of capital beyond normal depreciation. Such events are
 156 random, and appear in the model as a series of independent shocks.⁴ We express the loss in period t
 157 as a fraction δ_t^C of the existing capital stock (the damage ratio), and assume that at least some of the
 158 damage in the previous period is made up in the current period. The revised expression becomes

$$K_{t+1} = \underbrace{(1 - \delta) K_t}_{\text{net existing stock}} + \underbrace{I_t}_{\text{productive investment}} - \underbrace{\delta_t^C K_t}_{\text{climate damage}} + \underbrace{L_t}_{\text{loss \& damage expenditure}}. \quad (6)$$

159 The investment I_t that appears in this equation represents gross additions to productive capital stock.
 160 However, some capital expenditure is non-productive, including the cost of hardening capital to
 161 withstand a particular magnitude of climate event. We use x to denote the magnitude of an event,
 162 while x_d is the magnitude of the “design event”. The engineer’s task is to design the physical capital

³ Milly et al. [32] have been criticized for overstating the case for non-stationarity. In many analyses, stationarity remains a reasonable assumption. In any particular study a judgement must be made between a stationary or non-stationary analysis.

⁴ Independence is not an appropriate assumption for all types of extreme weather events. Droughts, in particular, tend to appear in multi-year groups. However, it is a reasonable assumption for storms. To capture periodic changes in global climate, such as the Pacific Decadal Oscillation (PDO) or El Niño-Southern Oscillation (ENSO) the frequency of storm appearance can change over time, while storms in a particular location are treated as independent of one another.

163 stock such that any event of magnitude less than x_d should inflict minimal damage, while allowing
164 for some damage for events above that level.

165 We assume that the total cost of capital, when built to withstand an event of magnitude x_d ,
166 inclusive of adaptation cost, is a multiple $m_a(x_d)$ of the cost of the productive capital. Denoting the
167 total cost with I^{tot} , we write a modified equation (6),

$$K_{t+1} = (1 - \delta) K_t + \frac{1}{m_a(x_d)} I_t^{\text{tot}} - \delta_t^C K_t + L_t. \quad (7)$$

168 If no storms are provided for, so that $x_d = 0$, then there are no adaptation costs, so $m_a(0) = 1$. Adaptation
169 costs rise with the magnitude of the design event, so $m_a' > 0$.

170 The final term in equation (6) is the cost of rebuilding damaged capital (loss and damage). We
171 assume that at most a fraction ℓ of GDP can be devoted to rebuilding in any period. This means that
172 there will ordinarily be a stock of damaged capital waiting to be rebuilt, D , where

$$D_{t+1} = D_t + \delta_t^C K_t - L_t. \quad (8)$$

173 With that assumption,

$$L_t = \min(\ell Y, D_t). \quad (9)$$

174 That is, the entire stock of damaged capital is repaired if funds permit. Otherwise, loss & damage
175 expenditure is limited to the maximum available funds for repairs.

176 2. Materials and Methods

177 In this section we develop a model for climate damage to productive capital stocks. We first
178 discuss the relevant calculations under a stationary climate, then under a non-stationary climate, and
179 then construct a model specifically for Barbados.

180 2.1. Balancing construction costs against climate damage under stationarity

181 For commercial infrastructure, such as we consider in this paper, an explicit cost-benefit
182 calculation is often applied to investment in protective capital. We implement such a calculation in
183 this section. In contrast, public infrastructure is usually built according to a specified return period
184 (e.g., a 50-year event). In that case, the magnitude of the design event can be calculated from the
185 design return period and the probability distribution $F_X(x)$ using equation (2).

186 For commercial investment, we note that a given level of gross investment I^{tot} includes both the
187 gross increment of productive capital I and adaptation costs. From equation (7), the relationship is

$$I = \frac{1}{m_a(x_d)} I^{\text{tot}}. \quad (10)$$

188 To weigh adaptation cost against the reduction in future damage, we add to the construction
189 cost the discounted potential damage to (depreciated) productive capital. In this case we need the
190 average expected storm damage, which will depend on both the design event and the shape of the
191 distribution. We write this as $\bar{\delta}^C(x_d; \sigma)$, where σ is a vector of parameters for the distribution.
192 Assuming stationarity, and a discount rate i , the discounted average cost of repairing damage, C_d , is
193 equal to

$$C_d = \frac{\bar{\delta}^C(x_d; \sigma) I}{1+i} \sum_{t=0}^{\infty} \left(\frac{1-\delta}{1+i} \right)^t = \frac{\bar{\delta}^C(x_d; \sigma) I}{\delta+i}. \quad (11)$$

194 In this equation, the discounted value of productive capital declines at the normal depreciation rate,
195 excluding climate damage. We assume that climate damage is fully repaired in the subsequent
196 period, so it adds to the cost with a one-period discount. (The simulation model described later in the

197 paper has a quarterly time step.) This is a more restrictive assumption than in equation (6), where
 198 expenditure on repairs can extend over several time periods. We adopt it both because it greatly
 199 simplifies the calculation and because it is meant to represent the calculation of an engineer
 200 attempting to find an optimal design threshold. From that vantage point, the engineer would have
 201 little basis to guess how long repairs might be delayed due to future cash-flow constraints. The result
 202 is an overestimate of the actual discounted repair costs, because the discount applies to the start of
 203 the rebuilding period, but is not applied over the course of rebuilding.

204 We emphasize that the discount rate in equation (11) is the one that a firm would choose when
 205 comparing between competing investments. We therefore avoid the contentious debate over the
 206 appropriate social discount rate [38]. Unlike social discount rates, for which experts provide a wide
 207 range of values [39], discount rates used by firms for investment decisions are comparatively
 208 standard and uncontroversial.

209 The total cost C can now be expressed as

$$C = I^{\text{tot}} + \frac{1}{\delta + i} \bar{\delta}^C(x_d; \sigma) I = \left(m_a(x_d) + \frac{1}{\delta + i} \bar{\delta}^C(x_d; \sigma) \right) I. \quad (12)$$

210 This “engineering” cost contains only internal costs borne by the entity that must build and maintain
 211 the capital stock. It excludes actual or imputed external costs, and does not consider social benefits.
 212 Thus, it seeks to represent the costs to which economic actors respond. Alternative assumptions, such
 213 as insuring new investment against climate damage, can be implemented by modifying this equation.

