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Abstract

We offer results from an artificial simulation exercise that was designed to answer three fundamental questions that lie at the heart of anticipatory adaptation. First, how can confidence in projected vulnerabilities and impacts be greater than the confidence in attributing what has heretofore been observed? Second, are there characteristics of recent historical data series that do or do not portend our achieving high confidence in attribution to climate change in support of framing adaptation decisions sometime in an uncertain future? And finally, what can analysis of confidence in attribution tell us about ranges of "not-implausible" *extreme futures* vis a vis projections based at least implicitly on an assumption that the climate system is static?

An extension of the IPCC method of assessing our confidence in attribution to anthropogenic sources of detected warming allows us to offer an answer to the first question. We can also identify characteristics that support an affirmative answer to the second. Finally, we offer some insight into the significance of our attribution methodology in informing attempts to frame considerations of potential extremes and how to respond.

Keyword: adaptation, detection, attribution, uncertain, climate change

Adaptation in an Uncertain World - Detection and Attribution of Climate Change Trends and Extreme Possibilities

Throughout its many pages, the contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (2014) identified changes to the climate system and socioeconomic development processes as key drivers of vulnerability, exposure, and hazards that *together* produce and influence material risk to human and natural systems. The authors of that report also noted an increase in the volume and geographic coverage of literature available for assessing the detection and attribution of the impacts and risks of climate change that offered new and relevant information which pertains to an expanding scope of related challenges to policymakers around the world; see specifically Cramer, et al. (2014) and Burkett, et al. (2014). Pachauri, et al. (2007) had previously reported that "Responding to climate change involves an iterative risk management process that includes both mitigation *and adaptation* and takes into account climate change damages, co-benefits, sustainability, equity, and attitudes toward risk (emphasis added)." It was then immediately clear that investments in either mitigation or adaptation depend upon efficiently processing information about the magnitudes of consequences of observed and projected climate change and their relative likelihoods – characteristics that will have been detected and quantified from historical data and then, perhaps, attributed to climate change and its anthropogenic sources so that ranges of future projections can be authored.

From the perspective of real time reactive adaptation, in other words, simply detecting changes that may have been driven by climate change and/or other factors can be sufficient to inform responsive decisions. Information required to assess decisions about anticipatory adaptation, as well as long-term development projects, are more complicated. By their very nature, they rely on the attribution of detected changes to human sources of climate change that can be differentiated statistically from attribution to other confounding factors. Confidence in attribution and its quantitative calibration is therefore critical to efforts designed to project ranges of possible risks that adaptation and investment decision-makers do, or at least should, take into account.

In communicating their findings in the fifth IPCC assessment, Burkett, et al. (2014) reported the possibility of assigning greater confidence in the projection of climate change related phenomena than in the detection and attribution of changes that have already been observed; Figure 1 is a representative visual from that chapter. Working from this conclusion, we developed several motivating questions for this paper:

> As a preliminary point of access question, how can the confidence in projected vulnerabilities and impacts be greater than the confidence in attributing what has heretofore been observed in ways that are consistent with expectations derived from first principles of statistical analysis?
>
> Are there characteristics of recent historical data series that do or do not portend achieving high confidence in attribution to climate change in support of framing adaptation decisions for sometime in an uncertain future?
>
> What can analysis of confidence in attribution tell us about ranges of "not-implausible" extreme futures (that are found in the tails of the distributions of impacts) vis a vis a static (but stochastic) future assumed from a static climate system?

Answering these questions in an adaptation context is essential because of the long-term nature of some adaptations as well as for plans to reduce greenhouse gas emissions. All three answers require an *understanding of the underlying physical and social processes by which confidence in* *impact projections can legitimately be evaluated* to illuminate the foundations of strategies for iterative risk management approaches to adaptation (and mitigation). That is to say, this understanding is necessary if the science and subsequent defense of adaptive and mitigative response decisions can navigate what might otherwise be viewed as both a contradiction of statistical rigor and an obstacle for rigorous policy evaluation of adaptation strategies. ***{Insert Figure 1 here}***

To explore these questions, we constructed an illustrative statistically based simulation model that was designed to investigate the effects of one of the most profound complications confronting decision makers – taking account of confounding factors imposed by, among other things, site-specific socio-economic development pathways in the context of anticipated climate change. These are the effects that must be considered when attributing observed climate changes to associated increases in risk *and* using that attribution to create projections into the future to support adaptation considerations. Figure 2 displays a schematic representation of this complication. It suggests, for example, why the science can support attribution of the recent drought in Texas (from 2011 through the end of 2013) to anthropogenic warming while it cannot yet support a similar conclusion for the recent five year California drought that also began in 2011 where diverse topography and the proximity of an ocean confound the statistics (of what would seem at first blush to be a “no-brainer” attribution). Based on a growing number of observations indicating the unequivocal anthropogenic drivers of the observed climate warming trend, though, we argue here that we should expect that the impact of more micro scale climate changes, and consequentially the micro scale manifestation of a globally coherent “climate signal,” will increase with time while the impact of confounding variables like geographical characteristics could remain constant (or at least trend less significantly in line with observable socio-economic variables). As a result, the relative strength of the climate change signal could reasonably be expected to grow over time and offer a logical foundation for the Figure 1 results.

{Insert Figure 2 here}

Before proceeding, we note here that statistical definitions of “attribution,” “prediction,” and “projection” are applied. “Prediction” denotes the model-derived estimated values for an output variable given a vector of input values usually selected from within (or close to) the domain of observed data. “Projection” denotes estimates of the output variable from input values outside the observed domain based on confidence in our understanding of underlying processes. Confidence in either depends on the strength of “attributing” observed outputs to climate variability and perhaps to trending anthropogenic climate change as compared to other confounding factors. In our illustrative model, the output index is risk calibrated in whatever units are most appropriate for a given context; climate variables and confounding human behaviors served as the critical inputs.

The next section reviews context and our motivation more completely before the third section describes the details of our simulation framework. It is an artificial framework, to be sure, so the specific numbers do not matter; rather it is meant to illustrate a simple analytical approach from which more generally applicable insights can be drawn from qualitatively rigorous conclusions. We turn to describing some illuminating results without and *then with risk-based adaptation* in third section; they are expanded in scope throughout some supplementary material. Concluding remarks in the closing section support our claim that we have confirmed generalizable hypotheses that help answer our motivating questions, but the discussion also suggests caveats and cautions in that regard.

Background

Confidence expressed by the IPCC about the validity of its findings is evaluated on the basis of assessments of the robustness of evidence and the degree of agreement in attributing a climate-related driver. As argued in Mastrandrea et al. (2010), it is therefore distinct from reporting only strict statistical confidence In many cases, rapidly advancing climate science has supported detection assessments described by robust evidence, but it has yet to eliminate the possibility that the relevant literature on attributing observed impacts all the way back to anthropogenic climate sources supports only low confidence conclusions (Cramer, et al, 2014). This possibility is of considerable academic interest for the authors of honest assessments of the state of knowledge at any point in time, of course, but it is of possibly larger interest to decision-makers charged with adapting to risks that may grow as climate change proceeds. They need to know when they might become equipped with attribution results that can be advanced with the higher confidence required to support and then implement efficient responses for the long term in addition to when emerging circumstances might create an urgency to respond. They also need to have some idea of what the most extreme futures might look like.

We took this state of knowledge as a point of departure and acknowledged that the magnitude and thus the significance of the climate signal can, at present in many cases, be low enough that any estimation of current and future climate risk to society is as sensitive to confounding factors as it is to observed climate change. That is, we took this observation to mean that our modeling effort should include situations wherein *current evaluations* of the consequences of a historically growing but not yet significant climate signal could be largely indistinguishable from what looks to be variability within a stationary climate change record. Because the climate signal can be expected to increase in the future on the basis of our current and growing understandings of process and other types of information (like laboratory experiments or experiences in other parts of the world), however, we also thought that we should include the possibility of futures where the level of risk and the sensitivity of risk to climate variables could both be expected to increase over time.

