

1 **Hurricane Risk Management Strategies for**
2 **Insurers in a Changing Climate**

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7 **Abstract**

8 The insurance sector is among the earliest private sector industries to see
9 substantial losses associated with climate change, and the risk signals em-
10 bedded in insurance premiums could be a key driver for how climate ad-
11 aptation decisions are made by individuals and communities. Therefore,
12 risk assessments made in the insurance sector are critical for determining
13 how the built environment responds to and rebuilds from natural disas-
14 ters, and how society prices in the changes in disaster risk associated with
15 climate change. Catastrophe models are the key tool the insurance com-
16 munity can use to bridge the gap between climate models and the ex-
17 treme events that are the primary way in which society experiences cli-
18 mate change. The following discussion provides concrete suggestions for
19 extending established catastrophe risk management practices to incorpo-
20 rate emerging climate risks. Incorporating climate change into hurricane
21 risk management requires risk managers to 1. Explore catastrophe and cli-
22 mate model sensitivity to inputs in the built environment, 2. Divide hurri-
23 cane risk by subperil so risk management strategies can be tailored to var-
24 iable levels of uncertainty, and 3. Translate climate impacts into metrics
25 that tie directly to decision-making and business outcomes. Each of these
26 steps also highlights opportunities for collaboration between the insur-
27 ance sector and scientific community. The general strategy of assessing
28 sensitivity to model inputs, tailoring risk management strategies to the
29 level of uncertainty in the hazard, and producing outputs that are useful
30 for end users is broadly applicable for climate data services across a wide
31 variety of sectors.

32 **Keywords:** Insurance, Climate, Catastrophe Modeling, Hurricane, Risk
33 Management

34

35 **Catastrophe Models: A key tool for linking cli-**
36 **mate change to risk**

37 Insurance industry disaster risk is generally managed through tools known
38 as catastrophe models. Catastrophe models were widely adopted in the
39 aftermath of Hurricane Andrew making landfall in Florida in 1992, and
40 further solidified following the Northridge earthquake in California in
41 1994. Because the most extreme events are not frequent enough to apply
42 standard actuarial techniques with a basis in statistical theory of large
43 sample sizes, these models offer a powerful tool to fill out gaps in histori-
44 cal coverage for rare and extreme events. Historical records of disasters
45 are heterogeneous in time and space, and even lengthy historical records
46 are typically insufficient to characterize events in the 100-250 year return
47 period range commonly assessed in the insurance industry. Even where
48 historical records are available, they might have impacted a building stock
49 that was materially different from what exists today, with many fewer
50 buildings in areas at high risk than is the case today, paired with older
51 building codes that would not reflect a current view of damage potential.
52 Catastrophe models allow insurers to assess the risk of plausible events
53 that may not be in the historical record and capture the effects of
54 changes in exposed building stock over time.

55 Catastrophe models vary somewhat in form, but generally come with the
56 same four basic components. Catastrophe models take in exposure as an
57 input, in the form of a database representing the locations that an insurer
58 covers in its policies, describing their location, occupancy (such as single-
59 family residential, or a commercial office building), construction type
60 (wood frame, steel), age, and other details of how the structure was built.
61 The physical environment is modeled through a hazard module, which is
62 an event set of thousands of years of hypothetical events, including tropi-
63 cal cyclones, earthquakes, floods, wildfires, etc. The hazard and exposure
64 feed into a vulnerability module, which builds a relationship between the

65 level of hazard and type of building – for example, the percent damage
66 that a single-family wood frame home will experience at a given wind
67 speed in a hurricane. Vulnerability typically reflects a combination of en-
68 gineering expertise and tuning to historical losses. Lastly, the amount of
69 damage produced by the vulnerability component is fed into a financial
70 model, which applies insurance policy terms like deductibles and limits.

71 Catastrophe models do not attempt to capture the same types of events
72 as a typical climate model. While climate models are best at producing
73 average projected changes in large scale patterns over long time periods,
74 catastrophe models are designed to capture low frequency/high severity
75 hazards in the tail of a probability distribution in single year increments at
76 high spatial resolution. To capture extreme tails of the hazard distribu-
77 tion, catastrophe models blend physical modeling with statistical sam-
78 pling of hazard parameters derived from the historical record, such as
79 number of storms, genesis locations, or storm trajectory by latitude/longi-
80 tude (Hall and Jewson 2007). Monte Carlo simulation of storm character-
81 istics is computationally cheap compared with the high resolution physi-
82 cal climate models needed to represent extreme events like hurricanes,
83 enabling catastrophe models to produce tens or hundreds of thousands
84 of years of simulated disasters to realistically reflect rare but high impact
85 events.

86 Although insurers have long been broadly aware of climate risk from an
87 enterprise risk and regulatory standpoint, the catastrophe modeling tools
88 that are most commonly used in daily decision-making and that feed into
89 risk appetite reflect a snapshot of risk at a particular time. Since catastro-
90 phe models are drawn from a statistical distribution built from historical
91 data, they are inherently designed for short-term climate impacts. At pre-
92 sent, they do not explicitly incorporate most forms of forward-looking cli-
93 mate risk.

94 The statistical distributions of events used to build a catastrophe model
95 become less and less representative of potential risk with climate projec-
96 tions that are further in the future, where events may happen that are
97 outside the distribution of historical experience. However, climate model
98 skill in attributing climate change impacts to extreme events tends to in-
99 crease for most hazards further in the future, as external forcing

100 continues to increase relative to internal natural variability. Therefore,
101 leveraging these complementary tools in combination can help to high-
102 light how climate change could impact extreme events, and how changes
103 in extreme events might play out in societal impacts and economic losses.

104 Although the most common catastrophe models are designed for the in-
105 surance sector, there are academic models that capture at least some
106 components of the catastrophe models used in the insurance sector.
107 Hazard models are the most common, such as the Columbia HAZard
108 Model (Lee et al. 2018) and Synthetic Tropical cyclOne geneRation Model
109 (STORM) (Bloemendaal et al. 2020). However, the hazard and vulnerabil-
110 ity components of a catastrophe model that are used to produce a loss
111 are not fully independent. With two unknown variables for any given loss
112 (hazard and vulnerability), the solution to produce that loss is not unique.
113 Two models could produce the exact same loss for an event, with one ar-
114 riving at that estimate through a higher assumption of hazard but a lower
115 assumption of vulnerability, and the other producing a lower amount of
116 hazard but higher vulnerability. Therefore, catastrophe models need to
117 be carefully ground-truthed using observational data on wind and storm
118 surge footprints, as well as engineering studies that link particular wind
119 speeds to a proportion of damage.

