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Country-Level Climate Uncertainty for Risk Assessments: Volume 1

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Abstract

This report uses the CMIP5 series of climate model simulations to produce country-level uncertainty distributions for use in socioeconomic risk assessments of climate change impacts. It provides appropriate probability distributions, by month, for 169 countries and autonomous-areas on temperature, precipitation, maximum temperature, maximum wind speed, humidity, runoff, soil moisture and evaporation for the historical period (1976-2005), and for decadal time periods to 2100. It also provides historical and future distributions for the Arctic region on ice concentration, ice thickness, age of ice, and ice ridging in 15-degree longitude arc segments from the Arctic Circle to 80 degrees latitude, plus two polar semicircular regions from 80 to 90 degrees latitude. The uncertainty is meant to describe the lack of knowledge rather than imprecision in the physical simulation because the emphasis is on unfalsified risk and its use to determine potential socioeconomic impacts. The full report is contained in 27 volumes.

ACKNOWLEDGMENTS

The authors are grateful to Group 0150 for providing support in preparing this report and for appreciating the potential impact of climate change on international security and on Sandia's mission.

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NOMENCLATURE

CMIP5	Coupled Model Intercomparison Project Phase 5
DOE	Department of Energy
SNL	Sandia National Laboratories
m	Meter
s	Second
da	Day
C	Degrees Centigrade
K	Degrees Kelvin
kg	Kilogram
yr	Year
m2	Square meters (area)
m3	Cubic meters (volume)

1. INTRODUCTION

A goal of climate science is to more accurately predict the physical consequences of climate change with less uncertainty. Until any reduced uncertainty is verified, however, existing estimates of uncertainty, albeit imperfect, remain unfalsified. While it is true that, for example, the “ensemble of opportunity” represented by the CMIP5 experiments is not a legitimate representation of uncertainty, and much less valid for the probabilistic quantification of climate outcomes, it does exist. Yet, assuming no uncertainty, or the parametric, downscaled, uncertainty of an individual model, or that the mean of the ensemble is the best (true) estimate, is possibly more problematic. A decade ago, Terbaldi, Schmidt, Murphy, and Smith produced a clear exposé of the issues for the Bulletin of Atomic Scientist[1] that remains meaningful today. They note that many decisions have to be considered in the present, whereas waiting for minimized uncertainty possibly imposes even greater risks and potentially removes the time window for effective response. It could be decades before valid uncertainty estimates are available.[2]

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[1] Bulletin of Atomic Scientists, *The uncertainty in climate modeling*, November 26, 2007 http://thebulletin.org/uncertainty-climate-modeling

[2] Qian, Yun, et al. "Uncertainty quantification in climate modeling and projection." Bulletin of the American Meteorological Society 97.5 (2016): 821-824.

Because the greater the uncertainty, the greater the risk[3], the most important aspect of climate change to human well-being is its uncertainty. Any decision that incorporates the uncertainty, then becomes a value-judgment of whether to hedge toward optimism that the uncertainty will go away or that the final best estimate of climatic conditions can be effectively accommodated by societal or engineering responses at the time. Or, the value-judgment may be to pessimistically apply the uncertainty out of concern for as yet unknown physics and abrupt climate change risks. Delineating uncertainty is a scientific endeavor, but acting upon it is a societal one. Implementing the societal decision to address the uncertainty, then leads to an engineering endeavor. Being conservative tends to have opposite implications for engineering versus science.[4] Conservative science strives to make statements where facts provide strong statistical evidence for accuracy or validity. Conservative engineering strives to avoid undesirable consequences and include contingencies for what is not known, until evidence justifies using reduced uncertainty. Several studies indicate that climate change could affect international security.[5,6,7,8,9] Security, especially future security, needs to be defined in terms of risk, where risk is a product of probability and consequence.[10] Climatic conditions could be much less or much greater than the best estimate. Further, year to year variations in extreme conditions can act as stressors that produce tipping points for existing regional tensions. Thus, the uncertainty in climate forecasts can dramatically change the risk profile if tail conditions impose high consequences. The analysis reported here attempts to characterize uncertainty in climate variables for use with security risk assessments. From a risk perspective, the emphasis is on how much is not known rather than on how much is known about the future climate.

In the context here, socioeconomic, technological, and geopolitical conditions affect and are affected by climatological conditions. Although climatological projections largely denote changes over decades, it is legitimate to consider, for example, the probabilistic impact climate has on the actual weather that affects water availability, crops, and damage from extreme weather. To determine potential impacts, this work considers how

[3] Backus et al., "The Near-Term Risk of Climate Uncertainty Among The US States." Climatic Change 116.3-4 (2013): 495-522. http://link.springer.com/article/10.1007/s10584-012-0511-8

[4] Boslough et al. "The Arctic as a test case for an assessment of climate impacts on national security." Sandia Report SAND2008-7006, Sandia National Laboratories, Albuquerque, NM 2008.

[5] National Intelligence Council, Implications for US National Security of Anticipated Climate Change, September 21, 2016. Report: NIC WP 2016-01, Washington, DC. http://www.eenews.net/assets/2016/09/21/document_pm_02.pdf

[6] Campbell, Kurt M., et al. The age of consequences: the foreign policy and national security implications of global climate change. Center for Strategic and International Studies, Washington DC, 2007. https://csis-prod.s3.amazonaws.com/s3fs-public/legacy_files/files/media/csis/pubs/071105_ageofconsequences.pdf

[7] Howard, William, et al. Report of the Defense Science Board Task Force on Trends and Implications of Climate Change on National and International Security. Defense Science Board, Washington DC, 2011. https://www.hsdl.org/?view&did=692151

[8] Hsiang, Solomon M., and Marshall Burke. "Climate, conflict, and social stability: what does the evidence say?" Climatic Change 123.1 (2014): 39-55. http://link.springer.com/article/10.1007/s10584-013-0868-3

[9] Hsiang, Solomon M., Marshall Burke, and Edward Miguel. "Quantifying the influence of climate on human conflict." Science 341.6151 (2013): 1235367.

[10] Kaplan, S., and B. J. Garrick. (1981). ―On the Quantitative Definition of Risk, Risk Analysis 1, no. 1, 11–27.

uncertainty across and within variables changes over time for monthly metrics, but maintains a decadal or longer perspective on those changes.

This report and its appendices provide the estimated uncertainty in climatic variables for 169 countries and autonomous-areas for the historical period (1976-2005), and for decadal time periods to 2100. They also provide uncertainty estimates for Arctic climatic variable across 26 geographical areas. Great effort was made to ensure the estimates across and within countries/areas are consistent, compatible, and comparable. Researchers can develop risk assessments using this information by sampling from the uncertainty distributions to determine possible climatic conditions and their impact on concerns of interest, such as food production, migration, economic activity, etc. **All the reports are publicly available[11] and the data are available upon request.[12]**

1.1 Uncertainty Means Greater Risk[13]

The focus of a scientific endeavor is to improve confidence in the validity of conclusions drawn from data and analysis. The focus is on the confidence in the accuracy of the result and the minimization of uncertainty. Risk, on the other hand, is concerned with the opposite position. The focus is on the maximum uncertainty and on the implications if the results are different from the best estimate. Consequently, our study emphasizes tails of the climatic (e.g., precipitation) distribution rather than the most likely part of the distribution that is generally of most concern to scientists and policy makers. We concentrate particularly on the tail of the distribution in which there are small probabilities *but realizable risks* that the effects and consequences of climate change could be much more severe than predicted from the best estimates.

Uncertainty is most commonly represented via a probability density function, which is sometimes simply called a "probability distribution." From a statistical perspective, the probability density function captures the idea of how often a given value can be expected to occur in comparison with other values. When the uncertainty increases, there is more of a chance that a variable, such as the local rise in temperature, will have a value different from the value that occurs most often, called the mode. The mode is the peak of the distribution.

Figure 1 conceptually illustrates two probability distribution functions with the same mode (i.e., location of the peak value) where the blue-line distribution has greater uncertainty than the red-line distribution. The left (y) axis shows the measure of probability, and the lower (x) axis shows the increased delta (Δ) change in average temperature compared to a world without climate change. The blue line is above the red line in the right-side tail of the distribution. Extreme levels are defined as those conditions well-removed from the mode of the distribution, for example, changes in

[11] https://cfwebprod.sandia.gov/cfdocs/CompResearch/templates/insert/pubs.cfm
[12] Contact Dr. Thomas Lowry, Sandia National Laboratories, tslowry@sandia.gov.
[13] This section is extracted from: Backus, George, et al. "Climate Uncertainty and Implications for US State-Level Risk Assessment Through 2050." SAND Report 7001 (2009). Sandia National Laboratories, Albuquerque, NM. http://prod.sandia.gov/techlib/access-control.cgi/2010/102052.pdf

temperature of over 5 degrees in Figures 1 and 2. Thus, there is a greater chance of the temperature occurring at extreme levels with the blue-line distribution. Figure 2 provides the same logic as Figure 1, where there is a greater concern with the average value (or mean) of the distribution than with the mode.

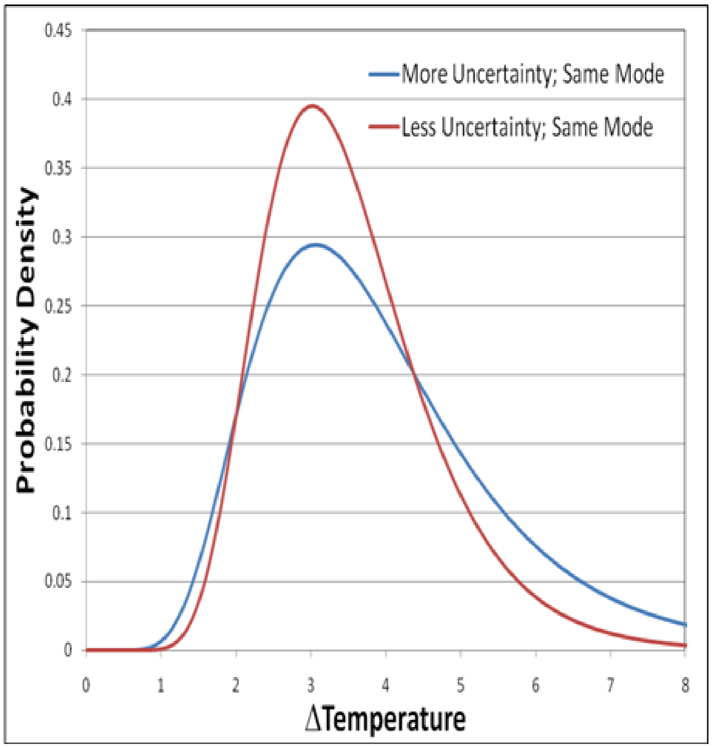

Figure 1: Probability Distribution with Constant Mean

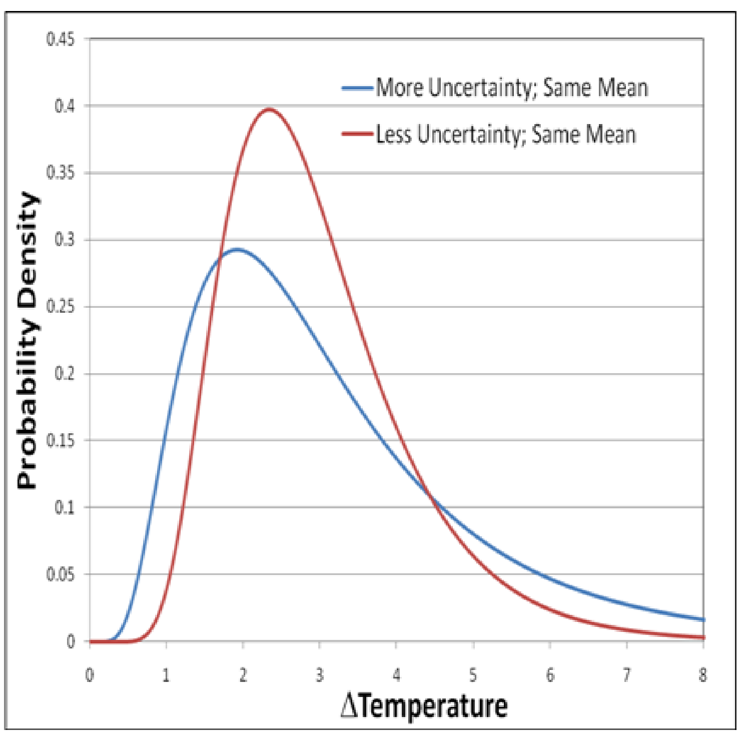

Figure 2: Probability Distribution with Constant Mode

In risk assessment, a useful perspective contains the cumulative distribution function (CDF). A CDF transforms the probability distribution, such as depicted above, to show the probabilities of exceeding the values of concern. For purposes of this study, we refer to these cumulative probabilities as “exceedance probabilities.” A CDF shows the probability starting at a 0% exceedance probability on the left side of a graph and increasing to the right toward 100%. A complementary cumulative distribution function (CCDF) is the reverse of a CDF. The CCDF is one (1.0) minus the CDF. It starts with the 100% exceedance probability on the left side and drops toward the 0% exceedance probability. Both CDFs and CCDFs are commonly used for presenting the uncertainty in climate change and for assessing the risks from climate change.

Figure 3 shows the CCDF associated with Figure 2. The lines in Figure 3 cross at the median of the distribution. The median is the point where there is an equal probability that the value, in this case the change in temperature, will be greater than or less than the value at the 50% exceedance probability. With skewed probability distributions, such as those often associated with climate change, the mode, mean, and median take on separate values. For a symmetric probability distribution like a Gaussian bell curve, which has equal tails on each side of the mode, the mode, mean and median all have the same value. For the skewed probability distribution associated with the blue curve of Figure 2, the mode is to the far left at approximately 2 degrees, the median is slightly to the right of the mode at approximately, in this example, 2.5 degrees, and the mean or average is at approximately 3 degrees.

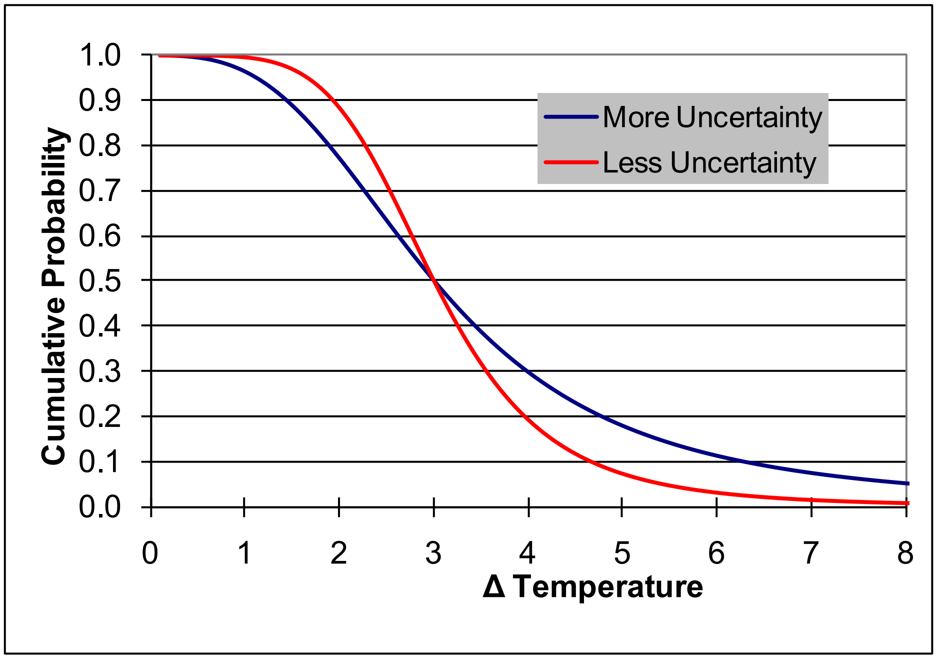

Figure 3: A CCDF with Uncertainty.