The point in this parallel modeling track was, therefore, to simulate underlying trends associated with climate change impacts that could easily, but not necessarily, become discernable from a stationary historically supported baseline at some point in the future. We argue that agreement over process that portends a stronger climate signal in the future could therefore be expected to eventually support higher confidence in projections of climate change impacts that would eventually justify some sort of risk-ameliorating adaptive response.

The Bifurcation Approach to Climate Change and Attribution

Since the manifestations of observed climate change are, by nature, subject to variability from year to year, it is not surprising when contributions to the current literature disagree over the magnitude of the climate signal for projecting the future. To reflect various climate signal trajectories in various contexts, we took account of multiple scenarios for climate signal magnitudes and confounding variables to demonstrate that, as the future unfolds, ranges of risk associated with the impacts of climate change over future decades may or may not become increasingly discernible in comparison to comparable ranges of risk along a counterfactual scenario wherein observed changes in climate were assumed to remain stochastically stationary around a indistinguishable trend (i.e., that the climate is not changing). These constructions created an environment where a variant of the IPCC (2014) approach to attribution could be applied – the approach that supported the unequivocal conclusion that increases in global mean temperature and some (but not all) continental scale mean temperatures were the result of anthropogenic forcing.

To be more specific, we explored conditions under which the IPCC (2014) bifurcation approach to attributing observed changes in global and continental mean temperatures to anthropogenic sources could be applied more generally and to cases with projected rather than actual data. Figure 3 illustrates the 2014 results of this approach for historical and predicted temperature trends from an ensemble of climate models that were run with and without anthropogenic forcing for periods of time where actual temperature experiences had been quantified. They tracked surrounding 90% likelihood ranges for the model results and looked for the time threshold where the range of trajectories from models that incorporated anthropogenic forcing bifurcated from the range of trajectories from the same models without human interference. For the globe, the bifurcation between 90 percent ranges of model runs with and without anthropogenic forcing occurred around 1980 and supported very high confidence in attribution of observed warming to human activity from that time forward; indeed, the adjective used in this case was “unequivocal”. For continents, statistical power was weaker across their smaller geographic coverage. Bifurcations occurred around 1990 for Africa, Australia and South America. For other continents, including Antarctica and Europe, bifurcations had not occurred as of 2010, indicating that attribution of observed climate change to anthropogenic forcing was still too weak for even high confidence attribution. ***{Insert Figure 3 here}***

Here, we explored the applicability of this “bifurcation” approach to more general contexts for which we do not (yet) have enough observations to offer a high confidence attribution conclusion. We explored future scenarios for which low or high confidence in future attribution would be based on a combination of the statistical power of historical data and our process understanding of how the future might unfold with and without various strengths of growing climate signals. To accomplish this widening of context, we took the macro-scale IPCC warming attribution results to mean that an estimation of climate risk could be assessed productively in comparison with model runs wherein climate variables remained stationary over the long term. Compared to these counterfactual baselines, the consequences of even a historically growing (but not yet significant) climate signal could remain largely indistinguishable from the no-trend baseline for a very long time because a bifurcation of the 90 percent confidence ranges would not appear in what might be deemed an applicable planning horizon for an adaptation decision. Along other runs that anticipated more rapidly growing significance in the climate signal, bifurcations could occur at earlier points of time so high confidence in attribution could be achieved.

To be clear, our version of the bifurcation approach to projected future impacts after accounting for potential climate signaling scenarios enabled us to show how we might determine the timing of high confidence in attribution – that is, evidence of rigorous bifurcation against stationary baseline distributions. At the point of anticipated bifurcation (based on process understanding), natural variability of the involved systems would fail to account for increased risk, and confidence in attribution of impacts to anthropogenic forcing would become unambiguous. That is to say, our approach was designed to explore the sensitivity of confidence in attribution across time to the magnitude of the climate signal.

The Complication of Confounding Factors

Though climate models can be highly complex, projection of the consequences of climate change impacts is equally complicated by a high degree of uncertainty about futures that will be shaped by social, economic, and political trends, as well as responses of the biophysical system (Cramer, et al, 2014); we take these to be “confounding factors” in the context of assessing confidence in attribution conclusions. In studying historical and present climate trends, climatologists minimize noise from natural fluctuations by focusing on climate averages over 30-year climate normal periods as reference points for comparison (Trewin, 2007). Models projecting impacts of climate change one to two climate normal periods into the future, effectively over time scales of 30 to 60 years, are consequentially difficult to calibrate, especially since risk simulations are usually based upon factors that neither natural nor human systems have experienced before (Stainforth et al., 2017). Furthermore, the robustness of historical evidence for system responses to temperature change, from which climate models are constructed, varies regionally.

Adaptation

The IPCC (2007 and 2014) and other assessments like the Third National Climate Assessment for the United States (Melillo, J.M. et al, 2014) have reported the emergence of adaptation as a central area of climate change research, as well as in the implementation of climate change strategies that include some degree of mitigation. To examine this complication, we followed the approach of the New York Panel on Climate Change (NPCC1, 2010) by assigning a threshold of tolerable risk - the point at which society becomes uncomfortable with the risks from impacts of climate change and therefore takes seriously the need to invest in adaptation. Figure 4 replicates an illustration of this modified precautionary principle from the New York City adoption of this approach to adaptation decisions; for details, see Rosenzweig and Solecki (2010) prepared for use by the New York City Climate Change Adaptation Task Force. We modeled our results for these types of decisions as an endogenous risk-reducing confounding factor and explored the resulting shifts in distribution of risk over time for each scenario. ***{Insert Figure 4 here}***

In our illustrative models, we assumed that approaching and passing the point of bifurcation between stationary and non-stationary futures would necessarily increase the confidence that climate change was indeed causing higher risk assessments and would thereby increase the likelihood of undertaking adaptation decisions. Forward-looking adaptation measures are often undertaken in response to a multitude of factors in addition to climate change effects, and the impact of adaptation on reducing societal vulnerability to risks associated with climate change produces only moderate efficacy in many cases. We expect that passing a bifurcation point *and* approaching a tolerable risk threshold would communicate a sense of urgency for adaptation from the public and their representative policymakers. Approaching the risk threshold before the bifurcation would, of course, be more problematic, but adaptation could still be in order because the then current regime of climate variability could be causing concern regardless of its source. Both contexts were incorporated in our simulations.

Approach and Methods

We began by exploring how and why confidence could be smaller in the present relative to the future by modeling risk (taken as an unspecified product of consequence and likelihood) as a function of climate change and confounding factors variables. In a warming climate, as noted above, we could expect that the impacts of climate change would, in many cases, increase over time with rising temperatures while the impact of confounding factors may remain constant (or at least change more slowly. To account for various spatio-temporal fluctuations in environmental conditions, we expected both influences to be stochastic for any given year. To simulate a meta-analysis of climate impacts, datasets consisting of 200 observations for climate change impacts and confounding factors over a 60-year period (from subsection 2.b, essentially two climate defining periods with year 1 representing the present) were simulated by a randomly generated exercise of modeled trajectories for risk that was designed to represent a simple version of the Figure 2 schematic.

Specifically, we assumed a straightforward linear model:

$\mathbf{Y_t = F\{X_t, Z_t, \varepsilon_t\} = X_t + Z_t + \varepsilon_t}$ w where

$\mathbf{Y_t}$ is an indexed indicator of physical, natural, or social risk in year t;

$\mathbf{X_t}$ is an indexed indicator of the impact of confounding factors on risk in year t;

$\mathbf{Z_t}$ is an indexed indicator of the impact of climate change on risk in year t; and

$\boldsymbol{\varepsilon_t}$ is a normally distributed error term (with a mean of 0 and a standard deviation of 1).