120 Tying the hazard and vulnerability modules together has historically lim-
121 ited the development of academic or public sector catastrophe models, as
122 private sector companies have access to insurance claims data that are
123 generally not publicly accessible, as well as combined scientific and engi-
124 neering expertise that is difficult to replicate in the academic space. On-
125 going work to develop open source or publicly available catastrophe mod-
126 els could help to spread the risk insights that are accessible in the
127 insurance industry to a broader set of end users in the public and private
128 sectors. For example, catastrophe models only capture direct physical
129 damage to the insurable built environment – they are not yet able to cap-
130 ture broader societal impacts such as transition risk, detailed supply chain
131 impacts, or climate-driven migration or social upheaval, all valuable po-
132 tential contributions from participants beyond the insurance industry.

133 For the purposes of this discussion, the risk analysis methodology will fo-
134 cus on North Atlantic hurricane risk, although much of what follows is

135 applicable to other tropical cyclone basins as well. The hurricane hazards
136 highlighted are not intended to be comprehensive, but rather representa-
137 tive of how hazards may interact with the built environment.

138

139 **Three recommendations for risk modelers**

140 The following sections will break down three key considerations to ad-
141 vance meaningful and actionable climate risk analytics within the frame-
142 work of insurance risk management.

- 143 1. Exposure: Explore sensitivity of climate-driven losses to inputs
144 from the built environment.
- 145 2. Hazard: Quantify scientific confidence and impact by subperil.
- 146 3. Translating climate data for decision-makers.

147 Each of these considerations highlights opportunities for leveraging catas-
148 trophe models to capture economic and societal impacts of climate
149 change on hurricane risk. However, each recommendation also has space
150 for further improvement with better tools and advances in the basic sci-
151 ence. Therefore, each section is followed by a “Research Opportunities”
152 subheading, showing key data or analytical gaps that are an opportunity
153 to improve quantification of the societal impacts of hurricanes in a chang-
154 ing climate.

155 **Recommendation 1 – Exposure: Explore sensitivity of climate-** 156 **driven losses to inputs from the built environment**

157 Climate hazards do not occur in a vacuum - they can only become disas-
158 ters when they intersect with an impacted community. Catastrophe mod-
159 els are particularly adept at capturing the impact of climate hazards on
160 the built environment, which may be subject to changes in risk that do
161 not scale linearly with the change in hazard. However, this means that as-
162 sessing climate impacts requires stringent data collection processes on
163 exposure inputs, or the resulting modeled impacts will not be meaningful.

164 Modeling water risk in the built environment

165 Several of the most immediately changing hurricane subperils, such as
166 storm surge and inland rainfall, are making hurricane damage wetter.
167 This poses a particular challenge for risk modelers, since water perils re-
168 quire a much finer degree of detail on exposed properties to produce
169 meaningful views of risk compared with more developed hazards like
170 wind and earthquake. Wind risk, for example, is relatively forgiving of mi-
171 nor errors in modeling the location of a building, as the average risk from
172 wind does not vary particularly dramatically at small spatial scales along
173 the coast. Flood risk, however, may vary widely even within a single
174 building parcel, and minor errors in location can easily cause properties to
175 be modeled in the middle of retention basins or roadside ditches, leading
176 to dramatic overestimates in risk. For this reason, modeling “climate risk”
177 often requires substantial investments in improved data about exposed
178 building locations in a book of business, long before examining any
179 changes in physical hazard. Advances in geocoding and capturing im-
180 portant building characteristics like basements and building elevation can
181 dramatically improve the realism of modeling hurricane-driven water risks
182 like surge and inland rainfall.

183 Furthermore, at the scale of metropolitan areas, hurricane flood risk may
184 not be distributed equitably. Redlining was a historical discriminatory
185 practice that deemed communities populated by racial and ethnic minori-
186 ties, and particularly Black communities, to be a bad financial risk. Com-
187 munities that experienced redlining are disproportionately located in ar-
188 eas of higher flood hazard (Katz 2021). The practice of redlining
189 systematically reduced property values as well, since it limited access to
190 mortgages and related financing, limiting the tax base for investments in
191 flood defenses like stormwater drainage infrastructure. After a disaster
192 has occurred, homeowners are more likely to receive post-disaster fund-
193 ing to rebuild, both through federal and insurance assistance - this home-
194 ownership bias exacerbates unequal disaster impacts in communities
195 with a higher proportion of renters (Fussell 2015). Climate-related water
196 risks may only compound this historical inequality, potentially leading to a
197 pattern of “climate gentrification” where only the wealthy have the re-
198 sources to harden their homes, lobby for defensive infrastructure, and

199 rebuild after major disasters. Investments in capturing socioeconomic
200 data for use in physical risk models (Tedesco et al. 2021) can help to pre-
201 dict where such impacts are likely, highlighting communities that would
202 benefit from additional investment in protective measures.

203 **Spatial distribution of hazard vs. built environment**

204 Even in the absence of changes in event frequency, risk and losses may
205 change if different areas are exposed to hurricane risk in the future. A
206 prime example of where this may play out is through poleward migration.
207 There is at least some suggestion that migration of storms toward higher
208 latitudes may be occurring in the historical record in some basins (Kossin
209 et al. 2014), which is most likely to be occurring beyond an extent explain-
210 able by natural variability in the North Pacific basin (Knutson et al. 2019).
211 This pattern may be driven by a change in tropical cyclone genesis loca-
212 tion (Daloz and Camargo 2018), which could theoretically lead to declines
213 in risk at very low latitudes. However, mid-latitude metropolitan areas
214 may see increases in risk whether poleward migration comes from mi-
215 grating genesis locations or an expansion in the parts of the ocean with
216 sea surface temperatures warm enough to support tropical cyclones.

217 Moving stronger storms over regions whose building codes were designed
218 based on historical wind return periods can increase losses through
219 higher building vulnerability, independent of any changes in storm fre-
220 quency. Building codes and enforcement are not standardized and vary
221 widely from state to state, but in general, more northerly states are less
222 likely to design for tropical cyclone wind risk. Even absent these building
223 code considerations, exposing mid-latitude metropolitan areas like New
224 York and Boston to hurricane risk, when these events have been histori-
225 cally rare, may substantially change the population that could be exposed
226 to hurricane risk in the future.