Figure 3 illustrates the probability that the high-temperature deltas associated with climate change are greater when there is a greater level of uncertainty. For instance, in the “red-line” lesser-uncertainty curve, the chance of exceeding a temperature of 6 degrees is approximately 2%, whereas for the “blue-line” greater-uncertainty curve, the risk of exceeding 6 degrees is approximately 11%. Further, the more uncertain blue line appears not to produce a 2% exceedance probability to well beyond 8 degrees, possibly not until a daunting 12 degrees, in this purely illustrative example. If the consequence of climate change also increases with temperature, the risk (the consequence multiplied by the probability) remains significant even at extreme conditions. Thus, the greater the uncertainty, the greater the risk.[14]

[14] Backus, George, et al. "Climate Uncertainty and Implications for US State-Level Risk Assessment Through 2050." SAND Report 7001 (2009). Sandia National Laboratories, Albuquerque, NM. http://prod.sandia.gov/techlib/access-control.cgi/2010/102052.pdf

2. CLIMATE RISK

For climate science, the discussion tends to revolve around justifying action through the high levels of certainty of when and where a climate impact will occur. Science strives to maximize the probability that its claims are true. For example, the IPCC "Summary for Policymakers" focuses on the likelihood of physical impacts from climate change compared to historical conditions.[15] There are five measures of "likely," going from greater than 99% to greater than 50% probability, whereas there are only three measures of "unlikely," with the lowest measure for conditions having less than a 5% probability.[16] In the realm of risk-assessment, conservative science's best estimates are considered "optimistic" rather than "conservative." Risk assessment is more concerned with the low-probability, higher-consequence conditions than with the high-probability, lower-consequence ones.[17,18] Therefore, risk assessment in this study concentrates on the implications for decision making from climate-change uncertainty, as opposed to impacts from the expected values. A focus on an expected value may lead one to believe, for example, that the trend in precipitation over time is more constant and benign than what the uncertainty indicates. Further, the trend in expected value could give the impression that precipitation should decrease (or increase) by a similar amount year after year. From an uncertainty perspective, however, there will be years where there is more precipitation followed by years where there is less precipitation.[19] For risk assessments, uncertainty remains until it is falsified with abundant differing data. Therefore, a risk analysis is conservative and legitimate when it errs on the side of maximized uncertainty.

2.1. Mean-value Versus Probabilistic Values

Another important consideration for a risk assessment is that the mean-value estimates of climate change forecasts are typically captured as a relatively smooth progression over time to greater departures from historical averages. In reality, the volatility inherent to climate change[20] means that the dangerous conditions associated with the future can be

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[15] IPCC, 2014: Summary for policymakers. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1-32. http://www.ipcc.ch/pdf/assessment-report/ar5/wg2/ar5_wgII_spm_en.pdf

[16] Mastrandrea, Michael D., et al. "The IPCC AR5 guidance note on consistent treatment of uncertainties: a common approach across the working groups." Climatic Change 108.4 (2011): 675-691. http://link.springer.com/article/10.1007/s10584-011-0178-6

[17] Kaplan, S., and B. J. Garrick. (1981). ―On the Quantitative Definition of Risk, Risk Analysis 1, no. 1, 11–27.

[18] Helton, J. C. (1994), ―Treatment of Uncertainty in Performance Assessments for Complex Systems. Risk Analysis 14, no. 4: 483–511.

[19] Backus, George, et al. "Climate Uncertainty and Implications for US State-Level Risk Assessment Through 2050." SAND Report 7001 (2009). Sandia National Laboratories, Albuquerque, NM, page 30. http://prod.sandia.gov/techlib/access-control.cgi/2010/102052.pdf

[20] https://climate4impact.eu/impactportal/help/faq.jsp and Kirtman, B., S.B. Power, J.A.

transiently experienced in the present.[21] Sampling of climate uncertainty that depicts the volatility rather than, for example, a smooth ensemble mean, more realistically addresses the impacts and risks that climate change portends. Uncertainty is critical for understanding impacts and determining appropriate countermeasures.[22] Many studies have considered the use-cases for climate data and the user needs.[23, 24] In many instances, the representation of uncertainty is considered key to communicating results.[25]

2.2. Country and Area-Centric Analysis

The consideration of the security implications from climate change requires a country-centric perspective, or a perspective across a group of countries. Therefore, despite the limitations and caveats discussed below, the results are based strictly on the area-weighted output from the historical and RCP 8.5[26] analyses within the CMIP5 collection of climate models runs available at the ESGF portal.[27,28,29] The grid-based output from each of the models was mapped to countries using the same area-weighting process. No model was treated differently. The ensemble of models is used to generate uncertainty distributions specific to each of 169 countries for selected land variables noted later. Except for the Arctic, data for marine areas and Antarctica are excluded from this analysis.

Adedoyin, G.J. Boer, R. Bojariu, I. Camilloni, F.J. Doblas-Reyes, A.M. Fiore, M. Kimoto, G.A. Meehl, M. Prather, A. Sarr, C. Schär, R. Sutton, G.J. van Oldenborgh, G. Vecchi and H.J. Wang, 2013: Near-term Climate Change: Projections and Predictability. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. https://www.ipcc.ch/pdf/assessment-report/ar5/wg1/WG1AR5_Chapter11_FINAL.pdf

[21] Backus, George A., Thomas S. Lowry, and Drake E. Warren. "The Near-Term Risk of Climate Uncertainty Among The US States." Climatic Change 116.3-4 (2013): 495-522. http://link.springer.com/article/10.1007/s10584-012-0511-8

[22] Clark, Martyn P., Robert L. Wilby, Ethan D. Gutmann, Julie A. Vano, Subhrendu Gangopadhyay, Andrew W. Wood, Hayley J. Fowler, Christel Prudhomme, Jeffrey R. Arnold, and Levi D. Brekke. "Characterizing uncertainty of the hydrologic impacts of climate change." Current Climate Change Reports 2, no. 2 (2016): 55-64.

[23] King, David, et al. "Climate change–a risk assessment." Centre for Science Policy, University of Cambridge. (2015). http://www.csap.cam.ac.uk/media/uploads/files/1/climate-change--a-risk-assessment-v11.pdf

[24] Zubler, Elias M., et al. "Climate change signals of CMIP5 general circulation models over the Alps–impact of model selection." International Journal of Climatology (2015).

[25] Déandreis, Céline, et al. "Towards a dedicated impact portal to bridge the gap between the impact and climate communities: Lessons from use cases." Climatic change 125.3-4 (2014): 333-347. http://link.springer.com/article/10.1007/s10584-014-1139-7/fulltext.html

[26] Van Vuuren, Detlef P., et al. "The representative concentration pathways: an overview." Climatic change 109 (2011): 5-31. http://link.springer.com/article/10.1007/s10584-011-0148-z%20/fulltext.html

[27] Earth System Grid Federation (ESGF) June to September 2015 http://esgf.llnl.gov/ https://pcmdi.llnl.gov/search/cmip5/

[28] Taylor, Karl E., Ronald J. Stouffer, and Gerald A. Meehl. "An overview of CMIP5 and the experiment design." Bulletin of the American Meteorological Society 93.4 (2012): 485-498. https://e-reports-ext.llnl.gov/pdf/482749.pdf

[29] Guide to cmip5 http://cmip-pcmdi.llnl.gov/cmip5/guide_to_cmip5.html

Sea level rise and its uncertainty is noted elsewhere,[30,31,32,33,34] and recent research indicates potential revisions[35,36] that would be too premature to assess here. Analyses of the impacts from sea-level rise are also noted elsewhere.[37, 38,39,40,41,42,43,44]

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[30] Church, J.A., P.U. Clark, A. Cazenave, J.M. Gregory, S. Jevrejeva, A. Levermann, M.A. Merrifield, G.A. Milne, R.S. Nerem, P.D. Nunn, A.J. Payne, W.T. Pfeffer, D. Stammer and A.S. Unnikrishnan, 2013: Sea Level Change. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. http://www.climatechange2013.org/images/report/WG1AR5_Chapter13_FINAL.pdf

[31] Strauss, B. H., S. Kulp, and A. Levermann. "Mapping choices: carbon, climate, and rising seas, our global legacy." Princeton, NJ: Climate Central (2015). http://sealevel.climatecentral.org/uploads/research/Global-Mapping-Choices-Report.pdf

[32] Slangen, A. B. A., et al. "Projecting twenty-first century regional sea-level changes." Climatic Change 124.1-2 (2014): 317-332. http://pordlabs.ucsd.edu/ltalley/sio219/winter_2015/slangen_etal_climchange2014.pdf

[33] Jevrejeva, Svetlana, Aslak Grinsted, and J. C. Moore. "Upper limit for sea level projections by 2100." Environmental Research Letters 9, no. 10 (2014): 104008. http://iopscience.iop.org/article/10.1088/1748-9326/9/10/104008

[34] DeConto, Robert M., and David Pollard. "Contribution of Antarctica to past and future sea-level rise." Nature 531.7596 (2016): 591-597.

[35] Hansen, James, et al. "Ice melt, sea level rise and superstorms: Evidence from paleoclimate data, climate modeling, and modern observations that 2 C global warming could be dangerous." Atmospheric Chemistry and Physics 16.6 (2016): 3761-3812. http://www.atmos-chem-phys.net/16/3761/2016/acp-16-3761-2016-discussion.html

[36] Jevrejeva, Svetlana Luke P. Jackson, Riccardo E. M. Riva, Aslak Grinsted, and John C. Moore, Coastal sea level rise with warming above 2 °C PNAS 2016 ; doi:10.1073/pnas.1605312113 http://www.pnas.org/content/early/2016/11/02/1605312113

[37] Werner, Adrian D., and Craig T. Simmons. "Impact of sea-level rise on sea water intrusion in coastal aquifers." Ground Water 47.2 (2009): 197-204. https://www.researchgate.net/profile/Craig_Simmons2/publication/23976090_Impact_of_Sea-Level_Rise_on_Sea_Water_Intrusion_in_Coastal_Aquifers/links/55a02b8508ae032ef0545700.pdf

[38] Nicholls, Robert J., and Anny Cazenave. "Sea-level rise and its impact on coastal zones." science 328.5985 (2010): 1517-1520. http://science.sciencemag.org/content/328/5985/1517

[39] Hallegatte, Stephane, et al. "Future flood losses in major coastal cities." Nature climate change 3.9 (2013): 802-806.

[40] Neumann, J. E., Emanuel, K., Ravela, S., Ludwig, L., Kirshen, P., Bosma, K., & Martinich, J. (2015). Joint effects of storm surge and sea-level rise on US Coasts: new economic estimates of impacts, adaptation, and benefits of mitigation policy. Climatic Change, 129(1-2), 337-349.

[41] Tebaldi, Claudia, Benjamin H. Strauss, and Chris E. Zervas. "Modelling sea level rise impacts on storm surges along US coasts." Environmental Research Letters 7.1 (2012): 014032.

[42] Yin, Jianjun, Michael E. Schlesinger, and Ronald J. Stouffer. "Model projections of rapid sea-level rise on the northeast coast of the United States." Nature Geoscience 2.4 (2009): 262-266.

[43] NOAA, Global sea level rise scenarios for the United States National Climate Assessment. US Department of Commerce, National Oceanic and Atmospheric Administration, Oceanic and Atmospheric Research, Climate Program Office, 2012.

[44] Weiss, Jeremy L., Jonathan T. Overpeck, and Ben Strauss. "Implications of recent sea level rise science for low-elevation areas in coastal cities of the conterminous USA." Climatic Change 105.3-4 (2011): 635-645

2.3. Ensemble and Probabilistic Consistency

To the extent possible, the analysis used the same ensemble of models for estimating the full set of relevant variables. This approach ensures the consistency of interpretation across variables over temporal and spatial dimensions.[45, 46] Nonetheless, not all climate models produce the same variables. In those instances, where some models did not report a particular variable, all available models within the fixed ensemble set were used, rather than adding the results from models outside of the selected set. Very few models contain Arctic area detail. Several, but not all, of the climate models in the CMIP5 collection produce the full set of variables for country-based concerns. As such, the ensemble set is maximally composed of the historic and RCP 8.5 runs for the models noted in Table 1. A brief overview and references for each model are provided in Chapter 9 of the Fifth Assessment Report.[47] The represented historical and future variable distributions correspond to the CMIP5 experiments 3.2 and 4.2, respectively.[48]

Access1.0	GISS-E2-H
Access1.3	HadGEM2-CC
BCC-CSM1.1	IPSL-CM5A-MR
BNU-ESM	IPSL-CM5A-LR
CanESM2	MIROC-ESM
CCSM4	MIROC5
CESM-CAM5.1	MPI-ESM-LR
CNRM-CM5	MRI-CGCMC3
CSIRO-Mk3.6	MRI-ESM1
GFDL-CM3	NorESM1-M
GFDL-ESM2M	NorESM1-ME

Table 1: List of Ensemble Models

[45] Zubler, Elias M., et al. "Climate change signals of CMIP5 general circulation models over the Alps–impact of model selection." International Journal of Climatology (2015).
[46] Tebaldi, C., & Sansó, B. (2009). Joint projections of temperature and precipitation change from multiple climate models: a hierarchical Bayesian approach. Journal of the Royal Statistical Society: Series A (Statistics in Society), 172(1), 83-106.
[47] Flato, G., J. Marotzke, B. Abiodun, P. Braconnot, S.C. Chou, W. Collins, P. Cox, F. Driouech, S. Emori, V. Eyring, C. Forest, P. Gleckler, E. Guilyardi, C. Jakob, V. Kattsov, C. Reason and M. Rummukainen, 2013: Evaluation of Climate Models. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. https://www.ipcc.ch/pdf/assessment-report/ar5/.../WG1AR5_Chapter09_FINAL.pdf
[48] Taylor, Karl E., Ronald J. Stouffer, and Gerald A. Meehl. "An overview of CMIP5 and the experiment design." Bulletin of the American Meteorological Society 93.4 (2012): 485-498. https://e-reports-ext.llnl.gov/pdf/482749.pdf

Accordingly, there are a maximum of 22 data points with which to calculate the uncertainty distribution for any variable. The small number of data points means that the estimated uncertainty in the uncertainty is appropriately larger than if all the models were utilized, due to the increased (Gaussian) standard error of the estimate.[49] Although it is possible to reduce the error by including all models that have any particular variable, this is counterproductive to a risk assessment because the relationship *among* multiple variables, such as temperature and precipitation is as important as the individual values. The use of a fixed ensemble ensures the prioritization of this consistency over efforts to reduce the calculated uncertainty of individual variables.

The evident uncertainty means the risk is not falsified and therefore should be included in assessment of impacts. High sensitivity to a particular variable or combination of variables would indicate the benefits of research that might reduce the uncertainty in model results, but simultaneously indicates the need for planning mitigations to such impacts when the uncertainty is irreducible.

There are those situations where, although all data are only from the ensemble of Table 1, some models do not report all of the variables in either the historical and forecasted period. A different ensemble set would have even more omissions. If the criterion was to include in the ensemble only models that had all the designated variables, the ensemble would only contain two models. The current ensemble was a judgmental tradeoff of either maximizing the correlational constituency across the variables versus distorting the consistency (from not using the same ensemble of models) between historical and forecasted values. The balance tended toward maximizing correlational consistency across the variables because many impact analyses would include the simultaneous impact of many variables. All models in any-sub-ensemble set are again all treated equally and used without weighting any particular model differently.