214 Good engineering practice suggests that the design should minimize the total engineering cost
 215 [40], which is achieved when x_d satisfies

$$m'_a(x_d) = - \frac{1}{\delta + i} \frac{\partial \bar{\delta}^C(x_d; \sigma)}{\partial x_d}. \quad (13)$$

216 This is a general expression that depends on the precise forms for the marginal adaptation cost and
 217 damage ratio. For the simulation model we assume specific functional forms, which we introduce
 218 later.

219 2.2. Balancing construction costs against climate damage under non-stationarity

220 In a changing climate in which storms are expected to become more severe over time, the choice
 221 of design period is not straightforward. Designing for the current climate means under-designing,
 222 while designing for the expected climate at the end of the design life means over-designing. The
 223 minimum cost is achieved somewhere in between [35].

224 We capture non-stationarity by introducing a time-varying fractional damage cost function into
 225 equation (11), the discounted cost of repairing damage,

$$C_d = \frac{I}{1+i} \sum_{t=0}^{\infty} \left(\frac{1-\delta}{1+i} \right)^t \bar{\delta}^C(x_d; \sigma(t)). \quad (14)$$

226 This is a general expression. It depends on the marginal adaptation cost, the dependence of the
 227 damage ratio on the event magnitude, and changes in the parameters of the distribution of storm
 228 events. Below, we will argue that the mean damage function can be assumed to grow exponentially
 229 over time,

$$\bar{\delta}^C(x_d; \sigma(t)) \cong e^{at} \bar{\delta}^C(x_d; \sigma(0)). \quad (15)$$

230 With this approximation we can explicitly compute the sum in equation (14) to find

$$C_d = \frac{\bar{\delta}^C(x_d; \sigma(0)) I}{\delta + i - (1 - \delta)(e^a - 1)}. \quad (16)$$

231 Following the same steps as before, we find that the magnitude of the design event should satisfy

$$m'_d(x_d) = -\frac{1}{\delta + i - (1 - \delta)(e^a - 1)} \frac{\partial \bar{\delta}^C(x_d; \mathbf{\sigma}(0))}{\partial x_d}. \quad (17)$$

232 We return to this expression below, after first constructing a nonstationary statistical model for peak
233 wind speed.

234 2.3. Wind speed model

235 A number of distributions are commonly used to describe the distribution of extremes in
236 hydrology and meteorology [24]. We use the Generalized Extreme Value (GEV) distribution, which
237 encompasses three families of distribution. The extreme value (EV) type I distribution (also called the
238 Gumbel) describes the distribution of the largest observation in samples arising from parent
239 distributions with exponential tails (e.g. the Normal and Gamma distributions), and corresponds to
240 a GEV with zero shape parameter. The EV II distribution (also called the Fréchet), corresponding to
241 positive GEV shape parameters, exhibits heavy or fat tails meaning that extreme quantiles can be
242 quite large. The EV III distribution (also called the Weibull), corresponds to negative GEV shape
243 parameters, is bounded by zero and is typically used to model the distribution of the smallest
244 observation in a sample, for instance low-flows in an annual streamflow record. The cumulative
245 density function of the GEV distribution is given by

$$P(x) = e^{-s(z(x), \xi)}, \quad z(x) = \frac{x - \mu}{\sigma}, \quad (18)$$

246 where

$$s(z, \xi) = \begin{cases} (1 + \xi z)^{-1/\xi}, & \xi \neq 0, \\ e^{-z}, & \xi = 0. \end{cases} \quad (19)$$

247 while the probability density function is

$$p(x) = \frac{1}{\sigma} s(z(x), \xi)^{\xi+1} e^{-s(z(x), \xi)}. \quad (20)$$

248 In these expressions, x represents the magnitude of a particular event. The distribution has a location
249 parameter μ and scale parameter, σ , each with the same units as x , and a dimensionless shape
250 parameter ξ .

251 We now turn to the specific case of Barbados. We take data on storms from the Caribbean
252 Hurricane Network's StormCARIB website (<https://stormcarib.com>), which includes dates, peak
253 wind speed, storm classification, and name for storms in the Caribbean. Data are available for
254 Barbados specifically, as well as for the Eastern Caribbean as a whole, from the mid-19th Century
255 through 2010. The StormCARIB data are based on "best track" data from the U.S. National Hurricane
256 Center's North Atlantic hurricane database reanalysis project (HURDAT) [41].⁵

257 Exploratory data analysis suggests a model in which the probability a certain peak wind speed
258 will be exceeded in Barbados is derived from a peak wind speed distribution for the Eastern
259 Caribbean as a whole, which is modeled using a generalized extreme value (GEV) distribution. We
260 therefore use the following model for Barbados,

$$P_{\text{BRB}}(w > w_t) = p_s P_{\text{EC}}(w > \phi w_t), \quad (21)$$

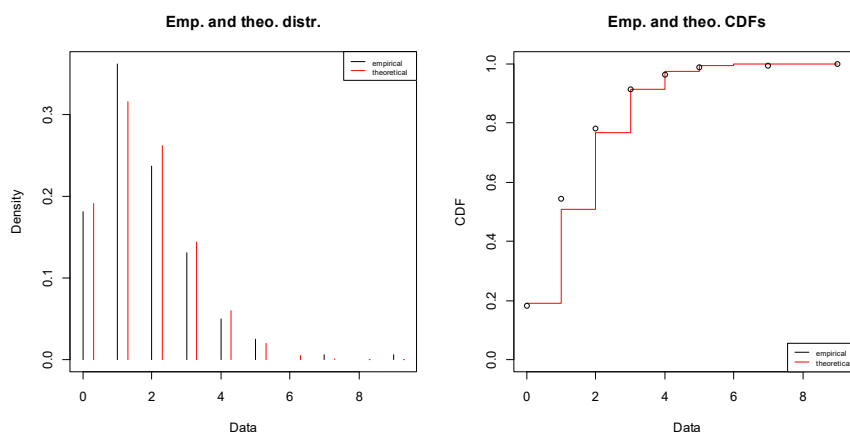
261 where p_s is the strike probability; specifically, the probability that a storm in the Eastern Caribbean
262 passes within 60 nautical miles, or 69 miles of the island. The parameter ϕ is the average value of the

⁵ A bias in historical data identified by Landsea [42] appears to have been corrected in the HURDAT database [43]. Thus, in contrast to Acevedo [28], we do not adjust historical wind speeds.

263 peak wind speed in the Eastern Caribbean divided by the peak wind speed observed in Barbados.
 264 The probability distribution P_{EC} is a cumulative GEV distribution.