227 **Critical thresholds**

228 Even where hazards are smoothly varying over time, the intersection be-
229 tween hazard and the built environment may lead to sharp discontinuities
230 in risk. Hurricane Sandy highlighted the cascading impacts that ensue
231 when a hazard intersects with critical pieces of infrastructure, as when

232 Sandy's storm surge entered the New York City subway system and took
233 the storm's impact from damaging to catastrophic. Every metropolitan
234 area has a point when damage becomes massively disruptive - whether it
235 is public transit like New York, a critical piece of the power grid (also inun-
236 dated in New York during Sandy, causing the blackout in lower Manhat-
237 tan), or the point when a downtown center is inundated. For coastal cit-
238 ies in particular, storm surge sitting on top of sea level rise brings many of
239 these pieces of critical infrastructure closer to this range of risk. Without
240 explicit defensive measures, cities may find that infrastructure designed
241 to be defended against a 1 in 100 or 1 in 250 year return period storm
242 surge may actually be impacted by the 1 in 50 or 1 in 30 year storm surge
243 in the future. Different pieces of infrastructure may have different levels
244 of risk tolerance – for example, a municipality is likely to be more com-
245 comfortable with a road being occasionally inundated compared with a nu-
246 clear plant. However, mapping and quantifying the risk to critical facilities
247 is a key component of preparing communities for future extreme events.

248 **Exposure research opportunities**

249 1. Publicly available exposure data

250 The insurance sector has access to a rich resource of data about the built
251 environment, both through individual portfolios of business that they
252 write, as well as “industry exposure” datasets produced by catastrophe
253 modeling companies. However, this data has some notable limitations.
254 Most importantly, it is expensive to build and maintain, so it is generally
255 proprietary and expensive to license. Detailed data about the built envi-
256 ronment is necessary for quantifying costs of increased hazard, but the
257 granularity of public datasets is generally not sufficient to capture high
258 gradient hazards like flood, and it lacks an ability to distinguish critical in-
259 frastructure. Investments in public data available to the research commu-
260 nity would fill a critical gap in quantifying economic impacts of climate
261 change.

262 Defining economic costs of extreme hazards like hurricanes is particularly
263 critical in a policy environment where decisions about mitigation and ad-
264 aptation pathways are at least partially based on the expected economic
265 costs of climate change. Extreme hazards are a key driver of economic

266 loss, but they are minimally captured in the economic models widely used
267 in the financial sector to model transition risk, which could lead to under-
268 estimation of the long-term costs of climate change on society.

269 2. Tools to capture detailed exposure characteristics

270 Hurricane water subperils, as well as other high-resolution hazards like in-
271 land flood and wildfire, require highly detailed information about the built
272 environment to produce meaningful model results. Investments in re-
273 mote sensing and machine learning to better identify details like building
274 footprints and first floor elevations are critical to meaningfully incorpo-
275 rate emerging climate hazards into the risk models used throughout the
276 insurance sector. This is an active area of private sector investment, but it
277 is also an area where academic researchers could contribute meaningfully
278 to managing climate risk.

279 3. Economic effects of physical risk on exposure values and in- 280 vestments

281 Forward-looking views of physical risk require projections of future expo-
282 sures, along with the usual forecasts of physical hazards. However, physi-
283 cal hazards may have impacts on property values, which can complicate
284 and materially affect the expected cost of extreme events like hurricanes.
285 Coastal flood is a key example of the complexity of assessing changes in
286 future economic risks from hurricanes, with knock-on implications for
287 both catastrophe and transition risk modeling.

288 Coastal flood risk is not only composed of storm surge from hurricanes.
289 For a given location, sea level rise manifests first through changes in
290 coastal flood event frequencies, beginning with extreme hurricane surge
291 events, and eventually moving through routine high tide flooding to com-
292 plete inundation. Sunny day or “nuisance” flooding, high-frequency
293 flooding driven by high tides combined with sea level rise, does not fall
294 within the traditional purview of hurricane catastrophe models, although
295 it can be exacerbated by bypassing hurricanes. However, the mechanism
296 of stacking high tide events on top of current and future sea level rise sce-
297 narios works much the same way as storm surge in a catastrophe model.
298 While often treated separately, storm surge and other types of coastal

299 flood actually represent a continuum of coastal hazard, which may inter-
300 sect in ways that could drive larger-scale climate risks.

301 While individual losses are small compared with storm surge, high fre-
302 quency coastal flooding events may have systematic risk potential due to
303 their impact on property values. Structures that experience routine
304 flooding may be harder to sell, and ultimately lose value or grow in value
305 more slowly than their lower-risk neighbors (Keys and Mulder 2020), as
306 damages accumulate and insurance premiums rise from repeated claims.
307 Since property values determine the amount of property taxes collected,
308 this may limit a critical potential funding source for future coastal flood
309 defenses. Coastal states that lack income tax, like Florida and Texas, have
310 fewer obvious local funding sources if coastal property tax bases were to
311 be impacted by a local decline in property values.

312 Property value risk is an area where insurers may be impacted on both
313 sides of their balance sheet – in physical hazards driven by their portfolios
314 of insured risks, as well as economic hazards within their investments.
315 Municipal bonds, investments in the mortgage market, and other invest-
316 ments tied to a clear physical location could potentially see areas of clash,
317 where a large hurricane could hypothetically trigger losses both from di-
318 rect physical damage, as well as longer-term slowing or reversal of invest-
319 ment returns concentrated in the same location. While investments are
320 chosen with a certain level of risk appetite for an economic shock, cli-
321 mate-driven financial risk has a different timeline for recovery than tradi-
322 tional economic shocks – unlike a recession, sea level is not expected to
323 retreat globally for centuries or more, so some assets may not be recover-
324 able. However, with a few exceptions like those noted above, invest-
325 ments typically have limited information about the physical locations of
326 their facilities, a critical data gap for incorporating hazard assessments for
327 extreme events like hurricanes into an investment portfolio.

328 Despite its importance for societal impacts of hurricanes, the interaction
329 between nuisance flooding and storm surges, particularly regarding socio-
330 economic risk, is comparatively understudied. For example, is a major
331 storm surge event more likely to cause widespread mortgage defaults if
332 the community has already been stressed by nuisance floods depressing
333 property values? The interaction between high frequency and low

334 frequency coastal flood events is also currently not generally incorpo-
335 rated into catastrophe modeling, suggesting a potential avenue for collab-
336 oration between the climate modeling, catastrophe modeling, and eco-
337 nomic literature.

338

339 **Recommendation 2 – Hazard: Quantify scientific confidence**
340 **and impact by subperil**

341 For a complex hazard like hurricanes, the question, “how does climate
342 change affect hurricane risk?” is so broad as to be virtually meaningless.
343 Within the framework of climate modeling, hurricanes are comparatively
344 small scale and extreme events, so the science remains in flux for some
345 aspects of the hazard. However, some characteristics of hurricanes have
346 seen clear, immediate impacts in the current climate. Rather than at-
347 tempting to roll hazards with wildly variable levels of uncertainty to-
348 gether, it is useful to break apart hurricanes into their associated subper-
349 ils and apply different risk management strategies based on their
350 corresponding scientific confidence and materiality of impact.