2.4. Geographical Resolution and Analysis Legitimacy

The highest resolution of the uncertainty data provided here is at the country level. For many countries, the local differences, for example between the Northeast and Southwest United States, are dramatic. Some would argue that the downscaling is necessary for risk assessments.[50] If the concern is over a small area, this may be true, but it is unclear that the historic relationships used for downscaling apply as climate change intensifies and it is unclear how they affect results in underestimation, exaggeration, or simply further biasing of the uncertainty characterization.[51,52] The analysis here is meant to denote

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[49] The error is also sometimes called the Standard Error of the Model and the Standard Error of the Regression.

[50] Auffhammer, M., Hsiang, S. M., Schlenker, W., & Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. Review of Environmental Economics and Policy, 7,181–198 (2013). doi: 10.1093/reep/ret016

[51] Clark, Martyn P., Robert L. Wilby, Ethan D. Gutmann, Julie A. Vano, Subhrendu Gangopadhyay, Andrew W. Wood, Hayley J. Fowler, Christel Prudhomme, Jeffrey R. Arnold, and Levi D. Brekke. "Characterizing uncertainty of the hydrologic impacts of climate change." Current Climate Change Reports 2, no. 2 (2016): 55-64.

[52] Wibig, Joanna, et al. "Projected Change—Models and Methodology." Second Assessment of Climate

relative change and risk compared to the historical values. In this regard, the uncertainty quantification is useful, albeit not perfect, for ranking areas with potential for dangerous impacts, and thereby possibly justifying additional, higher-resolution assessments of localized impacts. On the other hand, the information is immediately usable for first order assessments of the climate impacts on interconnected nations. Waiting expectantly for accurate, high-resolution projections may produce results too late for security-mitigation measures or mask risk through overconfidence in the levels of certainty.

2.5. Country-based Specificity

Table 2 shows the countries (land) explicitly characterized in this analysis. Minor island nations such as Palau, autonomous regions such as Aland, and micro states such as San Mario, were not analyzed, primarily due to their limited size making a mapping from the GCM[53] to climate uncertainty meaningless. Figure 4 shows the world map containing only those areas.

2.6. Using an Ensemble of Opportunity

Because many of the climate models share common elements or algorithms, the data produced across the models are not truly independent. Further, the results from the varied models represent an ensemble of opportunity and not a statistically legitimate representation of climate uncertainty. Nonetheless, the variation across models is the best proxy for actual climate-impact uncertainty currently available. The model results are used here without any de-biasing or skill weighting. That is, there is no attempt to reduce the uncertainty. For risk purposes, the results from each climate model are considered as legitimate of a possibility as those from any other model. Because the models are not truly independent, the equal-weight, raw-output ensemble still likely *underestimates* the actual uncertainty. That said, it is still the best estimate of the uncertainty to use for risk assessments.[54] Other efforts have utilized a single model with parameter variations and then incorporates downscaling, as an ensemble of runs to specify uncertainty.[55, 56] Inter-model uncertainty is greater than intra-model uncertainty. Therefore, from a risk perspective, the work here again adopts the ensemble of opportunity from CMIP5.

Afghanistan	Costa Rica	India	Mozambique	South Korea
Albania	Cote d'Ivoire	Indonesia	Myanmar	Spain

Change for the Baltic Sea Basin. Springer International Publishing, 2015. 189-215. http://link.springer.com/chapter/10.1007/978-3-319-16006-1_10
http://climate4impact.eu/impactportal/help/howto.jsp

[53] GCM: General Circulation Models

[54] Zubler, Elias M., et al. "Climate change signals of CMIP5 general circulation models over the Alps–impact of model selection." International Journal of Climatology (2015).

[55] Hadley Centre for Climate Prediction and Research (Exeter). ENSEMBLES: climate change and its impacts at seasonal, decadal and centennial timescales: summary of research and results from the ENSEMBLES project. Ed. Paul Van der Linden. Hadley Centre for Climate Prediction and Research, 2009. http://ensembles-eu.metoffice.com/docs/Ensembles_final_report_Nov09.pdf

[56] Ghosh, Subimal, and P. P. Mujumdar. "Climate change impact assessment: Uncertainty modeling with imprecise probability." Journal of Geophysical Research: Atmospheres 114.D18 (2009).

Algeria	Croatia	Iran	Namibia	Sri Lanka
Angola	Cuba	Iraq	Nepal	Sudan
Argentina	Cyprus	Ireland	Netherlands	Suriname
Armenia	Czech Republic	Israel	New Zealand	Svalbard
Australia	Denmark	Italy	Nicaragua	Swaziland
Austria	Djibouti	Jamaica	Niger	Sweden
Azerbaijan	Dominican Republic	Japan	Nigeria	Switzerland
Bahrain	Ecuador	Jordan	North Korea	Syria
Bangladesh	Egypt	Kazakhstan	Norway	Tajikistan
Belarus	El Salvador	Kenya	Oman	Tanzania
Belgium	Equatorial Guinea	Kuwait	Pakistan	Thailand
Belize	Eritrea	Kyrgyzstan	Panama	The Gambia
Benin	Estonia	Laos	Papua New Guinea	Timor-Leste
Bhutan	Ethiopia	Latvia	Paraguay	Togo
Bolivia	Finland	Lebanon	Peru	Tunisia
Bosnia & Herzegovina	France	Lesotho	Philippines	Turkey
Botswana	French Guiana	Liberia	Poland	Turkmenistan
Brazil	Gabon	Libya	Portugal	Uganda
Brunei	Gaza Strip	Liechtenstein	Puerto Rico	Ukraine
Bulgaria	Georgia	Lithuania	Qatar	United Arab Emirates
Burkina Faso	Germany	Luxembourg	Romania	United Kingdom
Burundi	Ghana	Macedonia	Russia	United States
Cambodia	Greece	Madagascar	Rwanda	Uruguay
Cameroon	Greenland	Malawi	Saudi Arabia	Uzbekistan
Canada	Guatemala	Malaysia	Senegal	Venezuela
Central African Rep.	Guinea	Mali	Serbia	Vietnam
Chad	Guinea-Bissau	Mauritania	Sierra Leone	West Bank
Chile	Guyana	Mexico	Singapore	Western Sahara
China	Haiti	Moldova	Slovakia	Yemen
Colombia	Honduras	Mongolia	Slovenia	Zambia
Congo	Hungary	Montenegro	Somalia	Zimbabwe
Congo DRC	Iceland	Morocco	South Africa	

Table 2: Countries with Uncertainty Distributions

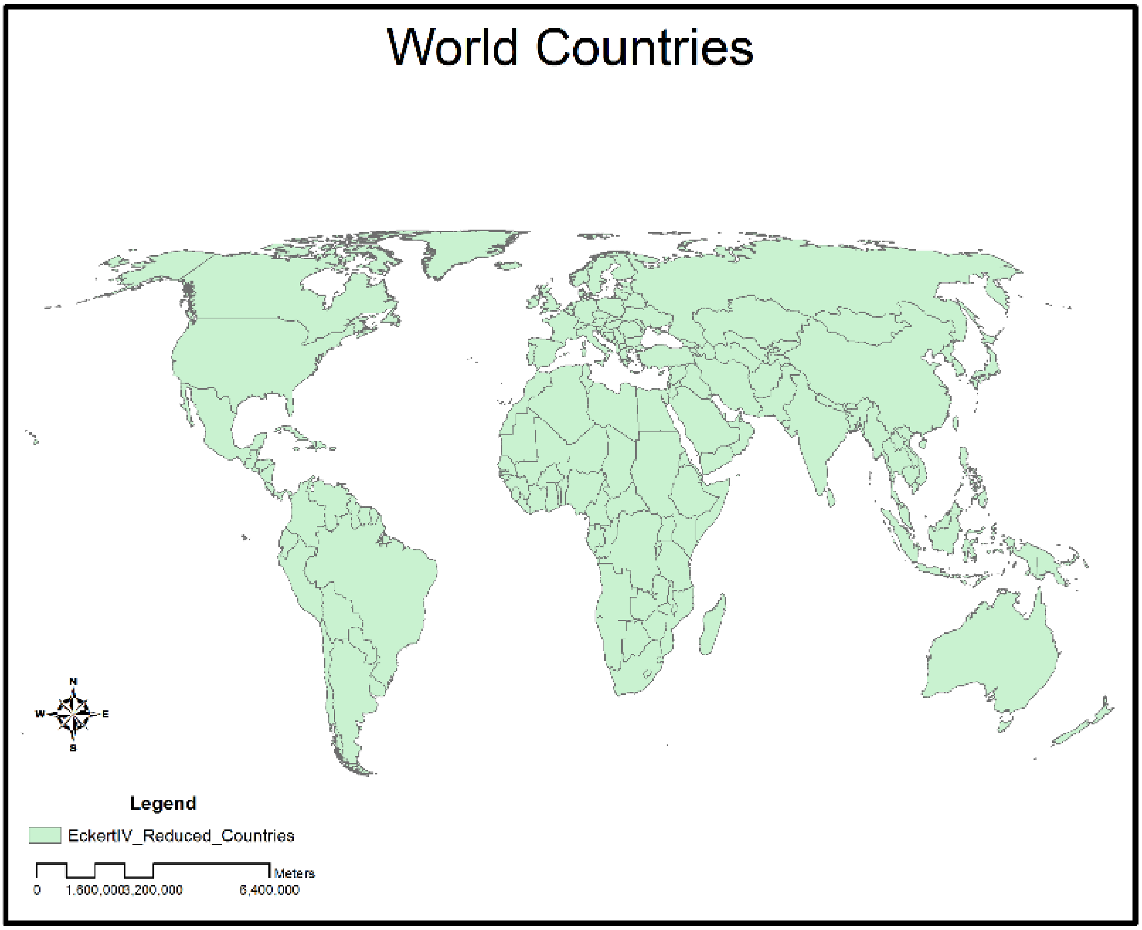

Figure 4: Map of Included Countries

2.7. Model-Bias and Delta-Change

None of the global climate models faithfully reproduce the historical data for all areas. Some are characteristically too low, too high, too fast, or too slow when compared to the actual dynamics. This difference is called a bias. Some models are consistently more skilled at reproducing observed results than other models. Many efforts have attempted to judge this skill level and to adjust the model to correct for the biases.[57,58,59,60] Other

[57] https://climate4impact.eu/impactportal/general/index.jsp?q=bias_correction

[58]Sanderson, Benjamin M., Reto Knutti, and Peter Caldwell. "Addressing interdependency in a multimodel ensemble by interpolation of model properties." Journal of Climate 28.13 (2015): 5150-5170.

[59] Teutschbein, Claudia, and Jan Seibert. "Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods." Journal of Hydrology 456 (2012): 12-29. https://www.researchgate.net/profile/Jan_Seibert/publication/256756594_Bias_correction_of_regional_climate_model_simulations_for_hydrological_climate-change_impact_studies_Review_and_evaluation_of_different_methods/links/02e7e523f6473149d1000000.pdf

[60] Auffhammer, M., Hsiang, S. M., Schlenker, W., & Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. Review of Environmental Economics and Policy, 7,181–198 (2013). doi: 10.1093/reep/ret016

studies note the problems with attempting bias corrections.[61,62] Several studies argue that the delta-change approach is the best and most robust means to consistently apply climate data for impact analysis.[63,64,65] The delta-change approach simply notes the relative difference between what the model produced in its historical runs to what it produced in its forecast. That additive or multiplicative delta is then referenced to or compared to the observed historical value of interest. As such, all uncertainty estimates used here should be used as a delta-change to the average. For analysis, the average-over-time is referenced to the historical average over the period or an interpolated value calculated for a specific year.[66] The interpolation can smoothly connect the forecasted value to the historical value along the boundary across the historical year 2005 and the (model) forecast year 2006. There is no reason to believe the answer is correct, but it is adequate for applying the relative change over the years to impacts on, for example, water availability and relative temperature impacts. For instance, if the delta change for a particular variable in 2050 is 10% higher, then the value in 2050 is 10% higher than its historical average value, independent of what the specific historical value actually was. Because economic and impact models are naturally referenced (implicitly or explicitly) to a "normal" weather (climatic) condition, the use of the delta change is a generically consistent means to represent the altered condition.

2.8. Temporal Specificity and Correlated Sampling

The uncertainty distributions are calculated by month. Within any model run, the climate conditions in each month are not independent from the climate in the months that precede it. At an aggregate level, the ensemble captures the average annual aspects of that correlation. However, the purpose here is to emphasize the uncertainty, and using a single seed for sampling the entire year would underestimate the actual variability. Therefore, it is more valid to start each month as independent for sampling purposes (again noting that the distribution is already shifted to correspond to that particular month and its relationship to the months around it). Similarly, other variables are correlated, such as temperature and precipitation. By using the same models for estimating the uncertainty across variables, the correlations (as an average, across models) are to some extent captured.

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[61] Ehret, U., et al. "HESS Opinions" Should we apply bias correction to global and regional climate model data?"." Hydrology and Earth System Sciences 16.9 (2012): 3391-3404. http://www.hydrol-earth-syst-sci.net/16/3391/2012/hess-16-3391-2012.pdf

[62] Tebaldi, C., & Sansó, B. (2009). Joint projections of temperature and precipitation change from multiple climate models: a hierarchical Bayesian approach. Journal of the Royal Statistical Society: Series A (Statistics in Society), 172(1), 83-106.

[63] Hawkins, E, Osborne, TM, Ho, CK and Challinor, AJ (2013) Calibration and bias correction of climate projections for crop modelling: An idealised case study over Europe. Agricultural and Forest Meteorology, 170. 19 - 31. http://eprints.whiterose.ac.uk/77973/10/challinor14.pdf

[64] Ibid., Auffhammer et al., 2013

[65] Ibid., Teutschbein and Seibert 2012.

[66] All "data" are the output from the models and not the physically observed quantities. The comparison is between the simulated historical values and the simulated forecasted values. That is, the risk assessments would be based on the simulated/forecast change in climate compared to the simulated/historical climate.

Given the monthly resolution and the limitation of using any ensemble, the independent sampling for each month is therefore justified. It could be hot and dry one day with a downpour the next day, while the mapping can and needs only to be representative of the monthly interval. In a similar vein, even though runoff may continue for many days after a major precipitation event, in terms of monthly values and assessing impacts, they are simultaneous. There are sophisticated methods to deal with joint probability distributions and model skill, mostly in regard to adaptation planning.[67,68] These methods reduce the uncertainly measures for the best estimates, but do not increase confidence in the uncertainty itself.

There is an alternative sampling logic to employ when two variables are strongly correlated, such as soil moisture and evaporation, and that is to sample related precipitation data using a single seed. For example, if there is a random draw of a 76% exceedance probability, use that exceedance value for selecting all the precipitation related values. Use an identical approach for variables highly correlated to the average temperature, such as the minimum and maximum temperatures. While sampling each variable independently probably implies excessive uncertainty, and maybe risk, a fully correlated relationship likely underestimates the risk.

There is also a correlation across regions. Sampling on a single region can cause "remote" bias relative to another region.[69] Remote bias occurs when two or more geographically regions are tightly coupled climatically, usually due to ocean currents. Independent sampling of each misses the correlation, while joint sampling largely reflects any biases (deviations from actual observation) artificially generated by the model algorithms. The use of a standard ensemble set and delta-changes mitigates this bias.[70] Therefore, if there is a joint assessment across multiple countries, it is not unreasonable to use the same seed for sampling the variable values across all the areas. Although legitimate for many types of analyses, using independent sampling across the areas, especially connected areas, again, likely underestimates joint risks. The use of varied correlational relationships is discussed later in section 3.1.