The $\mathbf{X_t}$**,** $\mathbf{Z_t}$**,** and $\mathbf{Y_t}$ indices can all be an aggregate of vectors of specific factors. The contribution of confounding factors to annual risk was reflected by two different trajectories for the X_t ; data points in either were, for each year, drawn randomly from normal distributions with constant means of 3 and 6 and standard deviations of 1. The point, here, was to reflect the inherent variability of confounding factors and their annual impacts on $\mathbf{Y_t}$.as well as an arbitrary anchoring assumption that the means of the distributions of these impacts would be stationary over time at one of two possible values.

Likewise, to account for present uncertainty about the magnitude of climate change impacts, we created four potential Z_t trending scenarios with low, medium, high, and very high climate signals; data points for each were drawn from normal distributions with mean of 3 plus a trend component and a standard deviation of 1). The $\mathbf{Z_t}$ trends caused the mean to increased annually by [0.5/30], [1.5/30], [3/30], and [6/30], respectively. The denominator of 30 means that the numerator represents the change in $\mathbf{Z_t}$ over a climate-defining period of three decades. To solidify a basis for comparison, we also created a baseline scenario in which climate change was assumed not to be occurring; that is, we imposed a stationarity constraint on climate along baseline scenarios by assuming that $\mathbf{Z_t}$ was distributed, in all 60 years, normally around a mean of 3 with a constant standard deviation of 1. Notice, now, that the mean value for $\mathbf{Y_0}$ could be 6 or 9 depending on whether confounding factors were high or low.

We finally assumed, following Rosenzweig and Solecki (2010), that adaptation policies could be enacted as $\mathbf{Y_t}$ approached a known *threshold of tolerable risk*, (a la by including a contingent amended scenario wherein adaptive measures would be implemented when in the high X_t scenario when $\mathbf{Y_t}$ grew above 10, our designated threshold for illustrative purposes. Beyond that point, the "effective" distribution of $\mathbf{X_t}$ would be normally distributed around a mean of 4 with the same standard deviation. For convenience, the modeling assumes instant adaptation without loss of qualitative generality. This structure simply indicated that adaptation could effectively reduce risks contributed by confounding factors in the high $\mathbf{X_t}$ baseline case (i.e., would be a positive confounding factor) and, for simplicity, would come into play along only along the high baseline scenario; along the low scenario, total variability in confounding factors and climate change drivers would always be too low for adaptation to provide any valuable risk reduction relative to the tolerable threshold of risk. This structure also stipulated that adaptive measures that lower the risk associated with confounding factors would be taken even in the baseline Z_t scenario, in which the climate was subject to a stationarity constraint. Here, we assumed that decision makers would take initiative to reduce the impact of confounding factors when the risk to society was sufficiently high, regardless of whether that risk increased over time. Finally, we imposed the simplifying assumption that the $\mathbf{X_t}$ and $\mathbf{Z_t}$ are uncorrelated.

An Illustrative Contextual Illustrating Example – "Summer in the City"

As an example of what we had in mind with this structure (see Figure 2, again, for the general schematic), consider the sensitivity of annual mortality and morbidity caused by extreme heat and/or frequent heat waves in two different urban areas located along the eastern seaboard of the United States. Here, the indicators of confounding factors are the site-specific components that influence $\mathbf{Y_t}$, the output of interest– components that are affected directly by increases in the local manifestation of global mean temperatures that have been attributed to anthropogenic sources. Both cities have experienced summer heat and associated heat-waves in growing intensity and frequency over the past few decades.

Figure 5 portrays two indicators of decadal trajectories of summer heat along multiple temperature pathways for each of two different emissions scenarios (one includes no mitigation and the other portrays the effect of robust mitigation) through the year 2100; they are derived from Figure 4.9 in National Research Council (2010). The six different climate (warming) trajectories display alternative strengths in specific signals for summer temperature along the east coast from Maryland to Connecticut. They are driven by two alternative emissions pathways with uncertain temperature manifestations; three temperature transients are differentiated by uncertainty about climate sensitivity to greenhouse gas concentrations and the behavior of various carbon sinks around the world to higher temperatures. They are reflective only of overall summer heat, but they can also be converted to display the frequency of heat-waves (3 consecutive days above 90 degrees F) and associated mortality and morbidity. ***{Insert Figure 5 here}***

The metropolitan area of one city, Baltimore perhaps, is relatively old and established with industrial activity scattered and growing across a widespread residential suburban area with a vibrant international port. Downtown is a hub of vibrant economic and cultural activity, so many people commute in private automobiles to center-city workplaces or events. Traffic jams are frequent every morning and again every afternoon. Roofs across the city are generally black, and there are few parks where a large number of trees can provide shade relief from the heat of the sun. The population of the city is growing because it is generally an attractive place to live. The heat-island effect is quite pronounced and growing; and there are health issues caused by ambient air pollution. All of these characteristics would be confounding factors that should be reflected in our model as components of index $\mathbf{X_t}$ along a *high sensitivity* baseline.

The metropolitan area of the other, New York City, is geographically similar, but its heat island effect has been diminished by city programs to expand mass transit, plant tens of thousands of trees wherever they can fit, paint a majority of the roofs white and/or cover them with urban gardens, and other positive adaptations. The correlation of health effects with extreme heat has also been ameliorated to some degree by emergency response programs that open "cooling centers" and divert electricity in peak times to the cooling infrastructure in most of the city's hundreds of thousands of commercial buildings and residential structures. All of these characteristics would be included in a second vector of confounding factors that would be reflected in our model as components of index $\mathbf{X_t}$ along a low sensitivity baseline. They are therefore reflections of city-led adaptations that have already been undertaken; and so they are reflections of a willingness to continue to adapt to future warming when a predetermined level of tolerable risk has been surpassed. As noted above, Rosenzweig and Solecki (2010) describes how NYC has invented and adopted this risk-based decision-threshold approach from a risk-management perspective.

Results and Discussion

To represent differences between any climate change scenarios and the no change baseline scenarios over time, we first generated 60 years of "observations" of $\mathbf{Y_t}$ for both cases from 200 randomly selected combinations of {$\mathbf{X(t), Z(t), \varepsilon(t)}$} for t = { 1, 2, … 60}. Denote outcome observations across 200 scenarios by

$$\{\mathbf{Y^j(1), Y^j(2), \ldots Y^j(60)}\} \text{for } j = \{1, 2, \ldots 200\}$$

with the index j identifying the specific trial combination (e.g., a combination of confounding factors with a specific climate change trend, and so on). We then identified the 5th and 95th percentile values for each year's set of observations for each trial from the collection of observations from the 200 runs of the model; denote them by

$$\{\mathbf{Y^{5th}(1), Y^{5th}(2), \ldots Y^{5th}(60)}\} \text{ and } \{\mathbf{Y^{95th}(1), Y^{95th}(2), \ldots Y^{95th}(60)}\},$$

respectively. To preserve internal consistency with the underlying model specifications, the trajectories used to represent the boundaries of the 90-percent likelihood ranges portrayed in Figure 6 were the single pathways {$\mathbf{Y^{j\text{-}5th}(t)}$}and {$\mathbf{Y^{j\text{-}95th}(t)}$} that, of all 200 runs, minimized the sums of the differences

$$\left|\mathbf{Y^j(t) - Y^{5th}(t)}\right| \text{and} \left|\mathbf{Y^j(t) - Y^{95th}(t)}\right|$$

over 60 years from t = 1 to t = 60. The resulting 90 percent confidence intervals surrounding mean or median pathways calculated for the 200 trials represented upper and lower bounds to which we applied the IPCC bifurcation approach described above. ***{Insert Figure 6 here}***

Panel A of Figure 6 portrays some representative results of these simulations in terms of upward trajectories of projected 90-percent intervals of climate risk that gradually deviate from their corrresponding 90-percent intervals for the stationary baseline (i.e., 200 runs derived from the same set of random draws for $\mathbf{X_t}$ and $\boldsymbol{\varepsilon_t}$ as well as $\mathbf{Z_t}$ *with a constant mean of 3*). Along any climate change scenario, the *increase* in climate risk, $\mathbf{Z_t}$, drives the increase in overall societal risk. In comparison to the baseline, risk was expected to rise over time in all non-stationary climate futures, though the difference between trajectories was designed to be (or not to be) substantial depending on the confounding factors that determine the sensitivity of the baseline and the strength of the climate signals' growth.