351 High-confidence perils, like increases in storm surge inundation, are ex-
352 plicitly included in catastrophe models in the current climate, and could
353 be added in near-term (5-10 year) time steps that are relevant for under-
354 writing, pricing, and portfolio planning. For lower-confidence perils, like
355 hurricane frequency, an exploratory approach that examines how much
356 the hazard would have to change to affect the business (rather than pro-
357 scribed time-based scenarios) is more useful for planning purposes, and
358 allows the organization to assess when and if action would be needed.

359 **Water subperils**

360 ***Storm surge***

361 Storm surge is the clearest and most immediate impact of climate change
362 on tropical cyclone risk. While the question of whether the component of
363 the surge caused by the storm itself is changing remains open (Grinsted et
364 al. 2012), sea level rise provides a higher platform for every incoming

365 storm surge (Knutson et al. 2020), increasing both depth and the inland
366 extent of the surge inundation footprint. The impact of sea level rise is
367 compounded by the locations of major concentrations of exposure, which
368 are often cities built on deltas that subside naturally, and in some cases
369 whose subsidence is enhanced by factors like groundwater withdrawals
370 (Nicholls et al. 2021).

371 Catastrophe models are built using sea levels that are close to those of
372 the present day, so this climate-related trend is explicitly included in mod-
373 eled loss results. However, forward-looking sea level rise scenarios, par-
374 ticularly projecting out into the medium term where portfolio optimiza-
375 tion decisions are made, are in comparatively early stages of
376 development, and are not consistently included in model results from
377 many of the largest catastrophe model vendors.

378 At the time scales that are most important for decision-makers in the in-
379 surance sector (up to 2050 at the latest), uncertainties in sea level rise
380 even among a wide range of emissions scenarios are comparatively small,
381 ranging from median [likely] global mean sea level rise by 2046-2065 of
382 0.24m [0.17-0.32m] in RCP 2.6 to 0.30m [0.22-0.38m] in RCP 8.5 (Inter-
383 governmental Panel on Climate Change 2014). While projecting global
384 mean sea level changes down to the local scale required for catastrophe
385 modeling is more challenging, the emergence of gridded products like
386 that produced by NOAA in the US (Sweet 2017) makes it possible to pro-
387 duce reasonably localized sea level projections. Capturing this regional
388 level of detail is critical for interpreting changes in storm surge risk over
389 time, as individual cities do not experience global mean sea level change.
390 For example, portions of the US East Coast are experiencing sea level rise
391 that is 50% or more above the global mean, predominantly but not exclu-
392 sively driven by post-glacial isostatic rebound (Piecuch et al. 2018).

393 Catastrophe model results highlight the impact that climate change can
394 have on tropical cyclone subperils, even within the historical record. A
395 study led by Lloyd's in the aftermath of Hurricane Sandy found that the
396 amount of sea level rise since 1950 had increased ground up losses by
397 30% in the New York metropolitan area (Maynard et al. 2014). Similarly,
398 this modeling framework can be used to assign economic losses to the an-
399 thropogenic portion of sea level rise from historical storm surge events

400 (Strauss et al. 2021). Increases in loss are not limited to the increase in
401 storm surge depth; higher storm surges also lead to greater inland extents
402 of storm surge footprints, with the greatest increase in extent on low, flat
403 coastlines. Consequently, loss increases may not be linear, but rather
404 may have step functions as surge footprints are able to reach major con-
405 centrations of buildings or critical exposure that would have stayed dry
406 with a lower baseline sea level. With adjustments for sea level rise, catas-
407 trophe models could be valuable tools to highlight these critical disconti-
408 nuities in loss potential.

409

410 ***Rainfall-Induced Flooding***

411 Hurricane rainfall is generally expected to intensify with climate change.
412 The Clausius-Clapeyron equation shows a ~7% increase in the moisture
413 that the atmosphere could potentially hold with every 1°C temperature
414 increase. Therefore, a warmer atmosphere itself provides a potential
415 mechanism to enhance hurricane rainfall. Rainfall increases could also
416 hypothetically be enhanced by stalling or other dynamical factors, as was
417 the case for Hurricane Harvey over Houston and Hurricane Florence in the
418 Carolinas (van Oldenborgh et al. 2017; Emanuel 2017a; Wang et al. 2018).
419 Rain damage may not necessarily correlate well with wind damage, as
420 major inland rainfall events have also been driven by tropical storms
421 (Tropical Storm Allison, 2001 in Houston) and unnamed but near-tropical
422 circulations (Baton Rouge flooding, 2016). This effect is enhanced along
423 parts of the Gulf Coast by the “brown ocean” effect, allowing storms to
424 maintain their structure, and at times even form, while over land (Ander-
425 sen and Shepherd 2014).

426 Rainfall impacts may also be enhanced by their intersection with the built
427 environment. For example, Hurricane Harvey produced the greatest
428 amount of rainfall for a US tropical cyclone in records going back to the
429 1880s, with seven rainfall stations breaking the prior record held by Hurri-
430 cane Hiki in Hawaii in 1950 (Blake and Zelinsky 2018). This could be
431 thought of as particularly unlucky, to have such a historic event happen
432 right over Houston, the fifth-largest metropolitan area in the United
433 States (United States Census Bureau 2021). Alternatively, it could be

434 interpreted that the record US tropical cyclone rainfall event and dra-
435 matic flood impacts happened in Harvey specifically *because* it happened
436 to occur over such a large metropolitan area.

437 A variety of methods have been proposed to enhance rainfall over metro-
438 politan areas, including surface roughness provided by buildings (Zhang et
439 al. 2018) and local aerosol pollution (Pan et al. 2020). Similarly, impervi-
440 ous surfaces like buildings, roads, and parking lots can enhance flood risk
441 by limiting avenues for rainfall to drain into the ground, forcing it to be-
442 have as overland flow instead and compounding the impact of increased
443 rainfall on flood behavior (Sebastian et al. 2019).

444 As this Houston example shows, cities are in the position of being
445 uniquely exposed to enhanced hurricane rainfall risk. Increased rainfall
446 inputs are expected from warmer air and sea surface temperatures, with
447 potential further enhancements specifically in tropical systems. The pres-
448 ence of a city may itself enhance local precipitation. And impervious
449 cover prevents rainwater from absorbing into the ground, leading to over-
450 land flow into rivers and other drainage networks. All of this is happening
451 where populations exposed to hurricane risk are the most concentrated.
452 This puts cities at an uncomfortable confluence of compounding climate
453 and exposure-driven hurricane flood hazard, so they would greatly bene-
454 fit from more sophisticated risk modeling.