Additionally, there is a bias across times scales - from the day-to-month issues noted above to corresponding year-to-decade ones. The need for sophisticated temporal correction to the bias depends on the time constants for the phenomena of concern. For example, to model the progression of a flood, very detailed (minute or hourly) temporal corrections are needed.[71] For determining economic, societal or security risks, the single monthly resolution captured via delta changes is appropriate.

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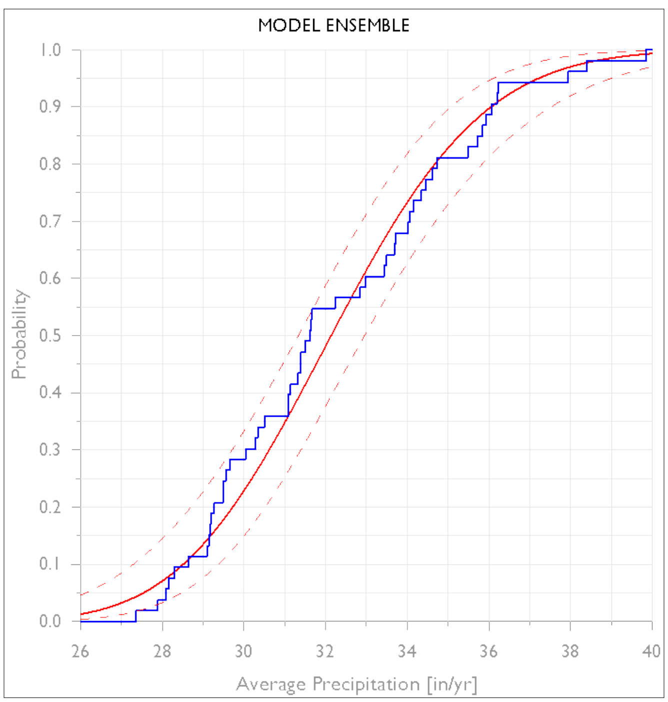
[67] Sanderson, Benjamin M., Reto Knutti, and Peter Caldwell. "Addressing interdependency in a multimodel ensemble by interpolation of model properties." Journal of Climate 28.13 (2015): 5150-5170.
[68] Ibid., Tebaldi, C., & Sansó, B. (2009).
[69] Wang, Chunzai, et al. "A global perspective on CMIP5 climate model biases." Nature Climate Change 4.3 (2014): 201-205.
[70] Ibid., Wang, Chunzai, et al.(2014)
[71] Haerter, J. O., et al. "Climate model bias correction and the role of timescales." Hydrology and Earth System Sciences 15.3 (2011): 1065-1079. http://www.hydrol-earth-syst-sci.net/15/1065/2011/hess-15-1065-2011.pdf

2.9. Uncertainty of the Uncertainty

Independent of the type of probability distribution estimated, the estimated uncertainty in the probability (called second-order probability) is calculated as a Gaussian distribution. Although the mathematical details are not presented here, this uncertainty of the uncertainty is estimated and noted in the appendices. Analyses can use this second-order uncertainty as a proxy to correct for what is not known about the estimated climate (first order) uncertainty. Incorporating second order uncertainty in a risk assessment requires a more intense effort than using the first order uncertainty. In general, risk assessments would only use first-order uncertainty. Because the estimate of the second-order uncertainty assumes a Gaussian shape, it will have no impact on the risk calculation for consequences that change linearly with changes in climatic conditions. For impacts that non-linearly increase with the deviation in conditions from the historical norm, the impacts on risks would be larger with the inclusion of second-order uncertainty.[72]

Figure 5 shows the second-order uncertainty in terms of confidence intervals on a Gamma distribution for US precipitation from a previous study.[73] The blue line is the ranked climate model data. The solid red line is the fit to the data and the dashed lines enclose the confidence interval. A confidence interval is the +/- 95% confidence



boundary. It is 1.96 times the standard error of the estimate.

Figure 5: Estimated Second-Order Uncertainty

[72] Backus, George, et al. "Climate Uncertainty and Implications for US State-Level Risk Assessment Through 2050." SAND Report 7001 (2009). Sandia National Laboratories, Albuquerque, NM, page 55. http://prod.sandia.gov/techlib/access-control.cgi/2010/102052.pdf
[73] Ibid. Backus et al. 2009

Figure 6 shows a conceptualization of second-order uncertainty for the extreme case of a Beta distribution. The blue dots represent data points. The solid black curve would be the estimate of the CDF. The dashed gray lines would be the confidence intervals characterizing the uncertainty. Because the uncertainty of the uncertainty is estimated as a normal distribution, the distribution extends beyond the confidence interval boundary. The green horizontal line conceptually shows the width of the confidence band, as opposed to the width being a vertical line. The reported standard error in the appendices is simply equal to the standard deviation of this second-order-uncertainty distribution, as centered on the mean of the first-order uncertainty probability's CDF.

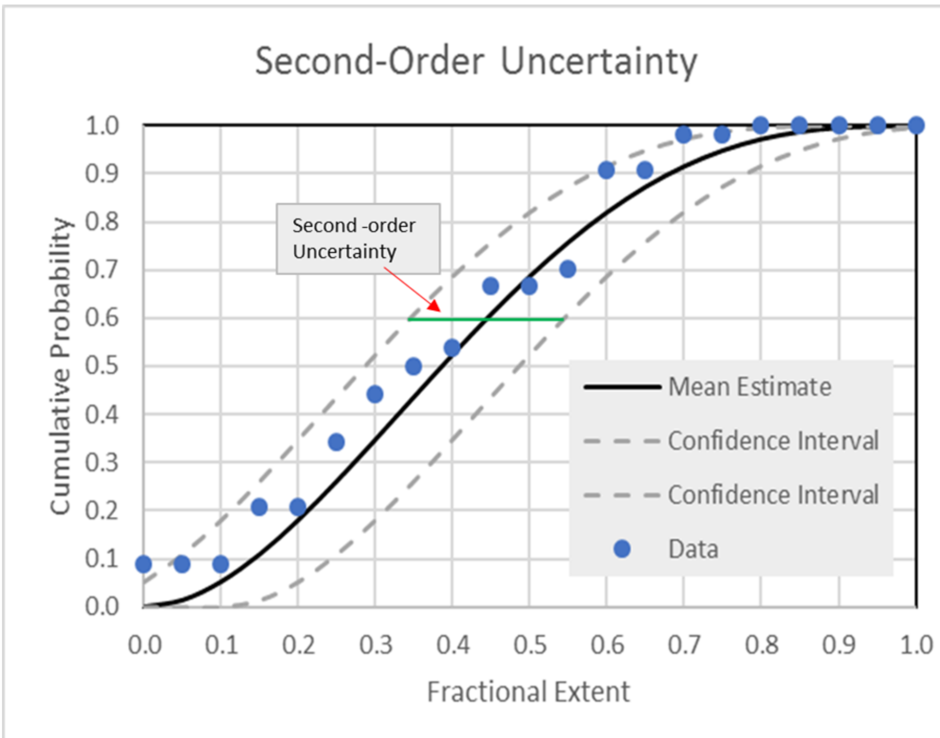


Figure 6: Illustrative Second-Order Uncertainty

With the focus on the CDF, it is implicitly assumed that risk analyses would be based on Latin-Hypercube Sampling[74] to obtain variable values for impact calculations. Because the second-order uncertainty is a probability density function, Latin-Hypercube Sampling[75, 76] is still effective.

[74] McKay, Michael D., Richard J. Beckman, and William J. Conover. "A comparison of three methods for selecting values of input variables in the analysis of output from a computer code." Technometrics 42.1 (2000): 55-61.

[75] Florian, Aleš. "An efficient sampling scheme: updated Latin Hypercube Sampling." Probabilistic engineering mechanics 7.2 (1992): 123-130.

[76] Helton, Jon C., and Freddie Joe Davis. "Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems." Reliability Engineering & System Safety 81.1 (2003): 23-69.

For distributions bound by 0.0, such as a Gamma distribution, or those bound on both sides, like the Beta distribution, there is the issue of how to represent the standard error at the boundary edge. It is not reasonable to have fractional ice coverage be less than zero or greater than 100%. A consistent and conservative approach is to add the error band, but discard any values that produce unrealizable conditions. This situation is shown in Figure 6. For a Gaussian CDF, the confidence interval can be applied unaltered over the entire range. While the truncation approach would seem to exaggerate the error as the estimated probability approaches zero, any other choice would assume information that is unavailable.[77] Therefore, until other information falsifies the risk, the risk remains. This truncation approach likely overestimates the error, as derived from available data, but because the ensemble itself likely underestimates the uncertainty, the results may be as realistic as any other. The approach does make the sampling easy and the applied uncertainty transparent.

The estimate of the second-order uncertainty (standard error of the CDF estimate) uses the conventional calculation of the standard error rather than using bootstrapping. As a minor point, compiling the current data was already computationally intensive and adding bootstrapping would have made the task non-viable. But more importantly, bootstrapping would likely show increased uncertainty at the tails over the conventional estimate provided herein. Although this greater uncertainty may be justified, the conventional representation of uncertainty would still likely lead to disconcerting consequences at tail conditions. Although the output "data" from the model are being used as representative data points, they are simply model output from an ensemble-of-opportunity, and treating them the same as typical observation data, as used in bootstrapping estimates of uncertainty, may be a formal attempt to add more credibility than is warranted.

Second-order uncertainty exists for both the historical and future periods. To maintain consistency when sampling both periods, it is preferred to use the same exceedance probability for the second-order uncertainty, for both periods. If the historical period is deemed fixed at its mean value, then applying second-order uncertainty in future assessments can be insightful -- as long as it is recognized that the low probability conditions may be more a result of the models' historical-calibration limitations than just forecast variance across the models. Again, in general, risk assessments would only use the, much-simpler-to-apply, first-order climate uncertainty. Note that analyses could additionally include uncertainty in the actual impacts, as determined in the impact models, as opposed to just including uncertainty in the climate variables.

[77] Another possibility could be resampling and bootstrapping, but even here, the correlations across the variables and within the ensemble could become distorted. It is unclear what trade-off is being made. It is unresolved that the results of this manipulation are more legitimate or less legitimate than just accepting the calculated standard error as the useful error metric.

3. RISK ASSESSMENT VARIABLES

Table 3 below shows the variables included in the analysis. These were selected to provide a minimalist set that was tractable and still enabled socioeconomic and security risk assessments. The data were converted to the dimensionality noted in the table, to be more compatible with impact models. Note that the estimated, uncertainty distributions generate a mean that is the average value of that variable, for the representative month, in the geographical area of interest, over the time period in question, such as a decadal interval.

For variables with small variations, the uncertainty is represented as a normal distribution.[78] The use of other distributions are noted in the table for variables whose uncertainty characteristics are generally accepted to have the features of that distribution. Note that, in general, the distribution describing the physically observed variance of a variable is not necessarily the distribution describing the uncertainty in the knowledge of that variable's value from the variation across the climate simulation models. Nonetheless, because any risk assessment is sampling the climate variable to calculate the impact from the weather (or other condition) it implies, the distribution used here often does correspond to its observed distribution. Each variable is discussed below, in turn.

3.1. Country-based Variables

For country risks, this analysis estimated the uncertainty distribution for the first nine variables of Table 3. Near-Surface Air Temperature is the monthly average and would impact agriculture, energy, human, disease, and economic activity. For example, the average temperature affects agricultural productivity and power plant efficiency. Maximum Temperature has impacts on agriculture, energy, humans, and economic activity. For example, high temperatures dramatically harm crops and reduce human labor-productivity. Minimum Temperature has impacts on disease and energy. For example, higher minimum seasonal temperatures reduce heating needs and allow the migration of diseases to new area. Precipitation has an impact on agriculture, water, diseases, energy, humans, and economic activity. Droughts and floods both come with severe consequences. Evaporation primarily impacts water supplies and can be used as a proxy for evaluating increased water loss from the surface of reservoirs. Relative Humidity has impacts on agriculture, humans, and energy. For example, the humidity affects human productivity and reduces cooling efficiency for energy needs. Moisture in Upper Portion of Soil Column is often used for impacts on agricultural productivity.

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[78] Stocker, T.F., D. Qin, G.-K. Plattner, L.V. Alexander, S.K. Allen, N.L. Bindoff, F.-M. Bréon, J.A. Church, U. Cubasch, S. Emori, P. Forster, P. Friedlingstein, N. Gillett, J.M. Gregory, D.L. Hartmann, E. Jansen, B. Kirtman, R. Knutti, K. Krishna Kumar, P. Lemke, J. Marotzke, V. Masson-Delmotte, G.A. Meehl, I.I. Mokhov, S. Piao, V. Ramaswamy, D.Randall, M. Rhein, M. Rojas, C. Sabine, D. Shindell, L.D. Talley, D.G. Vaughan and S.-P. Xie, 2013: Technical Summary. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. http://www.climatechange2013.org/images/report/WG1AR5_TS_FINAL.pdf

Surface Runoff has impacts on agriculture, water, and economic activity. The runoff values can be used as a proxy to scale historical flooding frequency and intensity to the potential for increased future flooding and intensity. The Maximum Near-Surface Wind Speed primarily has economic impacts. This variable can be used as a proxy to compare historical wind-damage frequency and intensity with the potential for increased future damage.

Each variable in Table 3 is discussed more fully below.

Variable Name	Dataset Timestep	Description	Native Unit	Converted Unit	Distribution
tas	mo	Near-Surface Air Temp	K	K	Normal
tasmax	mo	Maximum Near-Surface Air Temp	K	K	Normal
tasmin	mo	Minimum Near-Surface Air Temp	K	K	Normal
pr	mo	Precipitation	kg/m2/s	m/da	Gamma
evspsbl	mo	Evaporation	kg/m2/s	m/da	Normal
rhs	mo	Near-Surface Relative Humidity	%	% (monthly mean)	Normal
mrros	mo	Surface Runoff	kg/m2/s	m3/da	Gamma
mrsos	mo	Moisture in Upper Soil Column	kg/m2 in upper 0.1 m	m3/m3	Normal
sfcWindmax	mo	Maximum Near-Surface Wind Speed	m/s	m/da	Weibull
sic	mo	Sea Ice Area Fraction	%	m2/m2	Beta
sit	mo	Sea Ice Thickness	m	M	Gamma
ageice	mo	Age of Sea Ice	yr	da	Gamma
ridgice	mo	Sea Ice Ridging Rate	1/s	(m2/da)/m2	Gumbel

Table 3: CMIP5 Variables Having Uncertainty-Distribution Estimates

1. Near-Surface Air Temperature (CMIP5 short variable name: tas) is the mean (average) temperature measured in degrees kelvin (K), is sampled synoptically, and is normally, reported at 2 meters above the surface.[79] The values, as they are for all the variables, are for the average over the month, for that month, and over the time period of interest, for example 2016-2025, for the country of interest. Temperature variation, which in this case is its uncertainty, is conventionally described with a normal distribution.[80]

[79] All of the formal variable definitions come from: http://cmip-pcmdi.llnl.gov/cmip5/docs/standard_output.pdf

[80] Stocker, T.F., D. Qin, G.-K. Plattner, L.V. Alexander, S.K. Allen, N.L. Bindoff, F.-M. Bréon, J.A. Church, U. Cubasch, S. Emori, P. Forster, P. Friedlingstein, N. Gillett, J.M. Gregory, D.L. Hartmann, E. Jansen, B. Kirtman, R. Knutti, K. Krishna Kumar, P. Lemke, J. Marotzke, V. Masson-Delmotte, G.A. Meehl, I.I. Mokhov, S. Piao, V. Ramaswamy, D.Randall, M. Rhein, M. Rojas, C. Sabine, D. Shindell, L.D. Talley, D.G. Vaughan and S.-P. Xie, 2013: Technical Summary. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. http://www.climatechange2013.org/images/report/WG1AR5_TS_FINAL.pdf

2. Maximum Near-Surface Air Temperature (CMIP5 short variable name: tasmax) is measured, analyzed, and reported identically to that for the mean temperature above. To be statistically appropriate for the work here, it is the average over the month.