The projected rise of the climate risk trajectories resulted in the eventual bifurcation of the 90-percent ranges of climate risk vis a vis the baseline ranges for all climate scenarios – sometimes in the near future (for collections of high and very high $\mathbf{Z_t}$ climate trajectories) and sometimes in the much more distant future (for collections of low and medium $\mathbf{Z_t}$ trajectories). The bifurcation approach thereby demonstrated how it would be possible to report rigorously higher confidence in climate change impact projections than detected historical impact predictions. It is important to note that the bifurcation point marked the time period where the 95^{th} percentile scenario for the stationary climate assumption fell below the 5^{th} percentile scenario for the dynamic climate assumption – an important piece of information for adaptation decision-makers who appropriately worry about extreme futures as well as "best guess" means or medians.

Panel B of Figure 6 displays the results of repeating the confidence interval comparisons along confounding factor trajectories that allow endogenous adaptation to protect against intolerable levels of risk**.** These risk-based adaptive responses can lower the impact of confounding factors on $\mathbf{Y_t}$ output risk for the high $\mathbf{X_t}$ scenario for years following the earliest year in which Y_t exceeds 10. In this set of runs, we observed that adaptation can delay the point of bifurcation for the low and medium $\mathbf{Z_t}$ climate trajectories. In the high and very high climate trajectories, however, the differences from the same cases in the high $\mathbf{X_t}$ scenario are minor. Adaption functions, it would seem, are effective in keeping society below a threshold tolerable risk in the near future for scenarios in which the climate trajectory is growing slowly, but are not so effective in insulating society from a rapidly growing climate risk.

Figure 7 provides a different view of the results that adds some context to this observation by tracking the likelihood of crossing the threshold of intolerable risk at various points in time along all the baseline and all four climate change scenarios without and then with the possibility of endogenous adaptation. Along the low $\mathbf{X_t}$ confounding factor scenario, the rate of increase is highest from years 15 to 30 for very high $\mathbf{Z_t}$ case and appears to increase at a high and near-linear rate after year 15 for the high $\mathbf{Z_t}$ scenario. Along the high $\mathbf{X_t}$ confounding factor scenario, the rate of increase in probability is highest between years 0 and 15 for the high and very high $\mathbf{Z_t}$ scenarios, and between 30 and 45 for the medium $\mathbf{Z_t}$ scenario. ***{Insert Figure 7 here}***

The trajectories for the increase in probability in the adaptation scenarios begin in the same position as the high $\mathbf{X_t}$ scenario. As adaptation is incorporated into society's risk function, however, we observe that all but the very high Z_t climate scenario experience a window of time in which the probability of crossing the threshold is reduced from year 1. In our simulated runs, the probability of crossing the risk threshold is reduced for all two climate normal periods in the low Z_t case. In the medium and high Z_t cases, the climate signal outpaces adaptive measures after 30 and 15 years, respectively. That is to say, if mitigation policies fail to curb the climate signal and the planet faces a high or very high $\mathbf{Z_t}$ scenario past year 15, however, then society will continue to be vulnerable to risk by year 30 even with adaptation. These results underscore the fact that the tolerable risk approach to adaptation is not a one and done proposition. Figure 5, drawn from Rosenzweig and Solecki (2010 and 2014), shows that it was appropriately envisioned (at least for New York City) to be a flexible and iterative process. The implication is that a series of adaptations should be anticipated as the threshold threatens to be exceeded time after time (with the interval between adaptations perhaps shrinking over time) simply because increases in climate change risk driven by anthropogenic sources do not stop as a result of any single adaptation at a single location.

Table 1 offers some other synthetic results derived from our simulation experiment. They are essentially "laugh tests" with which to gain comfort in believing that these artificial simulation results are suitably comfortable reflections of how the real world can work. Figures SM-1 and SM-2 in the Appendix portray the results as histograms of the likelihood of crossing the threshold of tolerable risk over time without and with adaptation; they reflect the content of the table as well as the text immediately above.

Table 1: Inferences from increasing uncertainty in climate change signaling with reference to Figure 2 Some "laugh test" calibrations against reality.

1.	Given present uncertainty about climate change trajectories, including multiple scenarios can allow for the systematic evaluation of confidence in risk-based depictions of the significance of the attributed climate signal over time extreme and even moderate rates of change.
2.	By construction, bifurcations of confidence intervals between the range reflecting an attributed climate change signal and the baseline no climate change range can support anticipating high confidence in assessments' conclusions on the impacts of climate change on risk through its likelihood component at some point in the future.
3	Using the bifurcation approach, it is possible to speculate when responding to the proximity of a tolerable risk threshold will become more urgent because the high likelihood of its consequence would be confirmed.
4.	At the high extreme, the attributed climate signal range could become distinct in the very near future regardless of confounding factors.
5.	The sequencing of events and the decision criteria could have important implications on when adaptation is implemented depending on the point of bifurcation.
6.	If the climate signal is adequately low, then it could remain statistically buried among confounding factors and adaptation decisions would be based on characterizations of observed climate variability.

Conclusions and Discussion

From our illustrative models, we have shown that the occurrence of bifurcations for scenarios that proceed with and without anthropogenic forcing can inform decision-makers who worry about crossing thresholds of acceptable risk at a more local scale. Since the degree of assessed resilience given associated confounding factors are specific to each system, risks accompanying the climate change signal and any threshold for tolerable risk are likewise unique for each scenario and each location. We hope that calibrating our approach to predicted or projected data for various sectors at a specific location will provide useful, but only if it is supported by rigorous analysis and strong process understanding. Here, we have demonstrated that the bifurcation approach to attribution that was invented and then adopted by the IPCC for global and continental scales can be applied more locally – but only if one takes full account of the differences between prediction and projection.

We began with three fundamental questions. In the first, we asked how confidence in projected vulnerabilities and impacts could be greater than confidence in attributing what has heretofore been observed in ways that are consistent with expectations derived from first principles of statistical analysis. The results reported above show that including robust understanding of underlying processes that describe output risk along projected ranges of how the future might unfold can, in some cases, uncover bifurcations that support high confidence in conclusions that claim that anthropogenic sources (and their drivers) can be used to look rigorously into the future. Bifurcations are likely to emerge along high climate change scenarios (so they may be delayed by effective mitigation); in other words, we cannot forget that mitigation matters. Conversely, bifurcations may be obscured by confounding factors, especially if distributions of climate change uncertainty grow slowly as the future unfolds. Indeed, Panel B of Figure 6 shows that it is possible that an anticipated bifurcation that differentiates across alternative mitigation pathways can disappear until the distant future; in that case, though, investing in reactive adaptation to protect against the 95th percentile climate future along a mitigation emissions scenario could be sufficient to protect against lower manifestations of a weaker mitigation future.

We also began by pondering whether there are characteristics of recent historical data series that portend achieving high confidence in attribution to climate change in support of framing adaptation decisions for an uncertain future. The characteristics just noted show the answer here is positive. Bifurcation can add urgency to adaptation decisions that might otherwise be questionably appropriate when only current climate variability can describe the decision-making environment.

Finally, we noted almost in passing but perhaps most importantly, that bifurcation means more than differences in the median trends. Bifurcations, by their very construction, mean that the high 95th percentile future assuming no climate change (i.e., the worst possible future) deviate measurably from the 5th percentile future assuming that anthropogenic climate change is driving the future. Put another way, the worst possible future becomes the best possible future – an unsettling conclusion for long-term adaptation planning. It follows that anticipated dates of bifurcation assume even more significance – they signal a discontinuous change in the decision environment.

More broadly, our results confirm that the IPCC's method of evaluating the robustness of evidence and degree of agreement in scientific findings can produce more confidence in projected vulnerabilities in comparison with confidence based on assessments of observed impacts. This creates challenges in strategizing risk management policies that are both effective and economical. This paper emphasized the value of using a bifurcation approach to provide decision-makers with a framework useful for risk management when there is uncertainty in the severity of risk itself.