265 Data on storms for the Eastern Caribbean extends from 1851 to 2010, while that for Barbados
 266 extends from 1855 to 2010. For 3 out of 58 storms that reached Barbados, the peak wind speed
 267 recorded in Barbados exceeded that recorded for the Eastern Caribbean. Since Barbados is part of the
 268 Eastern Caribbean, we considered those to be recording errors and set the ratios equal to one.
 269 Otherwise, we used the ratio of the recorded peak wind speed in the Eastern Caribbean to that in
 270 Barbados. The average ratio, which is our parameter ϕ , we found to be 1.34, with a standard deviation
 271 of 0.41. This parameter is comparatively stable over time, despite an apparent rising trend. A one-
 272 sided, two-sample, Wilcoxon rank sum test for whether the mean before 1931 (the median year for
 273 storms in Barbados) is lower than after 1931 could not reject the null hypothesis of no difference
 274 between the means ($p = 0.41$).

275 We used count data of storms per year to estimate a Poisson model for storms with a peak wind
 276 speed of at least 40 mph⁶ for both the Eastern Caribbean and Barbados. Graphical representations of
 277 the fit for the Eastern Caribbean are shown in **Figure 1** and for Barbados in **Figure 2**. The parameter
 278 estimate for the Eastern Caribbean is $\lambda = 1.56 \pm 0.20$ (to two standard deviations), corresponding to a
 279 return period of 1.24 years, and for Barbados $\lambda = 0.37 \pm 0.10$, corresponding to a return period of 3.22
 280 years. To estimate the strike probability in equation (21), we computed a Poisson fit for the Eastern
 281 Caribbean for storms with wind speed $w_t = \phi \times 40.0 \text{ mph} = 53.6 \text{ mph}$ and compared the exceedance
 282 probability to that of a 40 mph storm in Barbados. The result is $p_s = 0.36$.



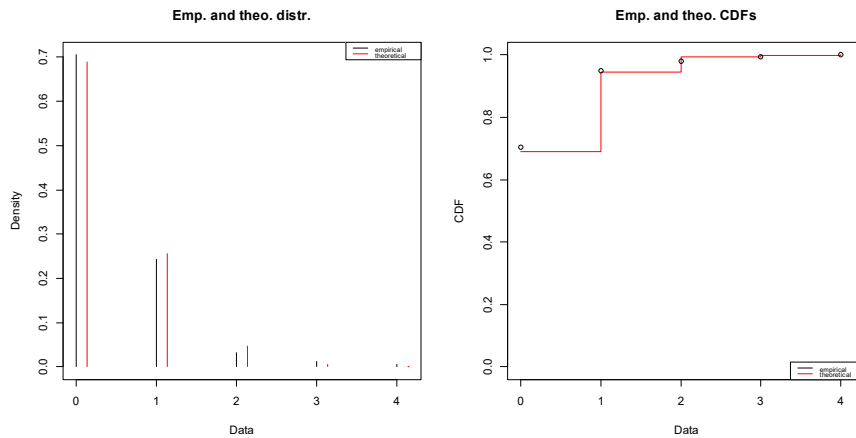
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284 **Figure 1:** Poisson distribution fit for storm events in the Eastern Caribbean

285 Next, we selected the peak wind speed in each year for the Eastern Caribbean. Wind speeds are
 286 not recorded for years without storms. Thus, there is no data for years when peak wind speed data
 287 fell below 40 mph, the minimum for a tropical storm. In those years we set the peak wind speed to a
 288 common value – the mean below the threshold – and fit a stationary GEV distribution⁷. We found the
 289 mean below the threshold in an iterative procedure in which we: 1) initialized the mean below
 290 threshold to one-half the threshold; fit the GEV; calculated the mean below the threshold with the
 291 fitted parameters; used that value for the next iteration; and iterated until the estimated mean below
 292 threshold converged to a tolerance of 10^{-7} mph. This procedure found an estimated mean (non-storm)
 293 peak wind speed below threshold of 3.95 mph.

⁶ Using the R fitdistrplus package ver. 1.0-11.

⁷ Using the R package ismev ver. 1.42.



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Figure 2: Poisson distribution fit for storm events in Barbados

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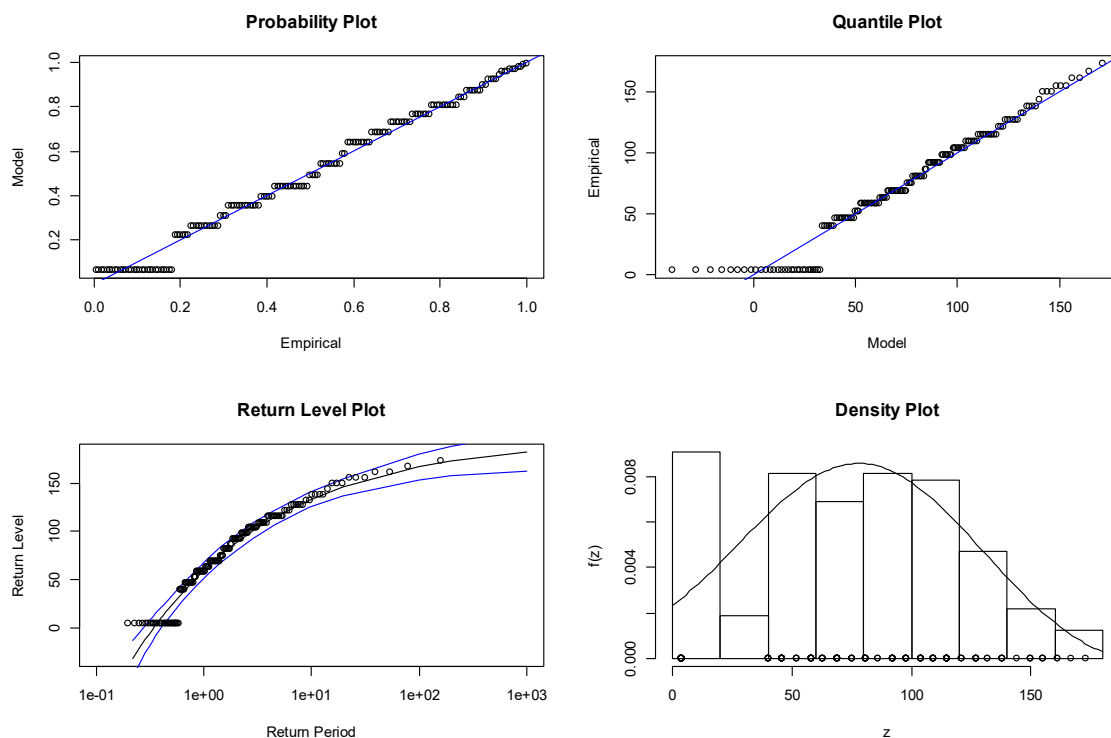
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Diagnostic plots for the fitted GEV distribution are shown in **Figure 3**. As shown in the figure, the full GEV parameter set is needed to capture the behavior at high wind speeds (*i.e.*, a Gumbel distribution would be inappropriate). The estimated parameters for the Eastern Caribbean are $\mu_{EC} = 60.1 \pm 8.1$ mph, $\sigma_{EC} = 45.9 \pm 5.9$ mph, $\xi_{EC} = -0.34 \pm 0.11$ (again to two standard deviations). This corresponds to a return period of 1.29 years for storms with the threshold peak wind speed (40 mph), in reasonable agreement with the Poisson estimate of 1.24 years.