455 Although historically not captured explicitly in catastrophe models in the
456 US, hurricane rainfall is a subperil that gained particular interest in the af-
457 termath of Hurricane Harvey, and is now more broadly incorporated into
458 hazard modeling. However, given the complexity of a peril that is chang-
459 ing via climate-driven hazard impacts, land use impacts, and whose loss
460 history reflects a blend of public sector (mostly residential flood losses, in
461 the National Flood Insurance Program) and private sector (larger com-
462 mercial flood losses), this is an emerging hazard in the catastrophe model-
463 ing community that will likely continue to evolve as climate impacts and
464 attribution continue to solidify.

465

466 ***Compound flood***

467 Many major coastal metropolitan areas are located along estuaries or del-
468 tas that are susceptible to both riverine flood and coastal flood risk. A
469 tropical cyclone can drive both risks occurring at the same time, with
470 storm surge running up waterways and preventing river waters from
471 draining as quickly, paired with intense inland rainfall enhancing river
472 flood at the same time. Therefore, although the return period of a flood
473 height can be calculated independently for coastal and river floods, best
474 practice would account for the strong correlation between these perils in
475 coastal areas that are exposed to storm surges. Furthermore, compound-
476 ing riverine and coastal flood events will be exacerbated by sea level rise
477 (Moftakhari et al. 2017). The science of compound hazards is compara-
478 tively immature, and it presents an opportunity to quantify risk in areas
479 where human exposure and impacts are particularly high. Capturing this
480 correlated hazard footprint is an area that is under development at many
481 catastrophe modeling vendors.

482

483 ***Wind subperil***

484 ***Wind frequency***

485 Changes in hurricane frequency and intensity due to climate change are a
486 key question posed by regulatory bodies, which partially reflects the fact
487 that this is a problem which catastrophe models are ideally suited to ad-
488 dress. The hazard portion of a catastrophe model is a database of hypo-
489 theoretical events and their associated frequencies, which may be constant
490 or vary by event, to produce a hazard distribution that matches the his-
491 torical record. Manually adjusting the frequencies of these events, or res-
492 simulating event catalogs by resampling, is a comparatively straightfor-
493 ward exercise that allows for exploring a range of frequency and intensity
494 change scenarios.

495 Unfortunately, frequency is one of the areas of hurricane science where
496 immediate climate-related impacts are least clear. Even at a global scale,
497 there is credible disagreement even on the direction of potential

498 frequency changes, much less the magnitude of those changes (Knutson
499 et al. 2020; Lee et al. 2020). In the insurance industry, tropical cyclone
500 risk is not managed at the global scale, but rather based on landfall fre-
501 quencies at the country scale. In the case of the US, landfall frequencies
502 are further downscaled to a regional scale, with loss tolerances designed
503 to maintain capital adequacy around specific regions like the US Gulf or
504 Northeast. Projecting future changes in frequency of hurricane landfalls
505 at the scale of a few states at sub-decadal time scales lies well beyond the
506 current state of climate science.

507 ***Wind intensity***

508 Much like frequency changes, catastrophe models are suitable tools to as-
509 sess the impacts in changes in intensity. Across a large stochastic catalog
510 of hypothetical events, intensity changes can be alternatively interpreted
511 as a change in frequency. For example, a 5% increase in the intensity of a
512 100mph hurricane could instead be thought of as an increase in the fre-
513 quency of 105mph events, shifting the entire probability distribution of
514 hurricane intensities towards stronger events.

515 Changes in intensity are less useful without an understanding of how that
516 change is distributed across the spectrum of storms. Intensity changes
517 are often reported as a mean change across all storms, either globally or
518 within individual basins (Knutson et al. 2020). But an increase in intensity
519 concentrated in low category storms would have a very different loss dis-
520 tribution than a similar change among stronger storms - building codes
521 along the coast typically are designed to protect at least against weaker
522 storms, but lower category storms are much more frequent than more in-
523 tense ones. Catastrophe models could assess competing influences on
524 loss with a change in intensity distribution, but a flat change across all
525 storms may be less applicable to risk management.

526 ***Wind risk management strategies***

527 The limited forward-looking skill in hurricane frequency projections and
528 comparative lack of detail in intensity projections pose a challenge to risk
529 modelers. Even when the scientific community can make reasonable fre-
530 quency projections for global tropical cyclone activity, that skill typically

531 declines when extrapolated to a single basin. And importantly, basin ac-
532 tivity does not cause property damage – landfall statistics are the ultimate
533 measure of real wind risk to an insured portfolio. However, these limita-
534 tions do not mean that insurers lack tools to manage future hurricane
535 wind perils.

536 A key consideration for insurers involves assessing which parts of the his-
537 torical record should be included when determining *current* frequency
538 distributions. In the North Atlantic hurricane basin, much of this debate
539 centers on the application of a correction to account for Atlantic multide-
540 cadal variability, a pattern which strongly influences hurricane activity via
541 increased sea surface temperatures, decreased sea level pressure, and re-
542 duced vertical wind shear in the tropical Atlantic (Goldenberg et al. 2001),
543 and which is correlated with greatly increased frequency of major hurri-
544 canes (Klotzbach et al. 2015), but may not actually represent a physical
545 oscillation with any predictive skill (Waite et al. 2020; Mann et al. 2021).
546 Catastrophe models have the option to represent hurricane frequencies
547 associated with the positive phase of the AMO, such as by producing me-
548 dium-term forecasts or conditioning frequencies on observational periods
549 in the same AMO phase rather than the full historical record, but usage of
550 these views would be complicated if the Atlantic multidecadal variability
551 lacks forward-looking skill.

552 Accounting for the degree of historical human influence on hurricane fre-
553 quency is controversial as well. Sea surface temperatures are unlikely to
554 return to their preindustrial state any time in the near future, but does re-
555 moving older storms limit the view of internal variability? In the Atlantic,
556 the 1960s-1980s experienced a low number of hurricanes, but was this
557 driven by anthropogenic aerosol pollution (Murakami et al. 2020) that is
558 not expected to return? Even if reasonable projections of basin-scale
559 event frequency can be made, can we disentangle the influence of sub-
560 basin processes like wind shear patterns, which may materially modify
561 landfalls (Kossin 2017) in ways that may not stay consistent with future
562 climate change (Ting et al. 2019)? Quantifying the climate change im-
563 pacts that have already occurred through the last century is key for un-
564 derstanding what baseline to use for current and future wind risk.