Scale and location also matters in examining climate change impacts and responses. IPCC (2007) shows this directly in its attribution of observed temperature change at global and continental scales to anthropogenic forcing. However, decision making in response to climate change typically occurs at a much finer granularity; the Baltimore and New York City examples show this with equal clarity. Wilbanks and Kates (1999) as well as Yohe (2010 and 2014) and Field, et al (2012) have already made this point. From our illustrative models, we expect that the occurrence of bifurcations across futures that are projected with and without anthropogenic forcing can inform those decision-makers who worry about crossing thresholds of acceptable risk at a local scale. A template protocol for their work based on this analysis is quite simple: calibrate climate and non-climate indicators and their drivers, link those calibrations to anticipated futures (specific to the drivers), and then look for anticipated bifurcation dates (or ranges, thereof) when high confidence that a dynamic climate will become a defensible primary reason for concern. Understanding how the bifurcation might occur (and when) then becomes a keystone foundation for making long-term adaptation plans.

Finally, determining whether a given magnitude of output risk can be attributed to a high climate signal or a high confounding factors baseline can be a daunting challenge, particularly with respect carefully distinguishing cases where responses to climate induced risks can only be informed by predictions of growing collections of current observations rather than effectively extended by ranges of future projections. Looking for bifurcations in the later case can play a role in this cataloguing problem. This is particularly true for our modeling. Evolving climate science and continued monitoring of the climate signal could decrease variance and thus the range of confidence intervals (based on either projections or more conclusive bifurcation results) in future assessments (with relative skill that depends on time dimensions). Were that to happen, risk impacts associated with geometrically expanding ranges of predictions outside of the range observation domain could be replaced in support of an adaptation decision-making process by ranges of projections that would decrease at a rate that could actually accelerate over time.

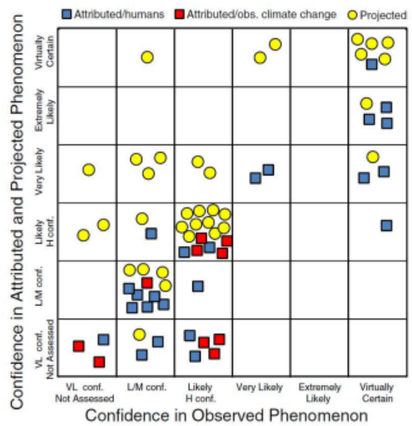


Figure 1: Confidence in Attribution and Associated Future Projections Relative to Confidence in Detection. Confidence in the attributed (squares) and projected 21st century (yellow circles) changes in climate system phenomena plotted as a function of confidence in their detection to date. Notice that confidence in projections is routinely larger than confidence in attribution based on historical observations. Source: Figure 1-6 of Burkett, et al, (2014) with reference to Table 1-2).

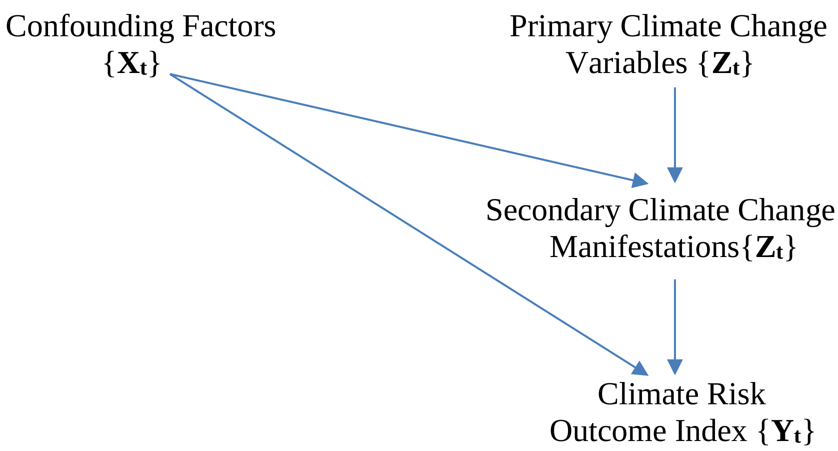


Figure 2: A Schematic of Climate Impacts when Accompanied by the Impacts of Compounding Factors. Climate risks at time t (denoted by $\mathbf{Z_t}$) can influence outcome indices (denoted by $\mathbf{Y_t}$) directly or indirectly through one or more confounding factors (denoted by $\mathbf{X_t}$). The interactions can be represent most generally by $\mathbf{Y_t} = \mathbf{F}(\mathbf{X_t}, \mathbf{Z_t}, \boldsymbol{\varepsilon_t})$, where $\boldsymbol{\varepsilon_t}$ represents a stochastic term. The first derivatives of F(-,-,-) with respect to any argument can be positive or negative as can cross-term second derivatives.

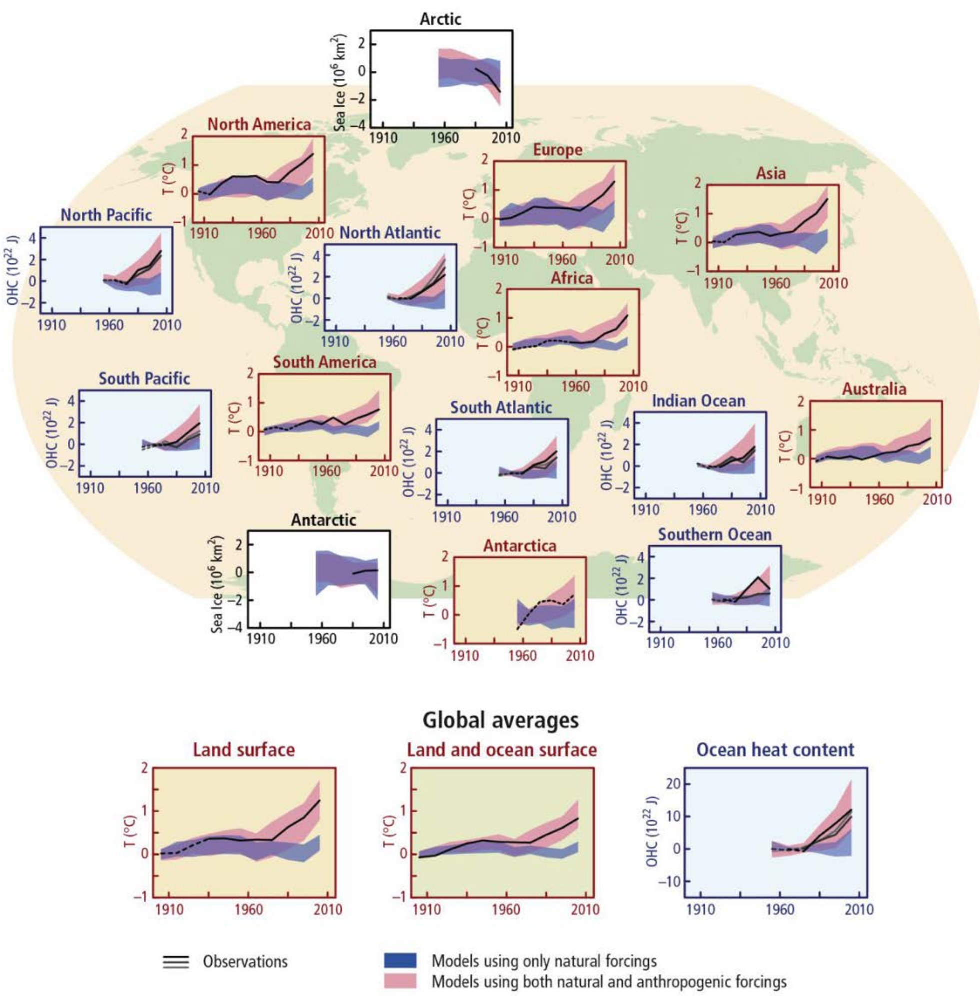


Figure 3: Attribution of Warming to Anthropogenic Sources (Sources: Figures 1.10 and SPM-6 in IPCC (2014c). The caption for the former replicated here reads: Comparison of observed and simulated climate change for change in continental land surface air 3 temperatures (yellow panels), Arctic and Antarctic September sea ice extent (white panels), and upper ocean heat content in the major ocean basins (blue panels). Global average changes are also given. Anomalies are given relative to 1880–1919 for surface temperatures, to 1960–1980 for ocean heat content, and to 1979–1999 for sea ice. All time series are decadal averages, plotted at the centre of the decade. For temperature panels, observations are dashed lines if the spatial coverage

of areas being examined is below 50%. For ocean heat content and sea ice panels, the solid lines are where the coverage of data is good and higher in quality, and the dashed lines are where the data coverage is only adequate, and, thus, uncertainty is larger (note that different lines indicate different data sets; for details, see Figure SPM-6 in IPCC (2014c). Model results shown are Coupled Model Inter-comparison Project Phase 5 (CMIP5) multi-model ensemble ranges, with shaded bands indicating the 5% to 95% confidence intervals.