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Figure 3: Diagnostic plots for storm data in the Eastern Caribbean as a stationary GEV

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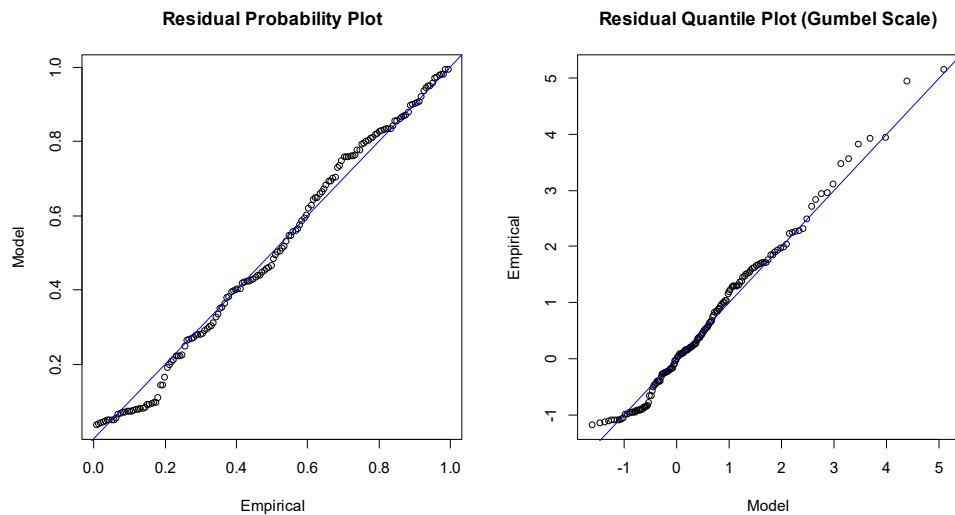
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Finally, we fit a nonstationary GEV model using as a covariate the global average sea surface temperature anomaly relative to the 1961-1990 average, which is provided by the Hadley Climate Research Unit (<https://www.metoffice.gov.uk/hadobs/>). The motivation for this covariate is that tropical storm intensity tends to rise with sea surface temperature [44], although not uniformly, because temperature and pressure in the atmosphere also affect the intensity of storms [45]. Sea surface temperature does not drive non-storm peak wind speeds, so we expect peak wind speeds in the upper part of the distribution to be more sensitive to sea surface temperature than in the lower

311 part. Consistent with this assumption, Elsner et al. [46] found the upper quintiles of peak tropical
 312 storm wind speed to rise over time and with changing sea surface temperature, but not the lower
 313 quintiles. Accordingly, for this fit we again set the peak wind speed for years with no data to 3.95
 314 mph, the value that we estimated for the stationary distribution.

315 Only the location parameter had a statistically significant correlation to sea surface temperature
 316 at the 5% level. Setting up a model with a temperature-dependent location parameter, the residual
 317 probability and quantile plots are shown in **Figure 4**. The estimated parameters are $\mu_{EC} = (65.6 + 36.5$
 318 $\tau) \pm (9.1 + 29.7 \tau)$ mph, $\sigma_{EC} = 45.8 \pm 6.1$ mph, $\xi_{EC} = -0.37 \pm 0.12$, where τ is the global average sea surface
 319 temperature anomaly.



320

321 **Figure 4:** Diagnostic plots for the nonstationary GEV distribution

322 The estimates for the location, scale, and shape parameters are for the Eastern Caribbean. To
 323 obtain estimates for Barbados, we divided the location and scale parameters by $\phi = 1.34$, leaving the
 324 shape parameter unchanged. Using the central estimates for the parameters, we find $\mu = 48.9 + 27.2\tau$
 325 mph, $\sigma = 34.2$ mph, $\xi = -0.37$. The average sea surface temperature anomaly between 1850 and 2010
 326 was $\tau = -0.13^\circ\text{C}$, corresponding to $\mu = 46.9$ mph. Combined with the estimate of 0.36 for p_s , that gives
 327 the return periods shown in **Table 1** for Barbados for tropical storms and category 1-5 hurricanes
 328 according to the Saffir-Simpson scale. Also shown are the observed frequencies from the
 329 StormCARIB database. The estimates are in reasonable agreement with observation, given the
 330 comparatively small number of observations for hurricanes.

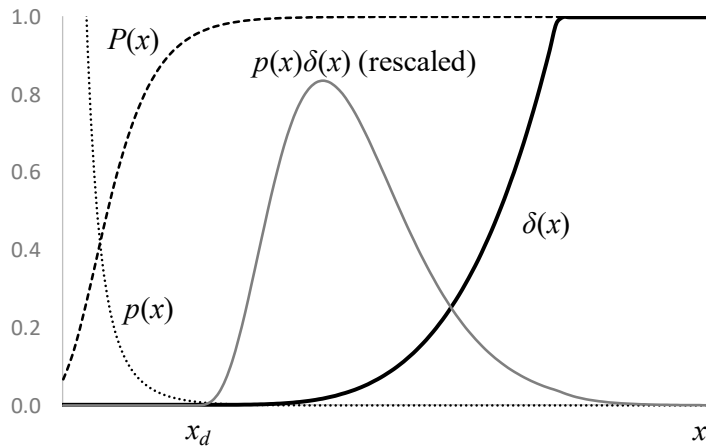
331 **Table 1.** Estimated and observed return periods for storms classified on the Saffir-Simpson scale.

Category	Threshold (mph)	Return period (years)		
		GEV estimate	Observed	Number of observations
Tropical storm	18	3	3	46
CAT 1	74	9	13	6
CAT 2	96	25	26	3
CAT 3	111	80	52	3
CAT 4	130	2,180	NA	0
CAT 5	157	Infinite	NA	0

332 We note that it is possible that the probability of Eastern Caribbean storms to strike Barbados,
 333 captured by the parameter p_s , may change in future. Historically, most storms have missed Barbados,
 334 but if the hurricane belt migrates southward as the climate changes, then the frequency could
 335 increase.