3. Minimum Near-Surface Air Temperature (CMIP5 short variable name: tasmin) is measured, analyzed, and reported identically to that for the mean temperature above. To be statistically appropriate for the work here, it is the average over the month.

4. Precipitation (CMIP5 variable: pr) is measured at the surface and includes both liquid and solid phases. The gamma distribution is widely used to represent precipitation variability and thus used here for uncertainty.[81]

5. Evaporation (CMIP5 variable: evspsbl) is the dissipation of water into the atmosphere due to conversion of both liquid and solid phases to vapor (from the underlying surface and vegetation). Although it is affected by a combination of physical phenomena, the net effects are its uncertainty, which is described with a normal distribution.

6. Near-Surface Relative Humidity (CMIP5 variable: rhs) is the relative humidity, in %, with respect to liquid water for T> 0 C, and with respect to ice for T<0 C. It is normally reported at 2 meters above the surface. Like evaporation, its uncertainty is described with a normal distribution.

7. Surface Runoff (CMIP5 variable: mrros) is the total surface runoff leaving the land portion of the modeled grid cell, or in this case, the country. The gamma distribution is also widely used to represent runoff variability and thus used here for uncertainty.[82]

8. Moisture in Upper Portion of Soil Column (CMIP5 variable: mrsos) is the mass of water in all phases in a thin surface soil layer, integrated over the uppermost 10 cm. This variable is closely linked to precipitation and runoff and is therefore described by a gamma distribution.

9. Maximum Near-Surface Wind Speed (CMIP5 variable: sfcWindmax) is normally reported at 10 meters above the surface. The Weibull distribution is widely used to represent wind variability and thus used here for uncertainty.[83] To be statistically appropriate for the work here, it is the average over the month.

[81] Gottschalk, Lars, and Rolf Weingartner. "Distribution of peak flow derived from a distribution of rainfall volume and runoff coefficient, and a unit hydrograph." Journal of hydrology 208.3 (1998): 148-162. https://www.researchgate.net/profile/Lars_Gottschalk/publication/223020819_Distribution_of_Peak_Flow_Derived_From_a_Distribution_of_Rainfall_Volume_and_Runoff_Coefficient_and_a_Unit_Hydrograph/links/0a85e531f0642da0c8000000.pdf
[82] Ibid. Gottschalk and Weingartner 1998
[83] Caretto, L. "Use of probability distribution functions for wind." Mechanical Engineering 483 (2010).

As noted earlier, all the temperature variables are well-correlated. Therefore, it may be appropriate to only use one random seed to sample all three distributions for an impact assessment. Because the actual correlation cannot be adequately quantified with available information, there is no justification for conditional sampling. Independent sampling is another option, but if the impact assessment is sensitive to all the temperature variations, the impacts could be dramatically overstated. A useful exercise could be to arbitrarily select various levels of correlation and run conditional-probability analyses to determine the sensitivity of the impacts or overall risk to the degree of correlation across variables. If the sensitivity produces unacceptable consequences for reasonably possible levels of correlation (or lack thereof), it could then be justified to devote research to more accurately determine the degree of correlation.

The same is true for the precipitation related variables of runoff and soil moisture. Although evaporation is jointly correlated with temperature and precipitation, an earlier discussion noted that at the monthly temporal resolution, they are best treated as independent. Further, biomass ground-cover also disconnects the evaporation from any simple temperature and precipitation relationship. Note that plant evapotranspiration is distinctly separate from the physical evaporation reported here.

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www.csun.edu/~lcaretto/me483/probability.doc

3.2. Arctic Variables and Spatial Resolution

For analysis, the Arctic region was divided into 15° longitude segments extending from 66.5° through 80° latitude segments. The pole area is divided into two semicircles extending from 80° to 90°, split along the 0° and 180° longitude line. There are uncertainty distributions for each area segment for the last four variables in Table 3. Figures 7 and 8 show this Arctic geometry for the eastern and western hemispheres. Figure 9 shows the combined country (land) and Arctic areas included in this report.

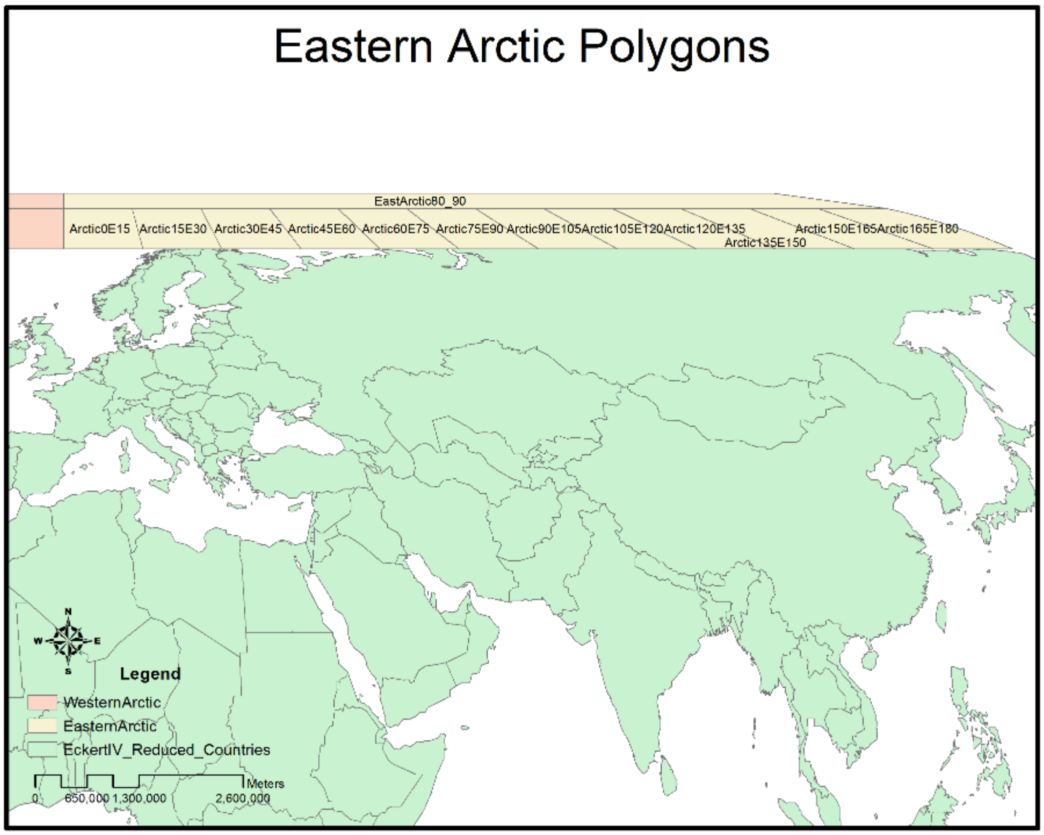

Figure 7: Eastern Arctic Areas

The Arctic data includes Sea Ice Area Fraction (the % of water covered by ice in a region), the Sea Ice Thickness (meters), Ice Ridging Rate (% of ice undergoing ridging per month), and the Age of the Ice (years). Note that Arctic data are very limited, sometimes to the extreme of having the data from only two or three climate models. In these situations, the purpose here is to show the process and to express the need for and implications of variable uncertainty. For these Arctic variables, the limited data are still useful for preliminary assessments and testing.

The analysis conceptualization original included the permafrost layer thickness (CMIP5 variable: tpf) for determining impacts on Arctic infrastructure development, but the data does not appear to be available for the Table 1 models within the ESGF portal. Other studies have considered the change in permafrost[84,85,86] primarily using proxies, but that work is beyond scope of this analysis and would not contain adequate information to produce uncertainty estimates comparable to those for the other variables.

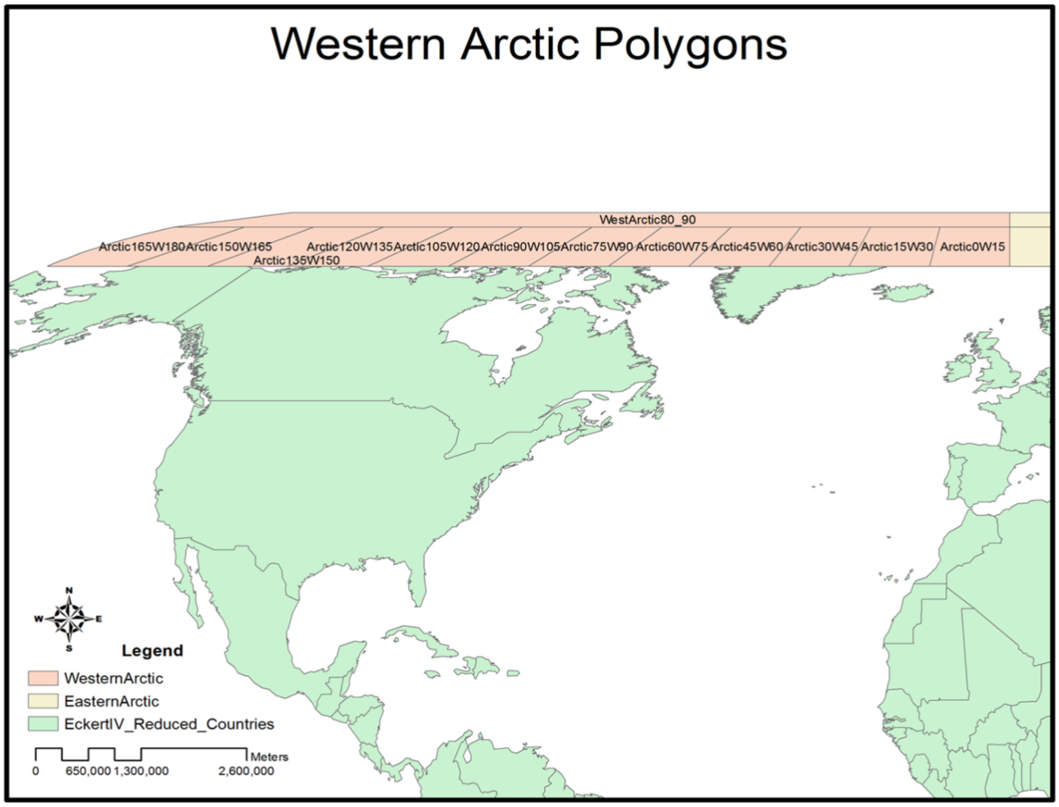

Figure 8: Western Arctic Areas

The Arctic variables are meant to be proxies, useful for understanding the risks of or from activities in the Arctic. Reduced ice in the Arctic corresponds to reduced hurdles to economic development or Arctic access, be it oil/gas production, shipping, mining, infrastructure development, or defense/homeland-security facilities. These variables are proxies because, for example, the ice thickness only partially indicates the need for icebreakers or the risk of using a vessel without ice reinforcement. Additionally, this proxy is partial because the values represent an average value of the ice thickness which corresponds to an implicit, unrealistic statement that the ice has one homogenous thickness over the entire region. In combination with the non-orthogonal ice-ridging, it is possible to obtain a more complete, but still partial, understanding of risk.

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[84] Slater, Andrew G., and David M. Lawrence. "Diagnosing present and future permafrost from climate models." Journal of Climate 26.15 (2013): 5608-5623.
[85] Koven, Charles D., William J. Riley, and Alex Stern. "Analysis of permafrost thermal dynamics and response to climate change in the CMIP5 Earth System Models." Journal of Climate 26.6 (2013): 1877-1900.
[86] Guo, Donglin, and Huijun Wang. "CMIP5 permafrost degradation projection: A comparison among different regions." Journal of Geophysical Research: Atmospheres 121.9 (2016): 4499-4517.

Each of the Arctic variables are discussed below.

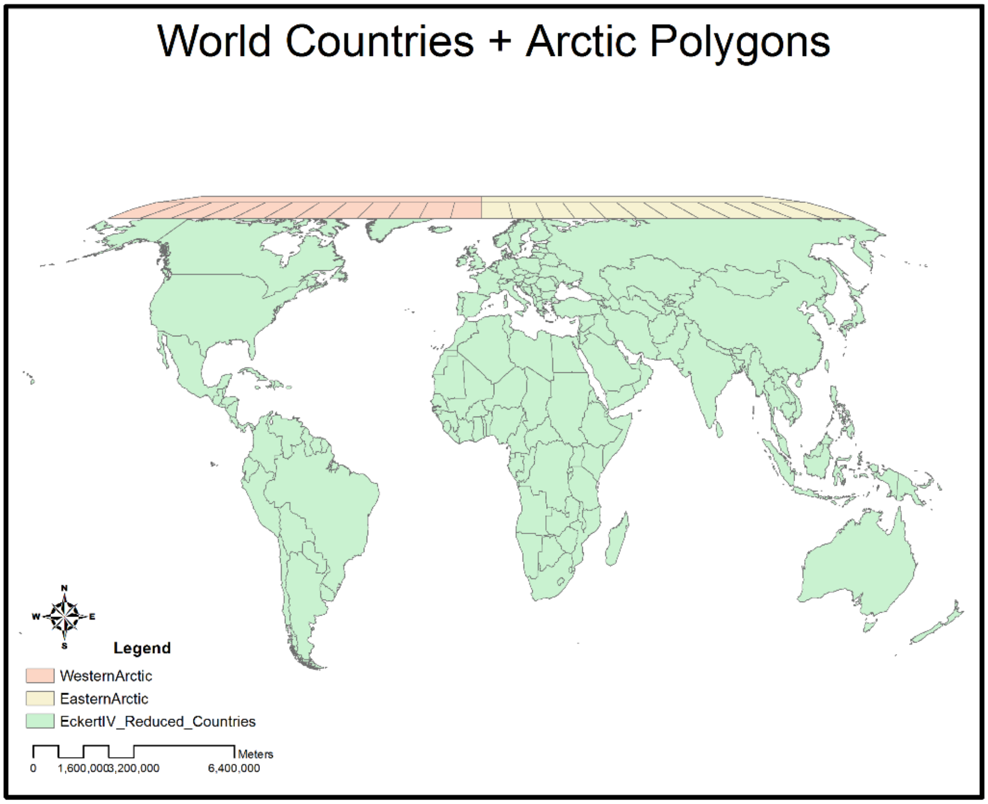

Figure 9: Combined Map of Country and Arctic Areas

1. The Sea Ice Area Fraction is the percentage fraction of grid cell covered by sea ice, often called the "extent." In the CMIP5 dataset, this variable is designated as "sic." Because it necessarily varies between zero and one, the Beta distribution is used to define the uncertainty of the Sea Ice Fraction.

2. Sea Ice Thickness is the mean thickness of sea ice in the ocean portion of the grid cell (averaging over the entire ocean portion, including the ice-free fraction). It is reported as 0.0 in regions free of sea ice. In the CMIP5 dataset, this variable is designated as "sit." With an inadequate number of models available to explore inter-model uncertainty, the use of intra-model uncertainty still does not clearly support either Weibull or a Lognormal distribution, and therefore the more flexible Gamma distribution appears to be best current choice[87,88] for both the age-of-ice and the thickness.