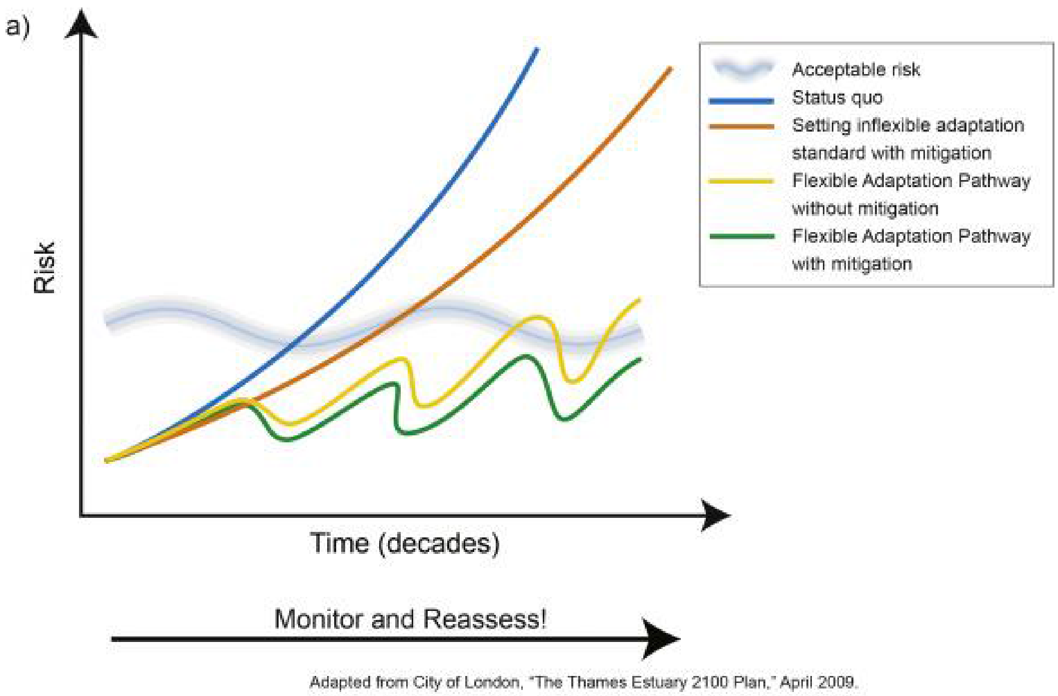
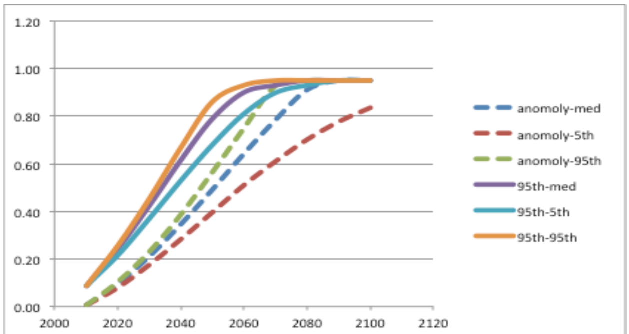
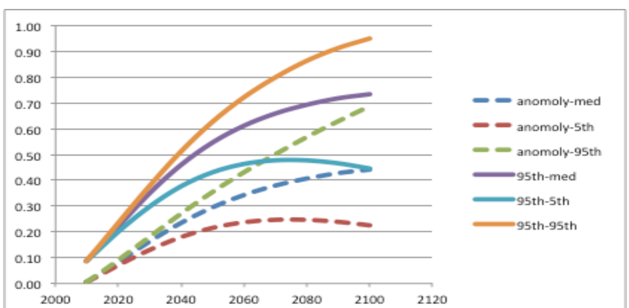


Figure 4: The New York City "Tolerable Risk" Approach to Adaptation Decisions. Tolerable ("acceptable") risk can be a productive decision threshold for adaptation decisions as the future unfolds. Once time adaptation in combination with mitigation simply delays the advent of intolerable risk (exaggerated consequences or likelihoods of threatening conditions).

Adaptations that are flexible and iterative can achieve a future wherein actual risk can be maintained below the threshold. With mitigation, though, flexible and iterative adaptation investments can be more productive. Source: Rosenzweig and Solecki (2014).



Panel A:



Panel B:

Figure 5: Likelihoods of Experiencing Anomalous and 95th percentile Heat Every Year along the "No-Policy" and Temperature Limiting Trajectories. From Yohe (2017), anticipated changes in the likelihood of experiencing the anomaly or the 95th percentile summer heat *every year* are derived from NRC (2010, page 102). For reference, #ONENYC (2017) reports an average of 2 prolonged heat waves per year during the baseline observation period (1971-2000); NPCC3-

CCATF (2017) portrays a plus or minus 2 range in that estimate around the same mean for the same historical period. The anomaly from 1971 through 2100 represents the warmest average summer temperature calibrated from June 1st through August 31st ; the 95th percentile represents the average summer temperature for the second warmest summer over the same time period. Reported projections for *each year* are calibrated along alternative emissions trajectories in terms of the likelihood that the average summer temperature will exceed the temperatures of anomalous year or the 95th percentile year (a tolerable risk threshold). Working with the median likelihood projections for the anomalous and 95th percentile projections, the results for the "no-policy" in Panel A show that the likelihood of experiencing the anomalous hot summer *every year* climbs from less than 5% to roughly 70% at 1.8 degrees C of warming and to 95% with 2.8 degrees C of warming. Panel B shows that the likelihoods of experiencing the 95th percentile summer heat *every year* are higher immediately and can still reach more than 75% in a policy future achieving a 2-degree cap on global mean temperature. (Source: Yohe (2017))