336 2.4. Calculating average climate damage

337 We expect the damage ratio $\delta^C(x; x_d)$ (the fraction of productive capital lost in an event that
 338 exceeds the design threshold) to rise with the magnitude of the event and fall with the threshold.
 339 Below the threshold the loss is zero, while at some magnitude above the threshold, damage will reach
 340 100%. Damage models used in engineering depend on the type of hazard. For storms, structural
 341 damage depends on wind speed and the size of the storm [47] and, near the coast, storm surge [48].
 342 Detailed studies consider the vulnerabilities of different structural components [49, 50]. In the
 343 simplest models, the damage ratio rises as the wind speed to a power [51, 52], as shown in **Figure 5**.



344

345 **Figure 5:** Hypothetical distribution and damage as functions of event magnitude

346 The average damage ratio $\bar{\delta}^C(x_d; \sigma)$ can be computed as

$$\bar{\delta}^C(x_d; \sigma) = \int_{x_d}^{x_{\max}} dx p(x; \sigma) \delta^C(x; x_d). \quad (22)$$

347 The maximum event magnitude, x_{\max} , depends on the distribution. In the specific case of the
 348 distribution we use for storm events in Barbados, we can write this equation using the rescaled
 349 location and scale parameters, as

$$\bar{\delta}^C(x_d; \sigma) = p_s \int_{x_d}^{x_{\max}} \frac{dx}{\sigma} s(z(x), \xi)^{\xi+1} e^{-s(z(x), \xi)} \delta^C(x; x_d), \quad (23)$$

350 where the vector of distributional parameters $\sigma = (p_s, \mu, \sigma, \xi)$. This equation gives a general expression
 351 for the mean damage ratio when extreme events follow the rescaled GEV distribution that we have
 352 estimated for Barbados. We next assume a specific form for the damage ratio.

353 Statistics for Barbados do not include casualty losses to commercial capital stocks. To find an
 354 estimate for the historical value for the average damage ratio, we took the estimate of GDP losses in
 355 Barbados due to storms from Acevedo [28]. For storms passing within 60 nautical miles, he found
 356 average annual losses of 0.2% of GDP. Not all of that will be associated with damage to productive
 357 capital. Arbitrarily assuming that half of the loss of GDP is due to loss of productive capital, we
 358 multiply 0.1%/year of GDP by a capital-output ratio of 4.5 years as estimated from data from the Penn
 359 World Table v. 9.0 [37], to find an estimated capital loss of 0.5% per year.

360 Past studies have found that climate damage can be assumed to increase with wind speed to a
 361 power. Nordhaus [51], in a widely-cited study, found damage in the US to rise as the 9th power of
 362 the maximum wind speed, while Bouwer and Wouter Botzen [52] found damages to rise as the 8th
 363 power. Both estimates are well above conventional models that assumed a power of two or three. In
 364 a study that accounted for the size of the storm, as well as peak wind speed, Zhai and Jiang [47] found
 365 an exponent on wind speed of 5, while Acevedo [28] found the power to be 3 for the Caribbean. We

366 adopt Acevedo's estimate as the power in our model, and apply it to wind speeds above the design
367 threshold. Thus, we assume

$$\delta^C(x; x_d) = \frac{A}{x_{d0}^n} \max(0, x - x_d)^n, \quad n = 3. \quad (24)$$

368 The parameter A is a scale factor to be found through calibration. To make A dimensionless, we divide
369 it by the initial value of x_d , x_{d0} , to the power n .

370 Substituting into equation (23), we find an expression for the mean damage ratio,

$$\bar{\delta}^C(x_d; \sigma) = \frac{A}{x_{d0}^n} p_s \int_{x_d}^{x_{\max}} \frac{dx}{\sigma} s(z(x), \xi)^{\xi+1} e^{-s(z(x), \xi)} (x - x_d)^n, \quad (25)$$

371 Computing the integral in equation (25) numerically for $x_d = x_{d0} = 65$ mph and the estimates of
372 μ , σ , and ξ reported earlier gives and setting the result equal to 0.50%/year (our estimate for the initial
373 mean damage ratio) gives a value for A of 0.15.

374 We constructed a numerical estimate of the integral in equation (25) using these parameters and
375 a range of possible values for x_d and the sea-surface temperature anomaly τ . To a good
376 approximation, we found that

$$\ln \bar{\delta}^C(x_d; \sigma) \cong \ln p_s - 1.12 - 0.06x_d + 1.54\tau. \quad (26)$$

377 From this expression we can identify the parameter a in equation (15) as $1.53 r_\tau$, where r_τ is the rate
378 of increase in sea surface temperature in °C/year. An automated search for breakpoints in a piecewise
379 linear fit to the Hadley temperature anomaly series identified breakpoints in 1876, 1913, 1939, and
380 1973. From 1973 to the end of the series, the temperature has been rising at 0.014 °C/year, giving an
381 estimate for a of 0.022/year. However, as we discuss below when describing the scenarios, it is likely
382 to rise more rapidly in future.

383 Next, we make an assumption for the form the of adaptation cost function. Taking the extreme
384 case in which capital stocks are not hardened at all ($x_d = 0$), there are no adaptation costs and $m_a(0) = 1$.
385 We assume an exponential cost function,

$$m_a(x_d) = e^{\theta x_d}. \quad (27)$$

386 Using equation (13) and the approximate function in equation (26),

$$\theta e^{\theta x_{d0}} = \frac{0.03\%}{\delta + i}. \quad (28)$$

387 Barbados' depreciation rate has averaged 5.2%/year, from PWT data. Assuming a discount rate of
388 7.0%/year (a typical value for engineering projects), this gives an estimate for θ of 0.0020/mph.

389 Using these parameter values, and equation (26) as an approximation for the average damage
390 ratio, we computed x_d using (17), to find:

$$x_d = 37.4 + 17.0 \ln \frac{p_s^e}{\delta + i - (1 - \delta)(e^{1.25r_\tau^e} - 1)} + 26.1 \tau^{\text{accept}}. \quad (29)$$

391 We have added a superscript "e" on the strike probability p_s and the rate of increase in the sea surface
392 temperature anomaly r_τ because they represent expectations of future climate change. The sea surface
393 temperature anomaly at the time of construction has a subscript "accept" to capture the possibility
394 that the accepted value may not reflect current conditions. We use this expression in the simulations.