565 Although a consensus on future changes in frequency is lacking, modeling
566 is more consistent in predictions for the most intense storms - generally
567 producing an increase in the proportion of the most intense storms (Cate-
568 gory 4-5 storms or Category 3-5, depending on the study), with an in-
569 crease in absolute number in all but those models where an overwhel-
570 ming decline in total storm number overwhelms the increasing proportion
571 of stronger storms (Knutson et al. 2020). Furthermore, there is evidence
572 that this trend is appearing even in recent historical records in the Atlan-
573 tic (Kossin et al. 2020), which may reflect a blend of natural and climate
574 variability, but places the change within the time frame that is most rele-
575 vant for insurance analytics.

576 While major hurricanes make up a small fraction of total storms, they
577 contribute disproportionately to damage and loss. Estimates that ac-
578 count for inflation, population, and growth of wealth arrive at roughly
579 80% of all US hurricane losses coming from storms of Category 3 or
580 above, even though they only account for about a third of US landfalls
581 (much of the remainder comes from surge-heavy storms like Hurricanes
582 Sandy and Ike). Similarly, the most intense Category 4 and above storms,
583 which produce ~10% of US landfalls, are responsible for roughly half of all
584 US hurricane losses (Weinkle et al. 2018). Furthermore, as the US popula-
585 tion continues to concentrate in major coastal cities that are exposed to
586 wind risk, losses will be compounded irrespective of any underlying cli-
587 mate trends. For insurers concerned about capital adequacy and near-
588 term climate impacts, it is clear that climate sensitivity testing should fo-
589 cus on changes in high category hurricanes, where the science is compar-
590 atively clearer, and where changes in frequency can drive the largest po-
591 tential impacts in losses.

592 The impact of large losses from major hurricanes on the US property in-
593 surance market is clearly visible in the Rate on Line index maintained by
594 the broker Guy Carpenter (Guy Carpenter 2020). After a substantial spike
595 in market prices for US property risk following the extremely active 2004-
596 05 Atlantic hurricane seasons, there was a long decline that coincided
597 with the US major hurricane drought (Hall and Hereid 2015). Market
598 prices did not consistently reverse their trajectory until after the US major
599 hurricane drought was broken in the 2017 Atlantic hurricane season.

600 These market fluctuations likely have a variety of causes, including a re-
601 cency bias on the part of decision-makers. An increase in available capital
602 competing for premium dollars, due to a lack of events requiring claims
603 payments, was particularly important in the reinsurance and insurance-
604 linked securities markets. There are disputes about how to define a ma-
605 jor hurricane drought (Hart et al. 2016), and pressure may be a more con-
606 sistent representation of a storm’s damage potential than wind speed
607 (Klotzbach et al. 2020), but however a major storm is defined, the com-
608 parative lull of the most intense US hurricane wind events clearly was as-
609 sociated with a long-term fluctuation in the US property insurance mar-
610 ket. This substantial market impact was driven by a gap in intense
611 hurricanes that likely occurred by chance, but changes in the background
612 frequency of major hurricanes could change the odds that such a drought
613 could recur in the future.

614 Changes in hurricane wind risk may threaten insurers from an operational
615 and claims handling perspective as well. Rapid intensification is a particu-
616 lar threat, since it makes hurricane forecasting unusually difficult, is a key
617 driver of major hurricanes (Lee et al. 2016), and may worsen with future
618 climate change (Emanuel 2017b, Bhatia et al. 2019). From the perspec-
619 tive of a building, it doesn’t matter how quickly a hurricane intensifies –
620 damage is determined by the intensity of the local wind field. However,
621 major insurers use track and intensity forecasts to position teams of
622 claims adjusters in advance of a storm, and may bring in external contrac-
623 tors for repairs if the local labor market is unlikely to be able to be suffi-
624 cient to support post-event rebuilding. Lack of predictive skill in rapid in-
625 tensification may cause claims teams to underestimate the needed
626 response, slowing claims handling or recovery due to underestimated
627 pre-deployment. If the events that cause the most economic damage are
628 the least predictable, that should be reflected in how insurers prepare to
629 respond immediately before and after a hurricane makes landfall.

630 **Hazard research opportunities**

631 1. Localizing water impacts

632 Risk managers are charged with managing water risks at the spatial scale
633 of individual locations. This means that spatially-averaged climate

634 impacts on water hazards, like global sea level rise on storm surges, are
635 less useful than detailed spatial projections. Gridded sea level products
636 are starting to fill that gap. However, adding storm surge on top should
637 ideally not behave like a bathtub, but rather reflect the changing hydrody-
638 namics of surge with a new baseline, to better capture inland surge inun-
639 dation.

640 As noted in the rainfall section, there is also some evidence for important
641 impacts on hazard related to the presence of the built environment, such
642 as extent of impervious cover. Cities pose the greatest potential for risk
643 accumulation in a single event, so capturing these local-scale impacts on
644 hazard is important to correctly represent risk where the exposed popula-
645 tion is the largest.

646 2. Deeper understanding of tail wind impacts

647 As noted above, the highest intensity storms drive the overwhelming ma-
648 jority of economic losses from hurricanes in the US. However, the most
649 extreme storms are also the most difficult to represent in climate models,
650 making this a critical research target to quantify the most societally im-
651 pactful risk.

652 3. Thinking beyond frequency

653 A variety of emerging research topics on wind risk have been proposed
654 for hurricanes, including changes in rapid intensification (Emanuel 2017b),
655 inland decay rates (Li and Chakraborty 2020), and track changes (Shuai
656 and Ralf 2021). Many of these risks would have material impacts on
657 property and life and safety risk without touching the frequency or sever-
658 ity of overall hurricane counts. Splitting hurricane risk by subperil high-
659 lights these emerging hurricane risk management topics, and although
660 confidence is currently low, further research could help to explore ways
661 that hurricanes may produce societal impacts in a more sophisticated way
662 than simply checking if there will be more hurricanes or fewer.

663 4. Explicitly modeling impacts of green infrastructure on hazard

664 Catastrophe models have opportunities for enhancement that could
665 make them more effective partners in climate adaptation. For example,

666 interest has grown in recent years in “green infrastructure” to build
667 coastal flood defenses against storm surge that utilize ecosystem services
668 from mangroves, marshes, oyster banks, and the like to minimize surge
669 damage. There is some evidence that these ecosystem services can pro-
670 duce material reductions in storm surge damage and losses, at times with
671 clearly quantified economic benefits defined in the scientific literature
672 (Narayan et al. 2017; del Valle et al. 2020; Reguero et al. 2021), but there
673 are opportunities to further explore cost-benefit tradeoffs between mo-
674 bile coastal wetlands compared with hard infrastructure like seawalls,
675 which catastrophe models could be well-suited to address.