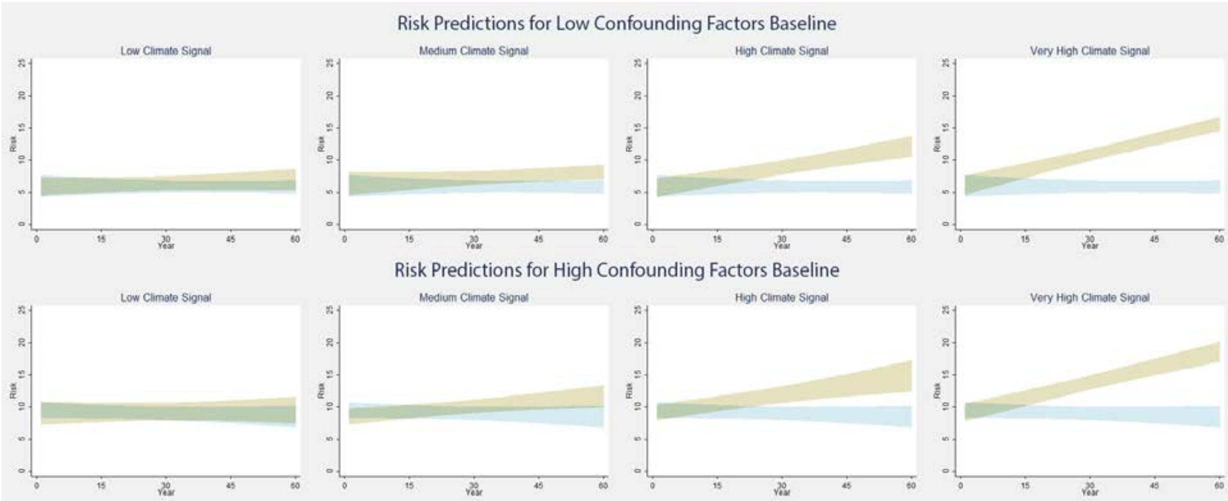


Figure 6: Panel B shows risk projections along climate change scenarios post adaptation designed to maintain tolerable levels of risk in comparison to the climate baseline. Adaptive responses aimed at preventing intolerable output risk can lower the impact of confounding factors on $\mathbf{Y_t}$ output risk for the high $\mathbf{X_t}$ scenario. Bifurcations of the climate change confidence intervals from the baseline confidence interval for different $\mathbf{Z_t}$ scenarios behaves as before, but compared to the high $\mathbf{X_t}$ scenario, overall risk increases more slowly within the first 15 years for the low and medium climate signal scenarios.

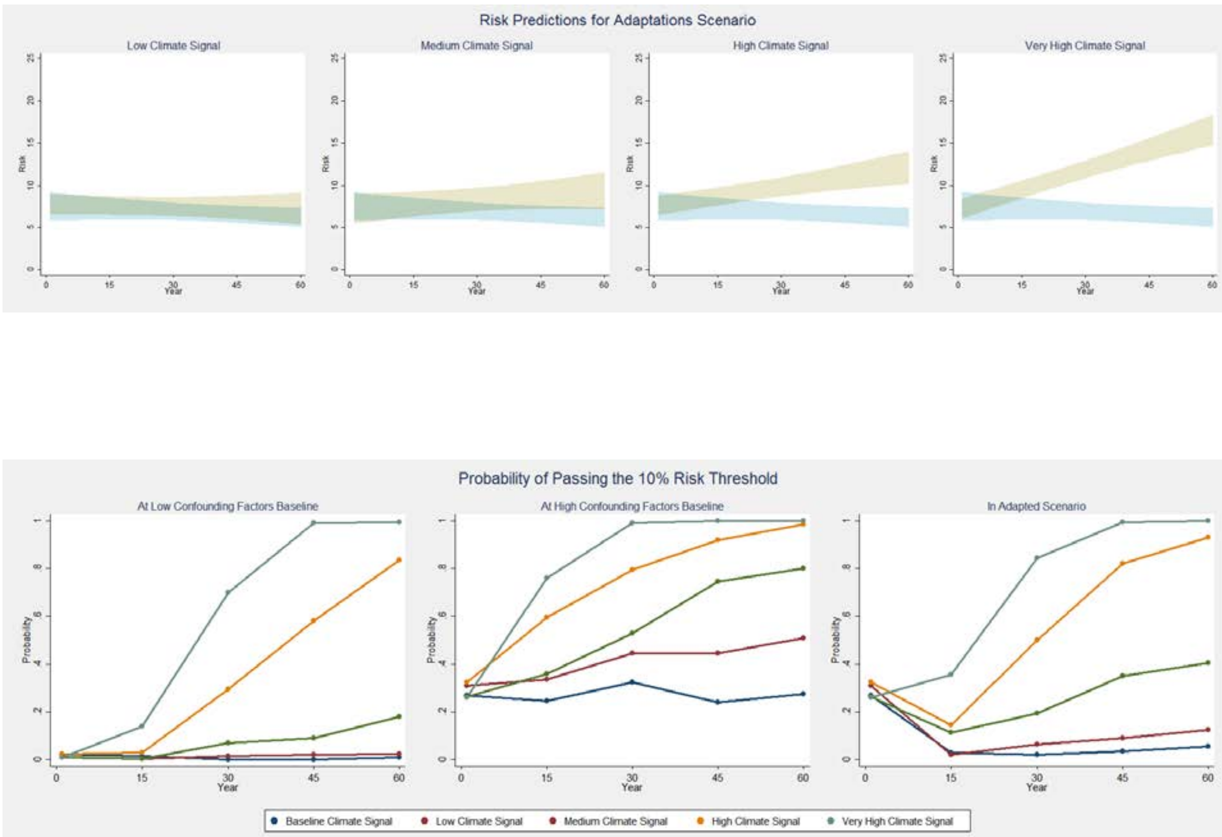


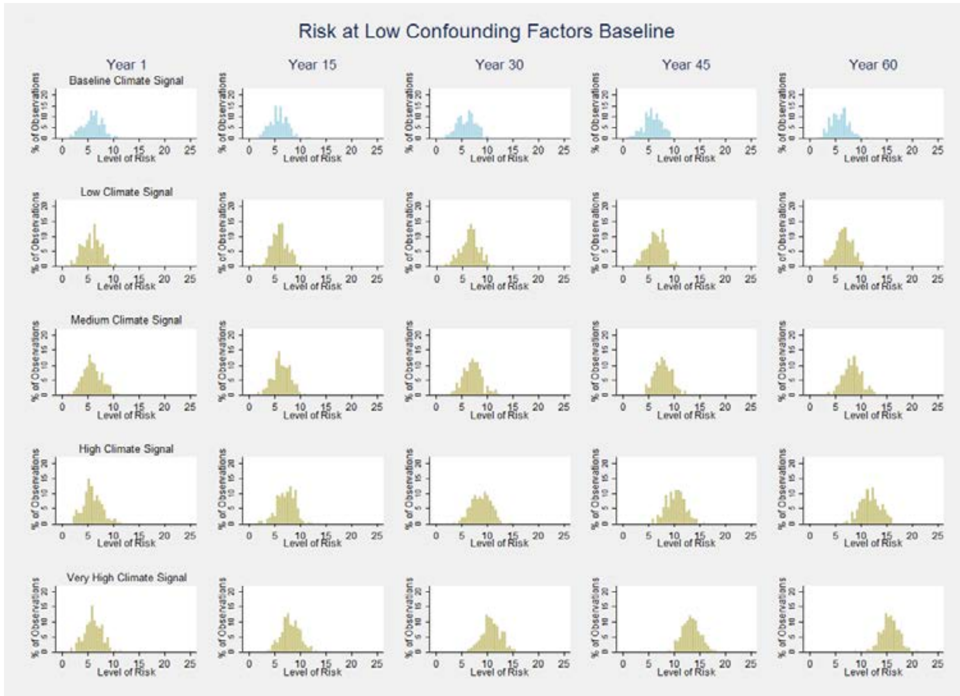
Figure 7: Sensitivity of risk over time. Probability of crossing the operative threshold of tolerable risk ($\mathbf{Y_t}$ =10) along any of the five scenarios at benchmark years in the future.