395 2.5. Linking to a macroeconomic model

396 In this section we develop a model of capital accumulation for Barbados to illustrate the
 397 operation of the climate damage model.⁸ Capital stocks with different design thresholds x_d will be
 398 affected to different extents by climate damage. We therefore construct a vintage model, with
 399 vintages $v = 65, 66, \dots, 125$, corresponding to ranges for the design thresholds x_d of [65, 66), [66, 67),
 400 ..., [124, 125) mph. The design threshold at a given time is selected using equation (29) given
 401 expectations for future climate and observations of current conditions. Capital accumulation follows
 402 equation (6) for each vintage,

$$K_{v,t+1} = (1 - \delta) K_{v,t} + I_{v,t} - \delta_{v,t}^C K_{v,t} + L_{v,t}. \quad (30)$$

403 Climate damage is calculated using the actual, not anticipated, climate, while the vintage
 404 corresponding to the design threshold is determined based on the anticipated climate.

405 GDP, Y , is given by a capital productivity κ multiplied by the total capital stock,

$$Y_t = \kappa \sum_{v=65}^{125} K_{v,t}. \quad (31)$$

406 For the loss and damage calculation, we maintain a stock of damaged capital for each vintage,
 407 constrain total loss and damage expenditure to lie below a fixed share of GDP, ℓ (set to 20% in model
 408 runs) and allocate it to different vintages based on their representation in the pool. Specifically,

$$L_{v,t} = \frac{D_{v,t}}{\sum_{v'=65}^{125} D_{v',t}} \min \left(\ell Y, \sum_{v'=65}^{125} D_{v',t} \right). \quad (32)$$

409 Drawing parameters from the Penn World Table v. 9.0 [37], we assume that investment grows
 410 at a steady rate g , equal to Barbados' long-run average GDP growth rate of 4.6%/year. All investment
 411 at time t flows to the vintage corresponding to the design threshold at time t as calculated from
 412 equation (29).

$$I_{d,t} = \begin{cases} I_o (1 + g)^t, & x_d \in [v, v + 1), \\ 0, & x_d \notin [v, v + 1). \end{cases} \quad (33)$$

413 We link capital stock to GDP using a constant capital productivity of 0.22/year and set the
 414 depreciation rate to 5.2%/year. We initialize GDP to the 2017 value of Bds\$9.35 billion (from the World
 415 Bank World Development Indicators database). Over the five year period 2014-2018, the mean sea
 416 surface temperature anomaly was $\tau = 0.53^\circ\text{C}$, corresponding to $\mu = 63.4$ mph. We adopt that as the
 417 starting value.

418 **3. Results**

419 We built the model described above as a system dynamics model in Vensim.⁹ We ran three
 420 scenarios: *stationary* (a stationary climate); *nonstationary no anticipation* (non-stationary climate but a
 421 design threshold that does not anticipate any climate change); and *nonstationary with anticipation* (non-
 422 stationary climate with accurate anticipation of future climate). We note that a further (and arguably
 423 far more likely) scenario is a nonstationary climate in which climate change is anticipated, but
 424 inaccurately. However, the scenarios we have chosen are sufficient for the purpose of this paper,

⁸ Three of the authors (EKB, CD, and TL) previously developed a macroeconomic model for Caribbean SIDS that includes export dependence and external debt [5]. In that model, capital accumulation is endogenous, depending on anticipated demand and capital utilization. In this paper we focus on climate impacts and anticipatory behavior, and specify capital accumulation exogenously. We leave the combination of the models to future work.

⁹ Code is available from the authors upon request. The model requires Vensim DSS.

425 which is both to demonstrate the model and to explore whether anticipatory behavior (or lack of it)
 426 can substantially affect both adaptation costs and loss and damage.

427 Each scenario was run from 2017 to 2050 in Monte Carlo mode, with storm parameters drawn
 428 from a GEV distribution. For the temperature anomaly we used trends from MAGICC/SCENGEN
 429 5.3 [53] (which reports global average temperature rather than sea surface temperature) with the “no
 430 policy” P50 scenario. We adopted a piecewise linear rate of increase with breaks in 2030 and 2040,
 431 from 0.53 °C in 2017, to 0.85 °C in 2030, 1.17 °C in 2040, and 1.52 °C in 2050. Because storms represent
 432 extreme events, it takes a very large number of runs to generate a representative distribution.
 433 However, a smaller number of runs is sufficient to give an idea of trends. We ran each scenario 10,000
 434 times, using the same pseudo-random number sequence for each scenario. The results are shown in
 435 the figures below. In each figure, the bands correspond, under stationary conditions, to 5-year return
 436 events (80%), 20-year events (95%), 100-year events (99%), and 500-year events (99.8%). Also shown
 437 is the outer boundary for all events (100%). The mean value is shown as a yellow line.

438 **Figure 6** shows adaptation expenditure as a share of GDP in the three scenarios. In the *stationary*
 439 scenario, even at the 99.8% year level, adaptation expenditure remains below 8% of GDP. It rises
 440 through anticipatory behavior in the *nonstationary with anticipation* scenario. In the *nonstationary no*
 441 *anticipation* scenario, delays in rebuilding lead to a fall in GDP in the more extreme scenarios, so
 442 although costs are the same as in the stationary case, they rise as a share of GDP.