676 Catastrophe models in their present state are designed to reflect a snap-
677 shot of risk at a single point in time, so leveraging the time-varying devel-
678 opment of coastal flood risk presents an opportunity to blend the
679 strengths of both climate and catastrophe models. By quantifying ex-
680 pected annual losses associated with storm surges under different de-
681 fense assumptions, a catastrophe model coupled with a probability distri-
682 bution of sea level rise out of a climate model could put an explicit price
683 tag on the choice of an effective but inflexible piece of gray infrastructure
684 like a seawall, compared with a coastal ecosystem that perhaps does not
685 stop every surge, but can dynamically respond to changing sea levels.
686 Without such tools, hard coastal defense projects like seawalls that make
687 sense with current sea levels cannot be sufficiently compared with mobile
688 ecosystems like marshes, which may migrate inland without human inter-
689 vention assuming no inland obstructions.

690 Similarly, a common way that cities attempt to reduce the impacts of in-
691 creased extreme rainfall (from hurricanes or otherwise) is via green
692 stormwater management – building in green spaces, rain gardens, and
693 other strategies to reduce impervious surfaces, absorb excess rainfall, and
694 minimize flood peaks. Despite clear benefits to flood risk, with knock-on
695 improvements in groundwater storage and other ecosystem services (Pru-
696 dencio and Null 2018), catastrophe models generally lack the ability to ex-
697 plicitly give credit for the risk reduction produced by these activities,
698 which could perversely disincentivize this key adaptation strategy, since
699 local spending on risk reduction would not lead to a corresponding reduc-
700 tion in modeled loss impacts.

701 **Recommendation 3 – Translating climate data for decision-**
702 **makers**

703 **Time horizon**

704 There has been a longstanding disconnect between the timing required to
705 make decisions in a business environment in comparison with the time
706 frames that generally receive the most attention in the scientific litera-
707 ture. The scientific community often focuses on the ~2050-2100 time
708 frame, where climate impacts are more likely to have emerged from natu-
709 ral variability. At this time scale, anthropogenic forcing is large relative to
710 natural variability, making trends and impacts on extreme events clearer.
711 Conversely, the insurance business wants to know what to expect for the
712 upcoming year, to correspond with the length of a standard insurance
713 contract, up to perhaps a decade in the future, for its underwriting and
714 portfolio management strategy. While insurers may do qualitative hori-
715 zon-scanning exercises beyond this time frame to consider broader prod-
716 uct strategy and emerging risks, quantitative risk assessment beyond the
717 portfolio steering time frame have limited practical applicability in the in-
718 surance decision-making framework. This time frame is heavily impacted
719 by interannual and decadal scale variability, where predictive skill in cli-
720 mate models is low, so at first glance it is difficult to give clear guidance.
721 Similarly, seasonal and sub-seasonal forecasting is available that relies
722 heavily on climate features like El Niño/La Niña, but for contracts that are
723 written to cover an entire year, the relative benefit to insurance compa-
724 nies of adjusting their risk appetite to match a forecast at the current
725 level of forecast skill is marginal (Emanuel et al. 2012).

726 However, this view does not consider that the models used to manage
727 risk are built using historical data. While recent events are included in
728 regular catastrophe model updates, these models also include events
729 from past decades that occurred in a climate that will not return within
730 the next century. A key potential space to incorporate climate risk comes
731 from understanding how much change in hazard has already occurred rel-
732 ative to a historical dataset that may span up to the last 50-100 years.
733 Trends in extreme hazards like hurricanes represent a complex mix of in-
734 ternal natural variability, potentially short-term external forcings like aer-
735 osol pollution, and long-term anthropogenic climate change, so

736 disentangling the influence of each for various hurricane subperils would
737 help risk managers to account for trends in historical data while preserv-
738 ing as much of the distribution of natural variability as possible. For ex-
739 ample, catastrophe models are not limited to only using storm surges
740 within the last few years, even though sea levels have risen throughout
741 the full historical record. By extracting the component of historical storm
742 tides that came from wind only, the full distribution of historical surge
743 events is preserved, and then added on top of current sea levels. This ex-
744 plicitly accounts for known climate trends up to present while still lever-
745 aging the full variability present in over a century of historical data. In this
746 sense, attribution exercises that quantify how much climate change has
747 impacted individual recent storms or trends in events is highly valuable
748 within the insurance sector, since they can then be explicitly modeled
749 while preserving a historical statistical distribution that better captures
750 decadal-scale natural climate variability.

751 Selecting an appropriate time horizon for risk assessment has also
752 emerged as a concern for climate risk disclosure in the regulatory space.
753 Different parts of the public and private sector have different risk toler-
754 ances and planning horizons. Insurers tend to focus on immediate and
755 short-term quantitative climate impacts, because their risk is driven by
756 extreme events like hurricanes, more than changes in mean conditions
757 that are better understood at longer time periods. Infrastructure plan-
758 ners may also need to think about extreme events, such as when design-
759 ing a seawall for future storm surges, but the design lifetime of a struc-
760 ture is much longer than an annual insurance contract, which can be
761 adjusted dynamically as new climate risks emerge. Even within infrastruc-
762 ture planning, a nuclear power plant likely has a lower tolerance for a fail-
763 ure in hazard defenses than a local street. A risk management framework
764 that includes (1) critically assessing the time scale at which material cli-
765 mate risks emerge, (2) cumulative tolerance for negative outcomes, and
766 (3) the ability to adjust as the climate changes is a useful thought exercise
767 for determining climate risk tolerance both within and outside of the in-
768 surance sector.

769 Within insurance, the short-term, quantitative assessment of climate risk
770 can be supplemented by longer term, qualitative analysis of emerging

771 risks and mitigation that are poorly captured in current tools. For exam-
772 ple, it is likely that building codes will continue to improve in the face of
773 more destructive hurricanes, but predicting the timing and magnitude of
774 these reductions in building vulnerability is not currently possible, lower-
775 ing the skill of long-term projections in hurricane economic losses. These
776 differing levels of skill at different time horizons must also be clearly artic-
777 ulated in the regulatory space, to avoid counterproductive or maladaptive
778 decision-making driven by quantitative modeling at longer time horizons
779 that exceed scientific knowledge.