[87] Mårtensson, Sebastian, et al. "Ridged sea ice characteristics in the Arctic from a coupled multicategory sea ice model." Journal of Geophysical Research: Oceans 117.C8 (2012).
[88] Stroeve, J. C., and A. P. Barrett. "Assessment of Arctic Sea Ice in the CMIP5 Climate Models." AGU Fall Meeting. Vol. 1. 2011.
http://www.cesm.ucar.edu/working_groups/Polar/presentations/2012/stroeve.pdf

3. The Sea Ice Ridging Rate is defined as the percentage of the ice area participating in ridging per unit of time. The proper interpretation of the ridging rate depends on how the information will be used.[89] When computing the mean over a time period, the time-specific samples, weighted by the area of sea ice, are accumulated and then divided by the sum of the weights.[90] The ridging rate is reported as "missing" or 0.0 in regions free of sea ice. In the CMIP5 dataset, this variable is designated as “ridgice.” The ridging rate can be transformed into a proxy for relative ridging thickness.[91] Because the data indicate negative as well as positive ridging rates, a Gumbel distribution is used to describe the uncertainty rather than the Gamma distribution.

4. Age of Sea Ice measures the average of age of sea ice, for the noted area. When computing the mean over the time period, the time-specific samples, weighted by the mass of sea ice in the grid cell, are accumulated and then divided by the sum of the weights.[92] The age is reported as "missing" or 0.0 in regions free of sea ice. In the CMIP5 dataset, this variable is designated as “ageice.” As discussed above, a Gamma distribution is used to describe its uncertainty.

In general, for Arctic variables, the CMIP5 analyses produce more realistic results than those of CMIP3. Nonetheless, they still show excessive seasonal changes and the spatial thickness is not well-produced.[93] The models also tend to make the ice too thin, affecting estimates of all these interdependent variables.[94] The use of the delta-change approach still allows a first-order evaluation of sea ice conditions over time for risk assessment purposes.[95]

There is no justification, via the data alone, for any correlated relationship among any of the Arctic variables. Therefore, all these variables should be treated as independent. There is certainly a causal relationship between ridging rates and ice thickness. As the ice thickness declines the potential for ridging increases, depending on temperature, currents and wind/wave conditions, but the relationship is non-linear because both zero ice-thickness and extreme thickness imply no ridging. Further, each Arctic area has a large geographical extent, and average thickness is not representative of local thickness. Consequently, treating thickness and ridging as independent best captures the lack of information (and data) regarding both processes.

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[89] Shoutilin, Sergey V., et al. "Dynamic-thermodynamic sea ice model: ridging and its application to climate study and navigation." Journal of climate 18.18 (2005): 3840-3855.
[90] This formal variable definition comes from: http://cmip-pcmdi.llnl.gov/cmip5/docs/standard_output.pdf
[91] Lipscomb, William H., et al. "Ridging, strength, and stability in high-resolution sea ice models." Journal of Geophysical Research: Oceans 112.C3 (2007).
[92] This formal variable definition comes from: http://cmip-pcmdi.llnl.gov/cmip5/docs/standard_output.pdf
[93] Stroeve, J. C., and A. P. Barrett. "Assessment of Arctic Sea Ice in the CMIP5 Climate Models." AGU Fall Meeting. Vol. 1. 2011.
http://www.cesm.ucar.edu/working_groups/Polar/presentations/2012/stroeve.pdf
[94] Shu, Qi, Zhenya Song, and Fangli Qiao. "Assessment of sea ice simulations in the CMIP5 models." The Cryosphere 9.1 (2015): 399-409
[95] Ibid.

4. CMIP5 DATA AVAILABILITY

All data was extracted from the models noted in Table 1. This set appeared to produce the most uniformity of output variables across the variable set. Tables 4 and 5 show which models provide what data for each of the country (land) variables for the historical and RCP8.5 experiments. Table 6 shows the data used for the Arctic uncertainty estimates. Blocks in green note the used data. Blocks in red note that the data are either not available or could not be located on the ESGF portal[96] at the time of this analysis. Orange notes that only partial data were available, typically only for a subset number of years. To maintain consistency across years, these data were not used in the analysis.

Model/Variable	tas/mo		tasmax/mo		tasmin/mo		pr/mo		evspsbl/mo	
Experiment	**h**	**8.5**	**h**	**8.5**	**h**	**8.5**	**h**	**8.5**	**h**	**8.5**
Access1.0	h	8.5	h	8.5			h	8.5	h	8.5
Access1.3	h	8.5	h	8.5			h	8.5	h	8.5
BCC-CSM1.1	h	8.5	h	8.5			h	8.5	h	8.5
BNU-ESM	h	8.5	h	8.5			h	8.5	h	8.5
CanESM2	h	8.5	h	8.5			h	8.5	h	8.5
CCSM4	h	8.5	h	8.5			h	8.5	h	8.5
CESM-CAM5.1	h	8.5	h	8.5			h	8.5	h	8.5
CNRM-CM5	h	8.5	h	8.5	h	8.5	h	8.5	h	8.5
CSIRO-Mk3.6	h	8.5	h	8.5			h	8.5	h	8.5
GFDL-CM3	h	8.5	h	8.5	h	8.5	h	8.5	h	8.5
GFDL-ESM2M	h	8.5	h	8.5	h	8.5	h	8.5	h	8.5
GISS-E2-H	h	8.5	h	8.5	h	8.5	h	8.5	h	8.5
HadGEM2-CC	h	8.5	h	8.5	h	8.5	h	8.5	h	8.5
IPSL-CM5A-MR	h	8.5	h	8.5	h	8.5	h	8.5	h	8.5
IPSL-CM5A-LR	h	8.5	h	8.5	h	8.5	h	8.5	h	8.5
MIROC-ESM	h	8.5	h	8.5	h	8.5	h	8.5	h	8.5
MIROC5	h	8.5	h	8.5	h	8.5	h	8.5	h	8.5
MPI-ESM-LR	h	8.5	h	8.5	h	8.5	h	8.5	h	8.5
MRI-CGCMC3	h	8.5	h	8.5	h		h	8.5	h	8.5
MRI-ESM1	h	8.5	h	8.5	h	8.5	h	8.5	h	8.5
NorESM1-M	h	8.5	h	8.5	h	8.5	h	8.5	h	8.5
NorESM1-ME	h	8.5					h	8.5	h	8.5

Data not available or not found
File was downloaded and processed
File was downloaded but data are inadequate

Table 4: Land Variables and Data Availability

[96] Earth System Grid Federation (ESGF) June to September 2015 http://esgf.llnl.gov/

Model/Variable	rhs/day		mrsos/mo		mrros/mo		sfcWindmax/day	
Experiment	**h**	**8.5**	**h**	**8.5**	**h**	**8.5**	**h**	**8.5**
Access1.0			h	8.5	h	8.5		
Access1.3			h	8.5	h	8.5	h	
BCC-CSM1.1			h	8.5		8.5		
BNU-ESM			h	8.5		8.5	h	8.5
CanESM2			h	8.5	h	8.5	h	
CCSM4					h			
CESM-CAM5.1								
CNRM-CM5			h	8.5	h	8.5	h	
CSIRO-Mk3.6					h		h	8.5
GFDL-CM3	h	8.5					h	8.5
GFDL-ESM2M	h	8.5					h	8.5
GISS-E2-H			h	8.5	h	8.5		
HadGEM2-CC		8.5	h	8.5			h	8.5
IPSL-CM5A-MR		8.5	h	8.5	h	8.5		
IPSL-CM5A-LR	h	8.5	h	8.5	h	8.5	h	8.5
MIROC-ESM		8.5	h	8.5	h	8.5		8.5
MIROC5	h	8.5	h	8.5	h	8.5	h	8.5
MPI-ESM-LR					h	8.5	h	8.5
MRI-CGCMC3	h	8.5	h	8.5	h	8.5	h	8.5
MRI-ESM1		8.5	h	8.5	h	8.5		
NorESM1-M	h	8.5	h	8.5	h	8.5		
NorESM1-ME			h	8.5	h	8.5		

Data not available or not found
File was downloaded and processed
File was downloaded but data are inadequate

Table 5: Land Variables and Data Availability (continued)

Model/Variable	sic/mo		sit/mo		ageice/mo		ridgice/mo	
Experiment	**H**	**8.5**	**h**	**8.5**	**h**	**8.5**	**h**	**8.5**
Access1.0								
Access1.3								
BCC-CSM1.1								
BNU-ESM								
CanESM2								
CCSM4								
CESM-CAM5.1								
CNRM-CM5	H	8.5	h	8.5	h	8.5		
CSIRO-Mk3.6								
GFDL-CM3	H	8.5	h	8.5				
GFDL-ESM2M	H	8.5		8.5				
GISS-E2-H	H	8.5	h	8.5				
HadGEM2-CC	H	8.5	h	8.5				
IPSL-CM5A-MR	H	8.5	h	8.5				
IPSL-CM5A-LR	H	8.5	h	8.5				
MIROC-ESM	H	8.5	h	8.5				
MIROC5	H	8.5	h	8.5				
MPI-ESM-LR	H	8.5	h	8.5				
MRI-CGCMC3		8.5		8.5			h	8.5
MRI-ESM1	H	8.5	h	8.5			h	8.5
NorESM1-M	H	8.5	h	8.5	h	8.5		
NorESM1-ME	H	8.5	h	8.5	h	8.5		

Data not available or not found
File was downloaded and processed
File was downloaded but data are inadequate

Table 6: Arctic Variables and Data Availability

5. UNCERTAINTY ESTIMATION

The uncertainty distributions were estimated using MATLAB® distribution routines. These routines fit the data to a Cumulative Distribution Function (CDF). The CDF is the integral of the Probability Density Function (PDF). This work uses two-parameter distribution functions based on the physical process involved and on previous empirical studies of the appropriate distribution. The sampling of the CDF determines the exceedance probability of a given value, which is the most appropriate metric for risk assessments.[97] Depending on the calculation of impacts, it is often advantageous to use the complimentary CDF (CCDF) which is just one minus the CDF. Many studies use exceedance probability[98] for risk assessments.[99,100,101]

To create the data set reported here, the gridded raw data from any CMIP model are first mapped onto a region using area-weighting. Even though the information is predominantly for use to calculate climate's impact on humans, both population and economic weighting cause inconsistencies among the physical variables. Definitionally, the use of any country-level resolution assumes homogeneity within the country. Other weighting methods tacitly contradict that base assumption.[102]

The resulting country level data from each individual model are then summed over the month of interest (if it is, for example, daily data), and over the years within the time interval. Each model represents one data point from which the probability distribution is estimated. As is statistically appropriate, this averaging method is applied even if the variable is the maximum temperature or maximum wind speed. Simplistically, if only the maximum of the maxima was used, the statistic would possibly only capture the temperature for the last year of the intervals (e.g., with idealized monotonically

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[97] Ghosh, Subimal, and P. P. Mujumdar. "Climate change impact assessment: Uncertainty modeling with imprecise probability." Journal of Geophysical Research: Atmospheres 114.D18 (2009).

[98] For use in risk assessments, exceedance probability is typically used across bins. For example, suppose the analysis only considers 10 bins of exceedance probabilities; ten 10% intervals from 0 to 100%, starting at 5%. An impact model can calculate the consequence (e.g., economic or food loss compared to historical conditions) at each exceedance value. There will be 10 points (5%, 15% …95%) that approximately capture the consequence over a 10% interval, centered at the designated exceedance probability. Risk is the sum of the consequences multiplied by the probability interval size. Finer resolution can produce more precise answers, but not necessarily more accurate ones.

[99] Hayhoe, Katharine, et al. "Emissions pathways, climate change, and impacts on California." Proceedings of the National Academy of Sciences of the United States of America 101.34 (2004): 12422-12427.

[100] Kunreuther, Howard C., and Erwann O. Michel-Kerjan. Climate change, insurability of large-scale disasters and the emerging liability challenge. No. w12821. National Bureau of Economic Research, 2007.

[101] Backus, George A., Thomas S. Lowry, and Drake E. Warren. "The near-term risk of climate uncertainty among the US states." Climatic Change 116.3-4 (2013): 495-522. http://link.springer.com/article/10.1007/s10584-012-0511-8 and Backus, George, et al. "Climate Uncertainty and Implications for US State-Level Risk Assessment Through 2050." SAND Report 7001 (2009). Sandia National Laboratories, Albuquerque, NM, page 30. http://prod.sandia.gov/techlib/access-control.cgi/2010/102052.pdf

[102] Backus, George, et al. "Climate Uncertainty and Implications for US State-Level Risk Assessment Through 2050." SAND Report 7001 (2009). Sandia National Laboratories, Albuquerque, NM, page 30. http://prod.sandia.gov/techlib/access-control.cgi/2010/102052.pdf

increasing temperature). The goal here is to calculate the representative maximum temperature for the interval. Additionally, the use of the data will be in comparison to the delta change relative to the historical period. Essentially, the question boils down to how much on average is the maximum temperature, or any other variable, increasing or decreasing.

Note that the extremes denoted by the tails of the uncertainty distribution for the variables do not, in themselves, represent an extreme in conditions. The variables themselves denote the average or the extremes, such as average surface temperature, and maximum wind speed, respectively. The uncertainty distribution is the envelope of values for the specific variable. Thus, a tail condition is merely a very unlikely value for that variable, which itself denotes average conditions.

5.1 Estimation Results

The analysis results are presented in the Appendices. There is a separate appendix for the historical and forecast periods of each variable in Table 3. The statistics for each variable cover a bin of years rather than one year. This approach reduces the amount of data presented and better reflects the variation in the variable over the period of time within that geographic location. **All the reports are publicly available[103] and the data are available upon request.[104]**

The tables typically provide statistical information for each decade. For the historical period, the single distribution corresponds to the time period of 1976 to 2005. Economic and infrastructure models typically subsume a historical average weather condition within the analysis. That is, the models completely neglect weather or implicitly assume an average value. For use with climate impact simulations, this historical information can act as an initial condition or if the simulation includes historical reproduction, the historical parameterization can be used as the 1990 condition and the centroid of the 2006-2015 parameterization can be used to interpolate between years. The climatic changes within this time period are effectively linear over time, such that the parameters can be construed as simply the average value of "weather" over the period or as the climate centered around the year 1990.[105]

The first forecast period is for the years 2006 through 2015 and a similar perspective would consider the uncertainty parameterization as the climate centered around the year 2010. Because risk assessments are not predictions, it would be acceptable to just sample the distribution each year for all the years in the interval. For more continuity, another logic would be to test the distributions that are on either side of the year of interest. For example, either 2004 or 2008 would use the historical and the first forecast interval. Draw a random number between 0 and 1.0 as the exceedance probability and determine

[103] https://cfwebprod.sandia.gov/cfdocs/CompResearch/templates/insert/pubs.cfm
[104] Contact Dr. Thomas Lowry, Sandia National Laboratories, tslowry@sandia.gov.
[105] The changes in climatological variables over the historical period are small and therefore using the single parameterization for all historical years or to interpolate is equally acceptable.

the value for both the (1976-2005) historical and (20016-2015) forecast distributions. Interpolate the value for the year of interest and use that value for the determining the impact for that year for that sampling. The interpolation can be linear or exponential depending how important the rate of change across interjacent years is to the analysis. This interpolation process will work for any year of interest. The other forecast intervals in the "forecast" appendices are: 2016-2025, 2026-2035, 2036-2045, 2046-2055, 2056-2065, 2066-2075, 2076-2085, and 2086-2100. The appendices note these intervals and the midpoint. The 2086-2100 period covers 15 years, simply to ensure coverage over the full range of CMIP5 model outputs.

The parameterizations are provided for each month of the "decadal" periods to recognize the disproportional impacts over different months of the year, such as due to time windows for agriculture or construction.