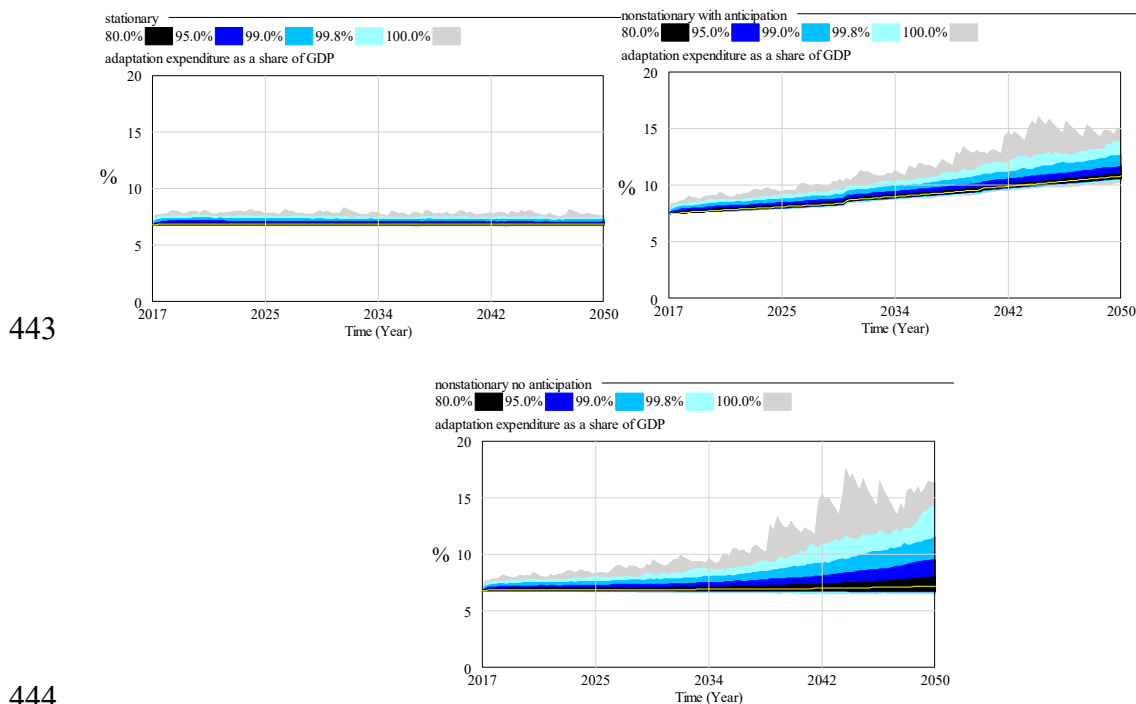
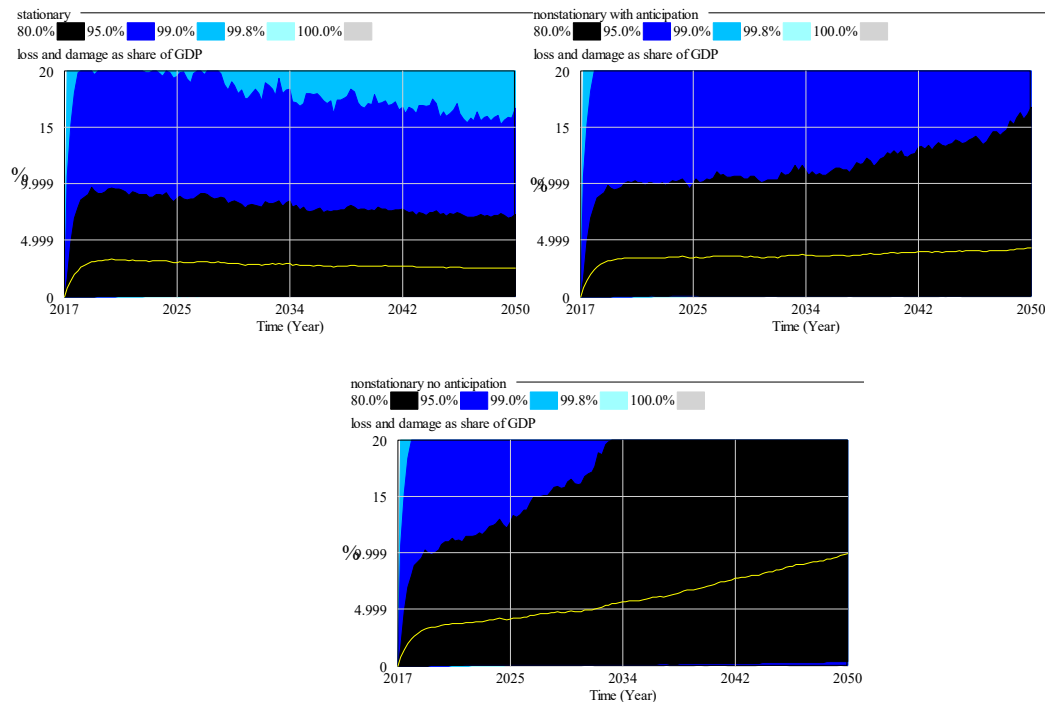


Figure 6: Adaptation expenditure as a share of GDP (as %) in the three scenarios

446 **Figure 7** shows loss and damage expenditure as a share of GDP in the three scenarios. Following
 447 the model assumptions, loss and damage expenditure in any given year is capped at 20% of GDP, so
 448 repairs may take several years to complete. (The backlog of damaged capital starts at zero, giving the
 449 discontinuity in the graph in the first years.) Under stationary conditions, mean loss and damage is
 450 around 3% of GDP, and in 80% of cases loss and damage expenditure is below 10% of GDP, but due
 451 to the accumulation of a backlog, there is a good chance that expenditure can be higher. In 99% of
 452 cases it reaches the maximum level. Note that total damage will be even higher than is shown in the
 453 graph because the model does not take into account the duration of the storm and only tracks damage
 454 to productive capital stocks. Damage to houses, crops, municipal buildings, public infrastructure,
 455 and so on is not accounted for.



456

457

458

Figure 7: Loss and damage expenditure as a share of GDP (as %) in the three scenarios

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460

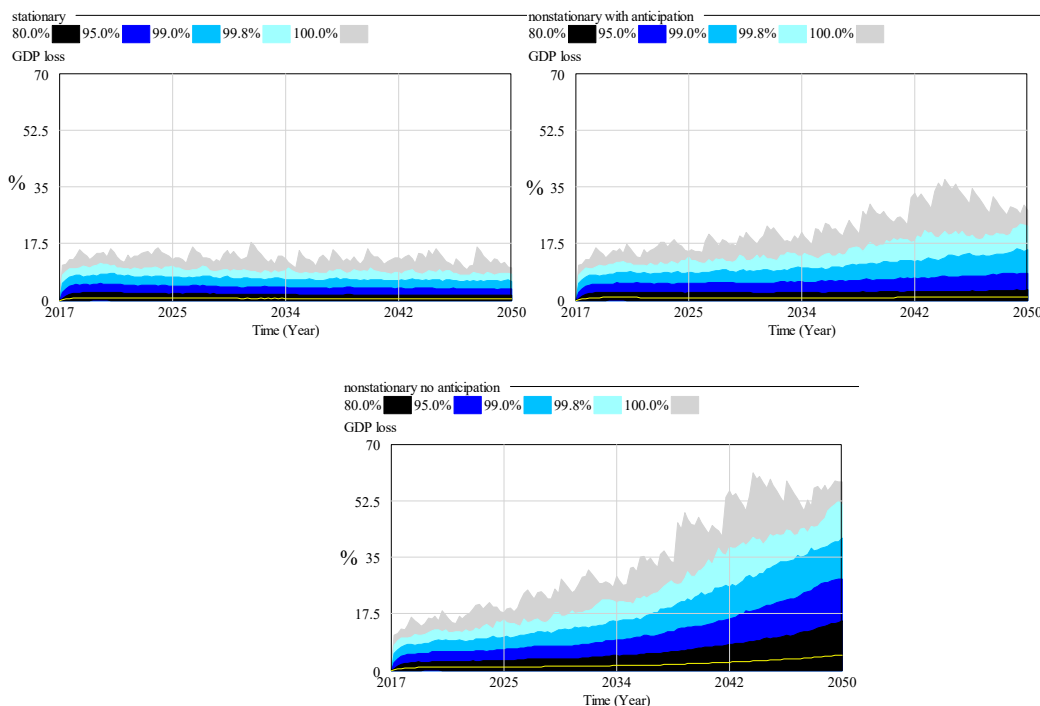
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The difference between anticipation of climate change and building in line with historical climate change can be clearly seen in the nonstationary scenarios in **Figure 7**. The optimal design threshold trades off anticipated damage against mitigation cost, so damages rise in both nonstationary scenarios, with damage at the 95% (or 20-year) level overwhelming the capacity to rebuild in both scenarios. Yet, damage rises only slightly in the *nonstationary with anticipation* scenario, while it rises substantially in the *nonstationary no anticipation* scenario.