Appendix

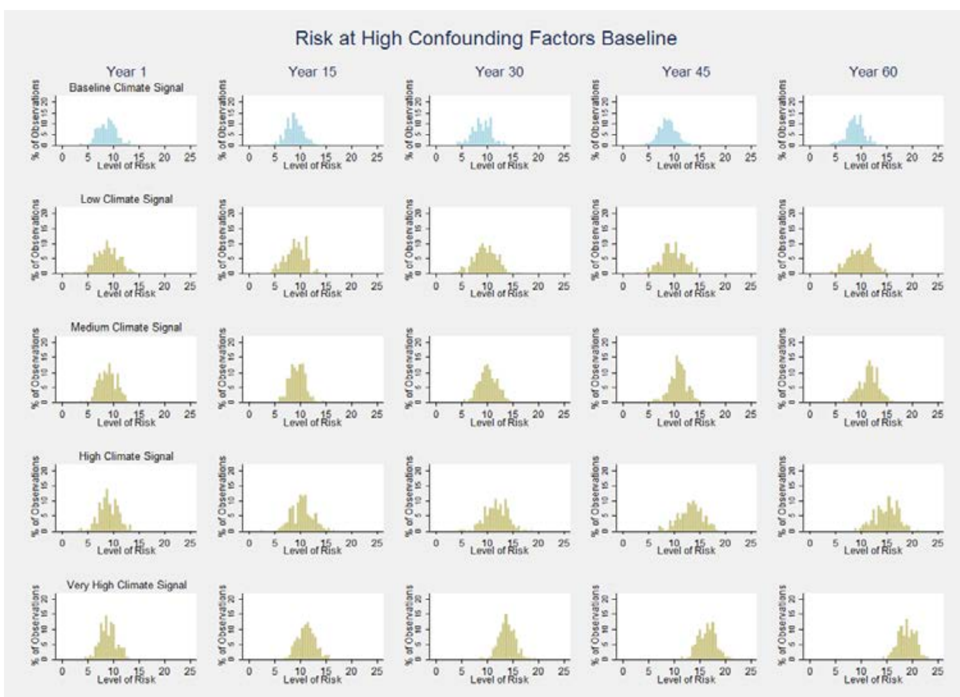
Supplementary Material

Here we present histograms of risk produced by the simulations that demonstrated the bifurcation of the risk intervals between the for positive trend climate change and baseline scenarios along two trajectories of confounding factors that were discussed in the text. Recall that year 0 represents the present day year zero histograms are a reflections of historical variability in risk as generated by the 200 simulation runs; these portrayals of annual baseline risk do not change substantially in mean or median as the future unfolds. The overlap of the climate change and baseline scenarios in early years demonstrate how current risk factors associated with climate change cannot yet be attributed with high confidence to climate change impacts. They show, as well, also that the range of risk projections will increase and create concerns for approaching or surpassing society's tolerable risk threshold of 10 as the future unfolds along climate change scenarios of any size.

Panel of Figure SM-1 shows distributions of risk projections at benchmark years along the low and high $\mathbf{X}_t$ scenarios for all $\mathbf{Z}_t$ scenarios. The probabilities of observations' crossing the 10 unit threshold of tolerable risk increase, as expected, over time at rates that increase with the magnitude of the climate signal. In the low $\mathbf{X}_t$ scenario, the probability of crossing the risk threshold remains low in year 60 for the low and medium $\mathbf{Z}_t$ scenarios, although the probability climbs above 50 percent by year 30 in the very high $\mathbf{Z}_t$ scenarios. In the high $\mathbf{X}_t$ scenario, the probability of crossing the risk threshold is projected to surpass 50 percent in the given time frame for all scenarios. For the high and very high $\mathbf{Z}_t$ scenarios, the 50 percent probability will be approached or achieved by year 15.



Panel A



Panel B

Figure SM-1: Shifts in risk distributions over time along low and high confounding factor baselines. These panels display distributions of risk projections at benchmark years along the low and high $\mathbf{X_t}$ confounding factor scenarios for all of the $\mathbf{Z_t}$ climate scenarios. The probabilities of observations' crossing the 10-unit threshold of tolerable risk increase, as expected, over time at rates that increase with the magnitude of the climate signal. Along the low $\mathbf{X_t}$ confounding factor scenario displayed in Panel A, the probability of crossing the risk tolerable threshold remains low through year 60 along the low and medium $\mathbf{Z_t}$ climate scenarios, although the probability climbs above 50 percent by year 30 along the very high climate change futures. Along the high $\mathbf{X_t}$ confounding factor scenarios displayed in Panel B, the probability of crossing the risk threshold is projected to surpass 50 percent over the 60 year time horizon for all scenarios. For the high and very high $\mathbf{Z_t}$ climate scenarios, the 50 percent probability is achieved by year 15.

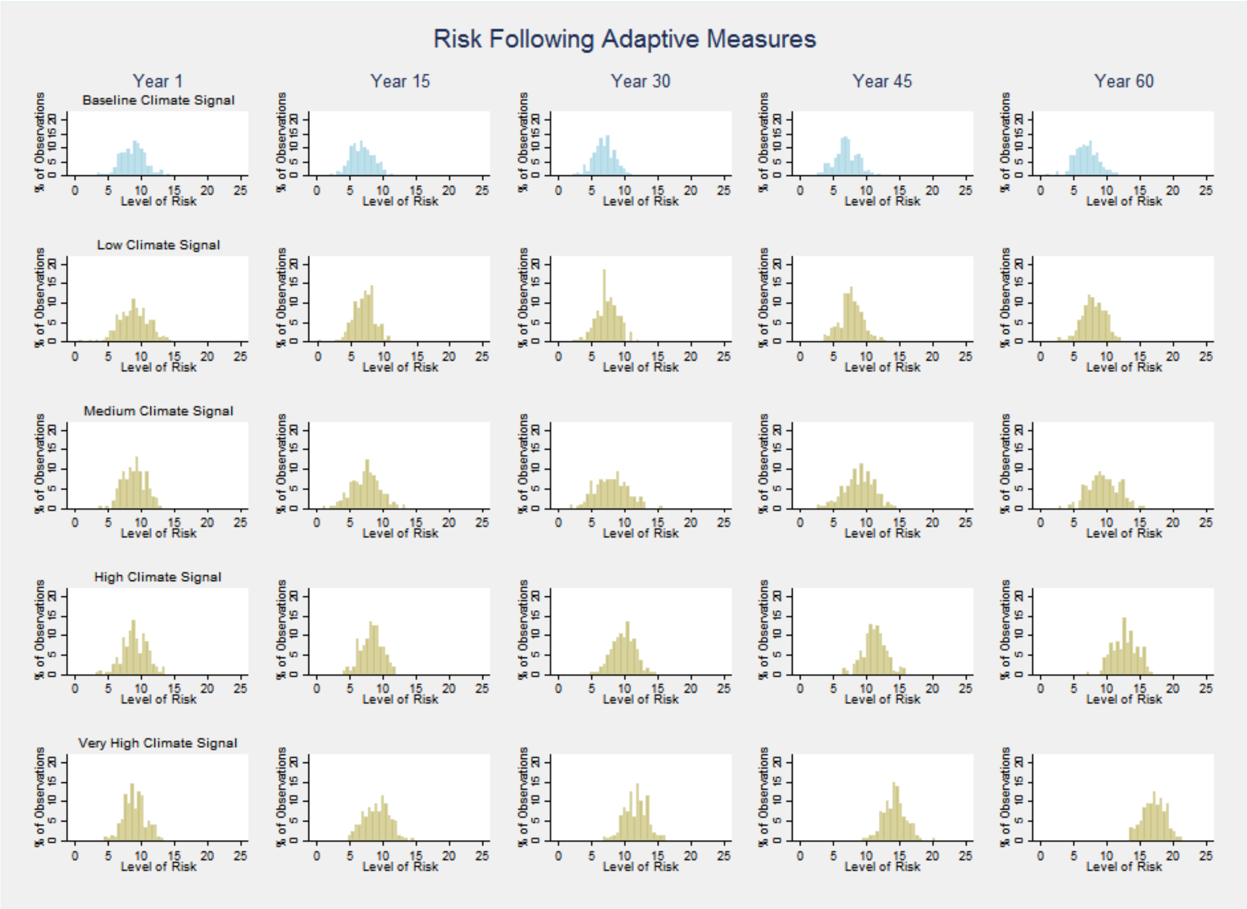


Figure SM-2: Shifts in risk distribution over time with adaptation. Endogenous adaptation (setting the mean value of $\mathbf{X_t}$ to 4 when output risk exceeds 10 units from then on along any scenario run) is shown to be effective along the high $\mathbf{X_t}$ baseline confounding factors scenario in shifting the distributions of risk outcomes down throughout the time horizon along the low, medium, and high $\mathbf{Z_t}$, climate change scenarios.

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