The columns for all the tables first include the country, then the type of distribution, the two parameters that define distribution (as noted in the next section), the standard error on the CDF estimate (the second order uncertainty), the beginning year of the data used to calculated the distribution, the last year of data used to calculate the distribution, the mid-year centroid, the month associated with the uncertainty distribution, and the short, CMIP5 variable name (noted earlier for each variable). In the appendices, the column headings have the appearance of Table 7.

Country	Distribution	Parameter 1	Parameter 2	Std Error	Start Year	End Year	Mid-Year	Month	Variable

Table 7: Appendix Column Designations

5.2. Probability Distributions

This section describes the basic information associated with each distribution, and most importantly, it shows the mapping of the estimated "Parameter 1" and "Parameter 2" noted in Table 7 (and the appendices) to the actual calculation of the distribution. Each distribution used for describing the uncertainty of the variables will be discussed in turn. The discussion first presents the graphical[106] portrayal of the distribution in its PDF form with representative parameter values. The CDF is not shown because all the distributions produce functions that have a sigmoidal shape and it is difficult to visually distinguish the unique characteristics of the CDF. The graphic is followed by the equation for the PDF and then the CDF. These equations are then followed by the calculations for the Mean, Median, and Mode, if they exist. Most statistical and analytical applications, such as R,[107] MATLAB,[108] and EXCEL,[109] have built-in routines to calculate these terms.

[106] All graphics come from the Wikimedia commons. For more information, see the Wikipedia entry for the specified distribution.
[107] https://www.r-project.org/
[108] https://www.mathworks.com/products/matlab.html
[109] https://support.office.com/en-us/article/Statistical-functions-reference-624DAC86-A375-4435-BC25-76D659719FFD

The first distribution is the Normal (Gaussian) distribution.[110] It is used for variables that have small deviations from the historical norm over time or for those typically described in the literature with a Normal distribution.

Normal Distribution: $Parameter1 = \mu,\ Parameter2 = \sigma$

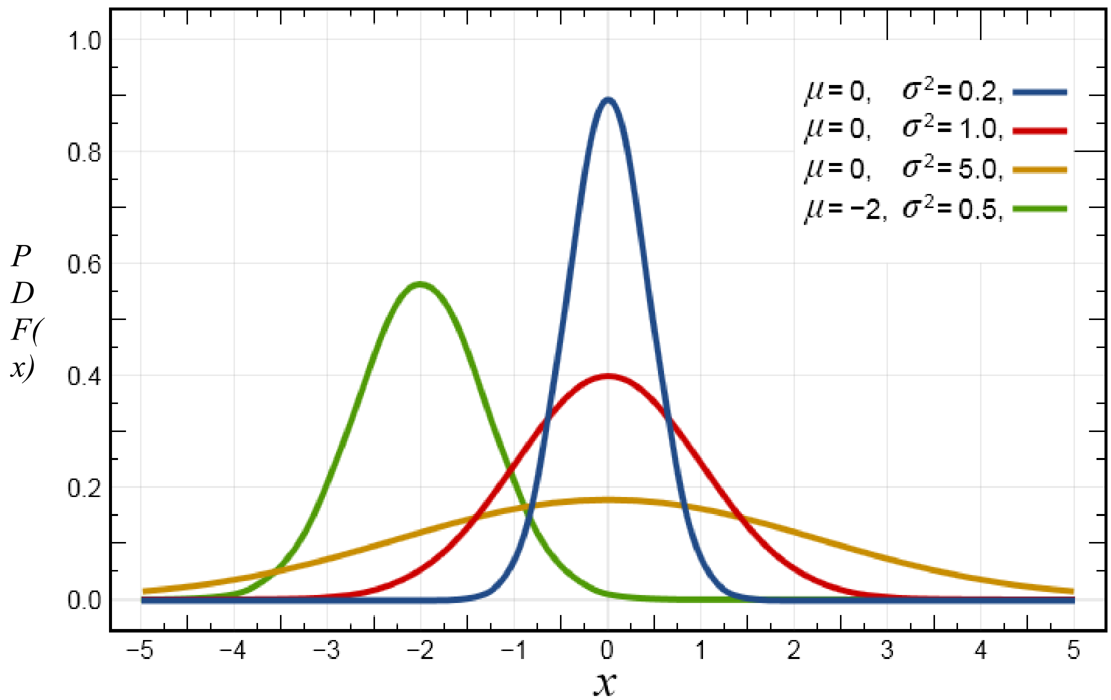

Figure 10: Normal distribution

$$PDF(x) = \frac{1}{\sigma * \sqrt{2\pi}} * e^{-(\frac{(x-\mu)^2}{2 * \sigma^2})}$$

$$CDF(x) = \frac{1}{2} * \left[1 + erf(\frac{x-\mu}{\sigma\sqrt{2}})\right]$$

Where $\mathrm{erf}(\cdot)$ is the Error Function.

$Mean = \mu$

$Median = \mu$

$Mode = \mu$

[110] The graphic is in the public domain. https://en.wikipedia.org/wiki/Normal_distribution#/media/File:Normal_Distribution_PDF.svg

The second distribution is the lognormal.[111] It is characterized as having only positive arguments (X values) and often a long tail to the right. Although this distribution is noted in the discussion of Arctic variables, the limited Arctic data indicated its actual use in uncertainty estimation was not justified.

Lognormal Distribution: $Parameter1 = \sigma,\ Parameter2 = \mu$

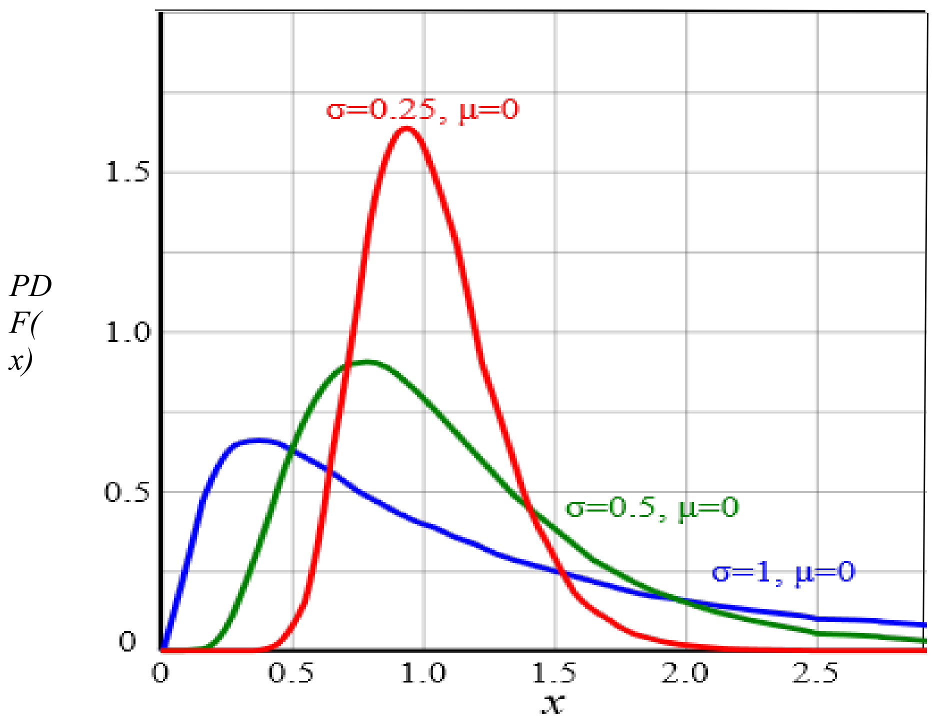

Figure 11: Lognormal Distribution

$$PDF(x) = \frac{1}{x\sigma * \sqrt{2\pi}} * e^{-(\frac{(ln(x) - \mu)^2}{2 * \sigma^2}}$$

$$CFD(x) = \frac{1}{2} * \left[1 + erf(\frac{ln(x) - \mu}{\sigma\sqrt{2}})\right]$$

$Mean = e^{\mu + \sigma^2/2}$
$Median = e^{\mu}$
$Mode = e^{\mu - \sigma^2}$

[111] Graphic is in the public domain. https://en.wikipedia.org/wiki/Log-normal_distribution#/media/File:PDF-log_normal_distributions.svg

The next distribution is the Weibull.[112] It is noted by having only positive arguments (X values) with highly varied behavior near the origin.

Weibull Distribution: $Parameter1 = \lambda,\ Parameter2 = k$

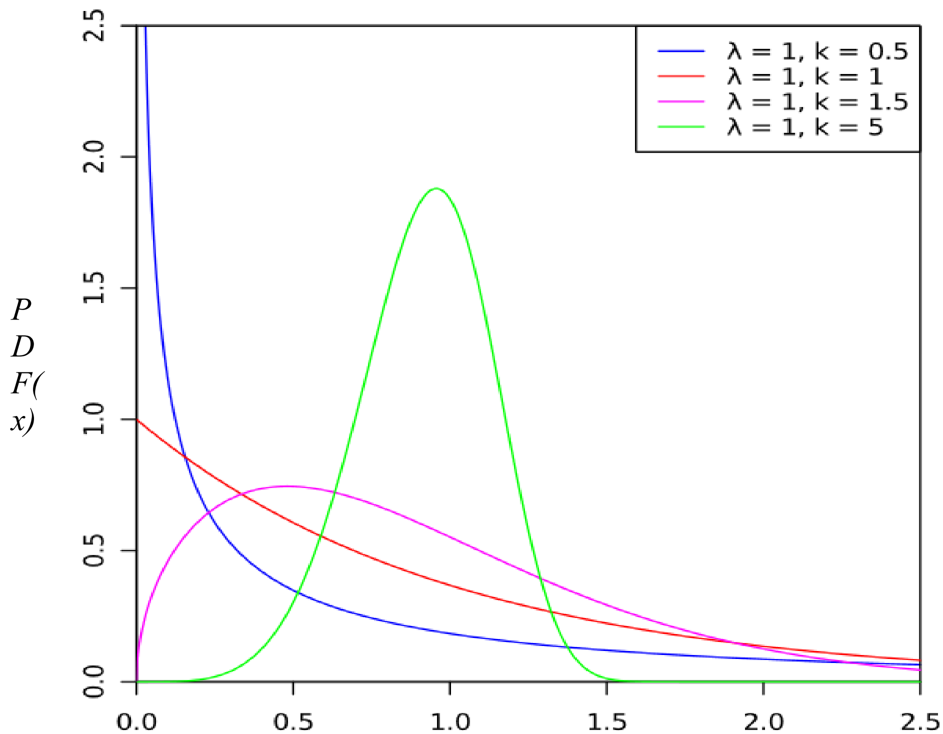

Figure 12: Weibull Distribution

$$PDF(x) = \frac{k}{\lambda} * \left(\frac{x}{\lambda}\right)^{k-1} * e^{-(\frac{x}{\lambda})^k}$$

$$CDF(x) = 1 - e^{-(\frac{x}{\lambda})^k}$$

$$Mean = \lambda * \Gamma(1 + \frac{1}{k})$$

$$Median = \lambda * (\ln(2))^{1/k}$$

$$Mode = \lambda * \left(\frac{k-1}{k}\right)^{\frac{1}{k}} \quad k > 1$$

$$Mode = 0 \quad k \leq 1$$

Where $\Gamma(\cdot)$ is the Gamma Function.

A Weibull (1, β) random variable is an exponential random variable with mean β.

[112] The graphic rights allow unlimited, free distribution. https://en.wikipedia.org/wiki/Weibull_distribution#/media/File:Weibull_PDF.svg

The Gamma distribution allows only positive arguments, but its parameters provide a high degree of flexibility in regard to the PDF shape.[113]

Gamma Distribution: $Parameter1 = k,\ Parameter2 = \theta$

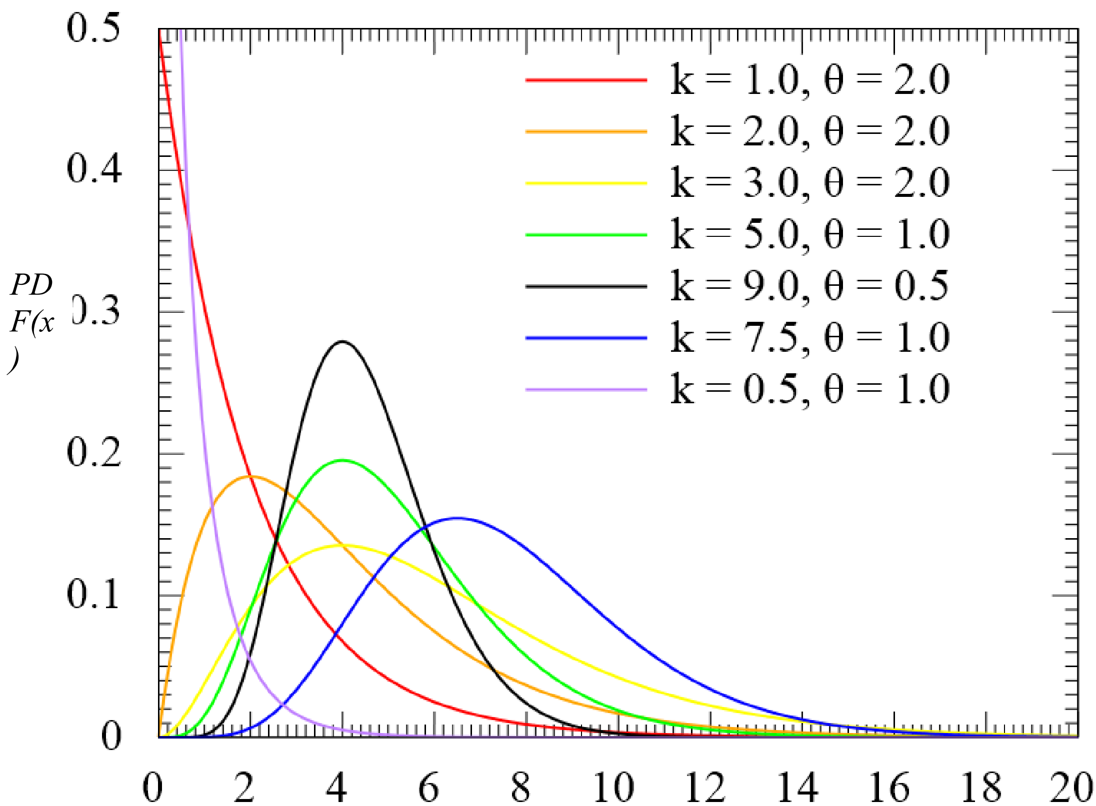

Figure 13: Gamma Distribution

$$PDF(x) = \frac{1}{\Gamma(k) * \theta^k} * x^{k-1} * e^{-\frac{x}{\theta}}$$

$$CDF(x) = 1 - \Gamma\left(k,\frac{x}{\theta}\right)/\Gamma(k)$$

Where $\Gamma(\cdot)$ is the Gamma Function and $\Gamma(k,x/\theta)$ is the Incomplete Gamma Function

$$Mean = k\theta$$

$$Median \approx k\theta * \frac{3k - 0.8}{3k + 0.2} \quad k \geq 1$$

[113] The graphic rights allow unlimited, free distribution. https://en.wikipedia.org/wiki/Gamma_distribution#/media/File:Gamma_distribution_pdf.svg

$Median \approx \theta * (0.391424k^4 - 1.29095k^3 + 1.6553k^2 - 0.0257641k - 0.0367065)$
$0.3 \leq k \leq 1, \theta \ll 1.0$

There is no closed-form solution for the median, but many mathematical packages have median calculators (e.g. MATLAB)

$Mode = (k-1) * \theta \quad k \geq 1$
$Mode = 0 \quad k < 1$

The shape of a Gamma distribution is quite flexible. Note that when k equals one, the gamma distribution becomes an exponential distribution.