465

466

467

Figure 8: Output losses (as %) relative to a steady growth path in the three scenarios

468

469

IAMs report damage as a GDP loss. For purposes of comparison, we calculated the loss relative to a baseline in which GDP grows at a steady rate of 4.6% per year. The results are shown in **Figure**

470 8. The mean values are comparatively small in the *stationary* and *nonstationary with anticipation*
471 scenarios (between 0.50% and 1.10% of GDP) because damaged capital is rebuilt, and the investment
472 expenditure is part of GDP. (Consumption expenditures, and therefore living standards, are reduced
473 because of expenditure for mitigation and loss and damage.) These values are higher than the 0.2%
474 per year estimated by Acevedo [28] and the study of Moore et al. [6], which found output losses for
475 Barbados between 0.20% and 0.25% of GDP in 2050. This is because the model tracks a backlog of
476 unrepaired damaged capital stocks, and cumulative damage increases subsequent GDP losses [17].
477 Without anticipation, mean losses are higher still, on the order of 4-5% by 2050. Moreover, due to
478 cumulative damage and the rebuilding backlog, even with anticipation there is a significant
479 probability of greater losses, as shown by the rise in the 80% and 95% confidence intervals.

480 4. Discussion

481 We drew on standard methods in engineering risk assessment to develop a model for damage
482 to commercial productive capital in a small island developing state. Detailed impact models like ours
483 are often used for local studies; such studies inform the damage functions used in the FUND model
484 [9]. However, to our knowledge there is no bottom-up model of damage to productive capital. The
485 closest we have found is the paper of Fankhauser and Tol [21], which introduced a temperature-
486 dependent depreciation rate into different types of neoclassical growth models.

487 The behaviorally-based damage model presented in this paper allows for greater flexibility than
488 do temperature-dependent damage functions. Anticipating a changing climate or designing for
489 current conditions produce different effective depreciation rates for the same change in global
490 temperature, in contrast to Fankhauser and Tol [21] or Moore et al. [6]. Firms may rebuild damaged
491 capital (as assumed in this paper) or suffer an extended loss of output. They may target a particular
492 rate of growth, while damage costs are made up through lower consumption (as in this paper and
493 FUND) or damages may be reflected in lower output and correspondingly lower saving and
494 investment (as in DICE and Fankhauser and Tol [21]).

495 The simulation results presented in this paper provide a counterpoint to the climate damage
496 models used in integrated assessment models. (In future work we plan to link the model documented
497 in this paper to the macroeconomic model documented in [5].) When running IAMs in an optimizing
498 mode, the results are highly dependent on an assumed social discount rate [54–59]. The analysis is
499 normative: the investment trajectory maximizes social utility, taken to be an increasing function of
500 consumption. In contrast, in this paper the analysis is descriptive. The discount rate is one that might
501 be used by a private firm deciding between different investments. The simulation results produced
502 by the model can be reviewed and critically assessed, and policy instruments chosen to make a
503 socially desirable outcome more likely. For example, we assumed that capital of a given vintage
504 would be rebuilt to its original specifications. Instead, it could be built to specifications of new
505 investment, thus following the recommendation to “build back better” [60]. Additional behavioral
506 extensions could include insurance against climate damage and publicly-funded recovery efforts in
507 the calculation of total costs in equation (12).

508 A further contrast is between the use of specific moments of distributions (such as the mean)
509 and a full distribution, as shown above in the model outputs. The importance of looking at the full
510 distribution in climate damage studies was urged by Weitzman [55, 61]. IAMs, when run in an
511 optimizing mode, assume that agents choose an optimal expected future path over which
512 expectations are calculated as the mean across different possible future states. The results in this
513 paper make clear how misleading mean values can be when distributions are asymmetrical and have
514 broad tails. In **Figure 8**, when climate damage is anticipated, mean GDP losses rise only slightly over
515 the current value. However, losses from 5-year and 20-year events roughly double by 2050,
516 suggesting a substantial probability of hardship arising from storm damage.

517 5. Conclusions

518 The dominant approach to computing climate damages in economic models is to use a
519 temperature-dependent damage function. This has some advantages at global level, where damage

520 estimates are aggregates over highly heterogeneous local impacts. However, they are less appropriate
521 for local studies, where a wide variety of modelled climate variables may be available, such as the
522 frequencies of extreme climate events, and it is possible and relevant to explore alternative behavioral
523 assumptions.

524 Local studies are particularly needed for small island developing states (SIDS), which must
525 contend with the compound uncertainties of heavy reliance on export markets and potentially rising
526 climate damage. SIDS rely on capital-intensive export industries, and both the capital stocks and
527 transport costs can be affected by tropical cyclones.

528 In this paper we drew upon the literature on engineering design and risk assessment to develop
529 a model for damage to commercial productive capital and applied it to the small island state of
530 Barbados. The model features behavioral variables that are not captured by temperature-dependent
531 damage functions, such as anticipation of future climate change. We found that anticipatory behavior
532 can substantially affect climate impacts on the economy.

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535 Writing – original draft, E.K-B., J.L, T.L, and C.D.; Writing – review & editing, E.K-B., J.L, T.L, and C.D.

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551

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