780

781 **Risk metrics**

782 Climate risk has often been treated as a type of emerging risk within the
783 insurance sector, with a focus on exploratory scenarios that are designed
784 to highlight potential impacts across different parts of the business (un-
785 derwriting, investments, regulatory risk, etc.). While such scenarios are
786 valuable in assessing broad-scale, interconnected risks at longer time
787 scales, they have limited utility in active decision-making. A hypothetical
788 scenario with a 50% increase in major hurricanes may appear alarming to
789 a risk manager, but without a clear and short-term time frame for when
790 such a change could be expected, it is difficult to justify making immedi-
791 ate adjustments to a portfolio of risks.

792 More valuable information from a risk management perspective comes
793 when climate risk is translated to use the same risk metrics that are used
794 in portfolio steering. This “normative approach” designs climate sensitiv-
795 ity tests around common business goals like profitability or maintaining
796 sufficient capital (Rye et al. 2021). Rather than framing climate testing as
797 an assessment of business impacts for a given amount of climate change,
798 this approach allows risk managers to the question around, and instead
799 run negative stress tests to determine what level of climate impact would
800 be sufficient to affect the risk appetite of the business.

801 The insurance industry uses a wide range of metrics to plan for risk appe-
802 tite, but some of the most common are tail risk metrics, expected losses,
803 historical events, and extreme disaster scenarios (Rye et al. 2021). Tail

804 metrics might include probable maximum loss (PML), a representative
805 large loss at a low expected frequency such as a 100 year or 250 year re-
806 turn period, or tail value at risk (TVaR), the average of all losses above a
807 given return period. In the insurance industry, tail metrics are often used
808 to assess capital sufficiency, to ensure that enough reserves are held to
809 pay claims after large events, and they are key drivers of an organization's
810 risk tolerance. Expected loss, or average annual loss (AAL), is the amount
811 of loss that occurs each year on average over a long period of time, which
812 insurers must cover with premium revenue to maintain long-term profita-
813 bility. Historical events and extreme disaster scenarios both represent
814 known loss values, which can be used as standalone scenarios, or compa-
815 nies can use frequency to assess risk tolerance - for example, how often
816 the company could sustain a Hurricane Andrew-level loss, or a Category 3
817 hurricane in New York City.

818 The value of a climate management approach driven by traditional risk
819 metrics is that it drives climate risk into the language used by risk manag-
820 ers across the insurance industry. Climate science is no longer limited to
821 the domain of scientific technical experts. As climate impacts move fur-
822 ther into the broader society, the role of translation - tracking and under-
823 standing the rapidly evolving scientific literature, contextualizing the level
824 of uncertainty, and turning climate hazards into decision-relevant metrics
825 - will spread further into more climate-affected industries. Insurance of-
826 fers an opportunity to set a clear example for how to turn science into de-
827 cision-relevant data for practitioners throughout the economy.

828 **Translating impacts research opportunities**

829 1. Hazard assessment at a wider range of time horizons

830 Decision-makers on the ground who will be directly impacted by climate
831 change, be it insurance companies, city planners, commercial risk manag-
832 ers, or homeowners taking out a mortgage, do not have the luxury of
833 waiting until 2100, when climate forcings are large enough to see clear
834 signals emerge far beyond natural variability. Particularly for rare events
835 like hurricanes, even large trends can take decades to emerge from his-
836 torical records that feature substantial multidecadal variability, as has

837 been the case in the literature looking at historical trends in major hurri-
838 canes (Vecchi et al. 2021).

839 Therefore, the end-users of hurricane climate information would greatly
840 benefit from added research activity in the messy present. This is not a
841 call for seasonal or decadal forecasting, per se, but rather a more robust
842 quantification of how much change seen to date is driven by anthropo-
843 genic forcing, compared with how much can be confidently attributed to
844 natural variability.

845 2. Engagement with end-users on time horizons and metrics

846 This discussion highlights key time horizons and metrics that are widely
847 used in the insurance sector, but other climate data end-users are likely
848 to have different needs. Infrastructure or city planners may want to look
849 50-75 years in the future, and a mortgage holder may want to understand
850 their cumulative flood risk over the next 30 years. The work of engaging
851 with climate data services end-users is slow and has struggled to gain pri-
852 ority from an incentives standpoint (funding, advancing toward tenure,
853 etc.). Enhanced interaction with social scientists may help improve com-
854 munication and co-development of climate analytics between the aca-
855 demic, public, and private sectors (Findlater et al. 2021).

856

857 **Conclusion**

858 In this article, I have presented three recommendations for how to lever-
859 age the capabilities of catastrophe risk management for dealing with cli-
860 mate change impacts on hurricane risk:

861 1. Risk modelers need to bring more data about the built environ-
862 ment to the table to meaningfully model emerging climate risks,
863 particularly for water subperils like storm surge and inland rainfall.
864 The substantial gaps in capturing the built environment in the cli-
865 mate modeling space shines a bright light on one of the most im-
866 portant contributions that catastrophe models could make to cap-
867 turing future societal impacts of climate-driven hurricane risk.
868

869 2. The unbundling of hurricane hazards into subperils that can be as-
870 sessed for relative confidence in their intersection with broader cli-
871 mate trends offers a model that could be widely applied to other
872 emerging climate hazards, like flood and wildfire risk. Where cli-
873 mate hazard confidence is higher, such as sea level rise, the near-
874 term impacts on hurricane subperils like storm surge are clear
875 enough that further dissecting of uncertainty will not fundamen-
876 tally alter what is now a risk management and policy problem (So-
877 bel 2021). However, lower confidence but high severity impacts
878 like changes in hurricane frequency can be explored through sensi-
879 tivity testing, and prioritized by their downstream societal and eco-
880 nomic impacts.

881
882 3. Finally, incorporating climate science into catastrophe modeling is
883 a clear case study highlighting the value of “climate translators” in
884 the private sector. Calls for climate risk disclosure have leap-
885 frogged the abilities of climate models (Fiedler et al. 2021), but
886 that does not mean that climate models have nothing to offer the
887 risk management community. Instead, emerging climate risks in
888 hurricane risk management will require both climate scientists and
889 catastrophe modelers to better understand the strengths and limi-
890 tations of each other’s data and toolkits. Translating climate sci-
891 ence into actionable information for end-users is critical across the
892 public and private sectors to help society adapt to the inevitable
893 climate challenges to come.

894 The entire economy will have to grapple with the ongoing impacts of
895 changes in extreme events like hurricanes. Insurance risk managers can
896 leverage their decades of experience in working with models designed to
897 quantify society’s most extreme natural hazards, which will bring valuable
898 leadership to the private sector response to climate change. The re-
899 sources and expertise in the catastrophe risk management community
900 are a key investment toward greater societal resilience in the face of cli-
901 mate change.

902

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