The Beta distribution only has arguments between 0.0 and 1.0, thus making it the description for variables describing a fraction ranging between 0.0 and 1.0.[114]

Beta Distribution: $Parameter1 = \alpha, \; Parameter2 = \beta$

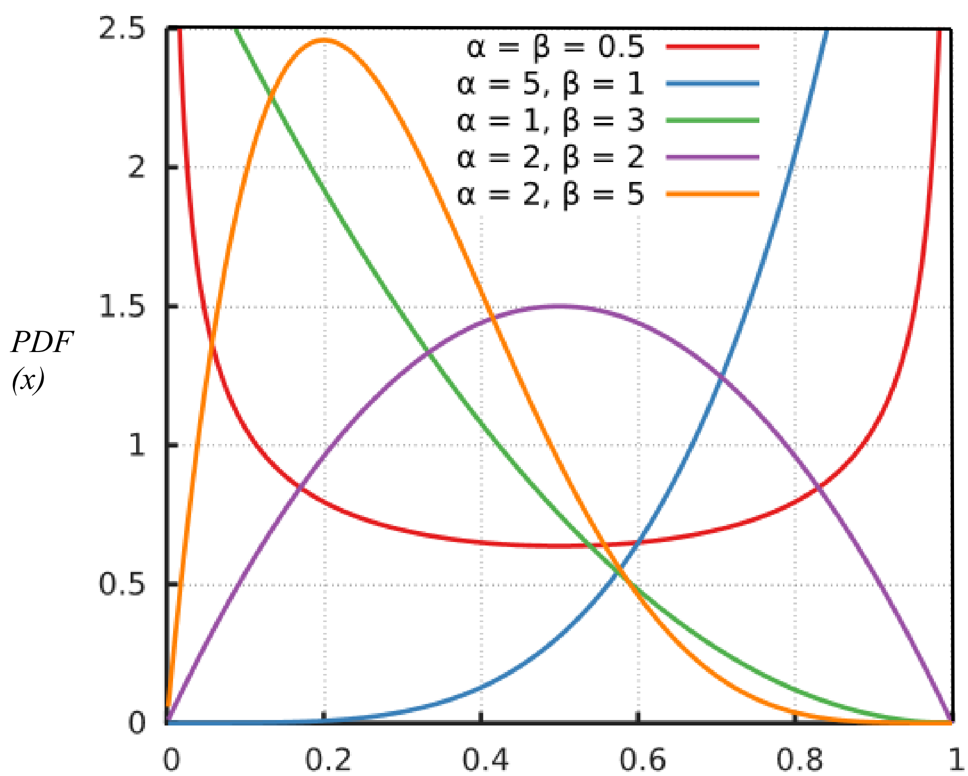

Figure 14: Beta Distribution

$$PDF(x) = x^{\alpha-1} * (1-x)^{\beta-1} * \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha) * \Gamma(\beta)}$$

[114] The graphic is in the public domain. https://en.wikipedia.org/wiki/File:Beta_distribution_pdf.svg

$$CDF(x) = \frac{B(x;\alpha,\beta) * \Gamma(\alpha + \beta)}{\Gamma(\alpha) * \Gamma(\beta)}$$

Where $B(x;\alpha,\beta)$ is the Incomplete Beta Function and $\Gamma(\cdot)$ is the Gamma Function.

$$Mean = \frac{\alpha}{\alpha + \beta}$$

$$Mode = \frac{\alpha - 1}{\alpha + \beta - 2} \quad \alpha,\beta > 1$$

$$Mode = 0 \quad \alpha,\beta \leq 1$$

$$Median = \frac{\Gamma(\alpha) * \Gamma(\beta)}{B\left(\frac{1}{2};\alpha,\beta\right) * \Gamma(\alpha + \beta)}$$

$$Median \approx \frac{\alpha - \frac{1}{3}}{\alpha + \beta - 2} \quad \alpha,\beta > 1$$

A Beta random variable with parameters $\alpha = \beta = 1$ is a uniform random variable.

The last distribution is the Gumbel distribution. It is related to the Weibull distribution through a log transformation.[115] This gives the distribution a varied right tail compared the varied left tail of the Weibull.

Gumbel Distribution: Parameter1=μ, Parameter2=β

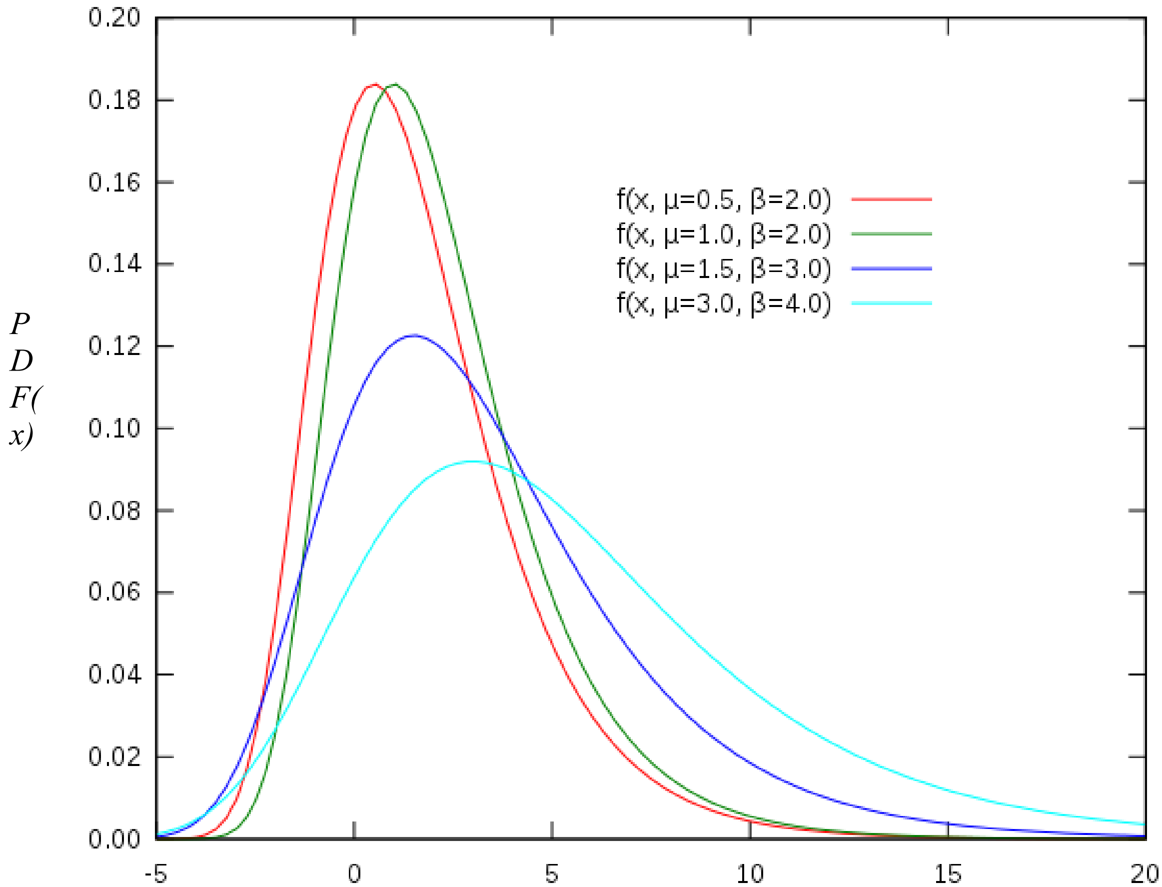

Figure 15: Gumbel Distribution

$$PDF(x) = \frac{1}{\beta} * e^{-(z - e^{-z})}$$

Where: $z = \dfrac{(x - \mu)}{\beta}$

$$CDF(x) = e^{-e^{-z}}$$

$$Mean = \mu + \beta\gamma$$

Where γ is Euler's constant.

$$Median = \mu - \beta * ln(\ln(2))$$

$$Mode = \mu$$

[115] The graphic is in the public domain. https://en.wikipedia.org/wiki/Gumbel_distribution#/media/File:Gumbel-Density.svg

6. SUMMARY: USING THE DATA

To make the documents manageable, the appendices are in 26 separate volumes. Each of the appendices contain information on a single variable. The available variables are noted in Table 3 of Section 3.1. The appendix is designated by the variable of interest. If the variable is country-based, then the data covers each of 169 countries (and autonomous areas) noted in Table 2 of Section 2.5. If the variable is Arctic-based, then the data cover each of the 26 geographical areas noted in Figures 7 and 8 of Section 3.2.

All the reports are publicly available[116] and the data are available upon request.[117]

The data columns for all the tables first include the country, then the type of distribution, the two parameters that define the distribution (as noted in the Chapter 5), the standard error on the CDF estimate (the second order uncertainty), the beginning year of the data used to calculate the distribution, the last year of data used to calculate the distribution, the mid-year centroid, the month associated with the uncertainty distribution, and the short CMIP5 variable name (noted in Table 3). The column headings look like those shown previously in Table 7.

The historical data only consider the referent 30-year period of 1976-2005. The forecast contains data for each decadal period from 2006 through 2100. Section 5.1 discusses the interpolation process for any specific or sequence of years between 1976 and 2100, should that be crucial to the risk analysis.

Background on the probability distribution (Section 5.2) is repeated in each appendix for the specific distribution used to represent the uncertainty of the variable featured in that appendix. Sampling is typically performed on the cumulative distribution function (CDF). The parameters define the values of the function and sampling defines the selected exceedance probability. The statistical language R, MATLAB, and Microsoft EXCEL contain routines for calculating the inverse of the CDFs noted here. Given the exceedance probability, the inverse determines the value of the variable, which can then be directly included in the impact analysis. The impact and the probability determine the risk profile.[118]

The data for each variable are contained in the report appendices, as noted in Table 8 on the next page. Despite its quantity, the data is quite easy to use for most applications. Select the variable of interest, go to the forecast volume and go to the country of interest. Go to the time period of interest and see the month or months of interest. For most analyses, just note the distribution type and record the two parameters. Do the same for the historical appendix. For history, just record the two parameters for the country and month(s). You can use most statistical or simulation applications to calculate the

[116] https://cfwebprod.sandia.gov/cfdocs/CompResearch/templates/insert/pubs.cfm
[117] Contact Dr. Thomas Lowry, Sandia National Laboratories, tslowry@sandia.gov.
[118] Backus, George A., Thomas S. Lowry, and Drake E. Warren. "The near-term risk of climate uncertainty among the US states." Climatic Change 116.3-4 (2013): 495-522. http://link.springer.com/article/10.1007/s10584-012-0511-8

historical mean with them. You can use the parameters from the forecast volume and your statistical or simulation package to sample for the future value at an exceedance probability. Take the ratio or delta between the forecast and historical values as input to the impact analysis. This approach conforms to the most basic analysis. As noted in the earlier chapters, the data can be used for much more sophisticated analyses.

Volume	Appendix	Description	Unit of Measure	Time Period
1	-	Main Text	All	All
2	A	Near-Surface Air Temperature	K	Historical
3	B	Near-Surface Air Temperature	K	Forecast
4	C	Maximum Near-Surface Air Temperature	K	Historical
5	D	Maximum Near-Surface Air Temperature	K	Forecast
6	E	Minimum Near-Surface Air Temperature	K	Historical
7	F	Minimum Near-Surface Air Temperature	K	Forecast
8	G	Precipitation	m/day	Historical
9	H	Precipitation	m/day	Forecast
10	I	Evaporation	m/day	Historical
11	J	Evaporation	m/day	Forecast
12	K	Near-Surface Relative Humidity	% (monthly mean)	Historical
13	L	Near Surface Relative Humidity	% (monthly mean)	Forecast
14	M	Surface Runoff	m3/day	Historical
15	N	Surface Runoff	m3/day	Forecast
16	O	Soil Moisture (Upper Column)	m3/m3	Historical
17	P	Soil Moisture (Upper Column)	m3/m3	Forecast
18	Q	Maximum Near-Surface Wind Speed	m/day	Historical
19	R	Maximum Near-Surface Wind Speed	m/day	Forecast
20	S	Sea Ice Area Fraction	m2/m2	Historical
21	T	Sea Ice Area Fraction	m2/m2	Forecast
22	U	Sea Ice Thickness	M	Historical
23	V	Sea Ice Thickness	M	Forecast
24	W	Age of Sea Ice	day	Historical
25	X	Age of Sea Ice	day	Forecast
26	Y	Sea Ice Ridging Rate	(m2/day)/m2	Historical
27	Z	Sea Ice Ridging Rate	(m2/day)/m2	Forecast

Table 8: Report Volume to Variable-Data Mapping

7. REFERENCES

Auffhammer, M., Hsiang, S. M., Schlenker, W., & Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. Review of Environmental Economics and Policy, 7,181–198 (2013). doi: 10.1093/reep/ret016

Backus, George A., Thomas S. Lowry, and Drake E. Warren. "The near-term risk of climate uncertainty among the US states." Climatic Change 116.3-4 (2013): 495-522. http://link.springer.com/article/10.1007/s10584-012-0511-8

Backus, George, et al. "Climate Uncertainty and Implications for US State-Level Risk Assessment Through 2050." SAND Report 7001 (2009). Sandia National Laboratories, Albuquerque, NM. http://prod.sandia.gov/techlib/access-control.cgi/2010/102052.pdf

Campbell, Kurt M., et al. The age of consequences: the foreign policy and national security implications of global climate change. Center for Strategic and International Studies, Washington DC, 2007. https://csis-prod.s3.amazonaws.com/s3fs-public/legacy_files/files/media/csis/pubs/071105_ageofconsequences.pdf

Caretto, L. "Use of probability distribution functions for wind." Mechanical Engineering 483 (2010). www.csun.edu/~lcaretto/me483/probability.doc

Church, J.A., P.U. Clark, A. Cazenave, J.M. Gregory, S. Jevrejeva, A. Levermann, M.A. Merrifield, G.A. Milne, R.S. Nerem, P.D. Nunn, A.J. Payne, W.T. Pfeffer, D. Stammer and A.S. Unnikrishnan, 2013: Sea Level Change. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. http://www.climatechange2013.org/images/report/WG1AR5_Chapter13_FINAL.pdf

Clark, Martyn P., Robert L. Wilby, Ethan D. Gutmann, Julie A. Vano, Subhrendu Gangopadhyay, Andrew W. Wood, Hayley J. Fowler, Christel Prudhomme, Jeffrey R. Arnold, and Levi D. Brekke. "Characterizing uncertainty of the hydrologic impacts of climate change." Current Climate Change Reports 2, no. 2 (2016): 55-64.

Déandreis, Céline, et al. "Towards a dedicated impact portal to bridge the gap between the impact and climate communities: Lessons from use cases." Climatic change 125.3-4 (2014): 333-347. http://link.springer.com/article/10.1007/s10584-014-1139-7/fulltext.html

DeConto, Robert M., and David Pollard. "Contribution of Antarctica to past and future sea-level rise." Nature 531.7596 (2016): 591-597.

Department of Commerce*, Global sea level rise scenarios for the United States National Climate Assessment*. US Department of Commerce, National Oceanic and Atmospheric Administration, Oceanic and Atmospheric Research, Climate Program Office, 2012.

Ehret, U., et al. "HESS Opinions" Should we apply bias correction to global and regional climate model data?"." Hydrology and Earth System Sciences 16.9 (2012): 3391-3404. http://www.hydrol-earth-syst-sci.net/16/3391/2012/hess-16-3391-2012.pdf

Flato, G., J. Marotzke, B. Abiodun, P. Braconnot, S.C. Chou, W. Collins, P. Cox, F. Driouech, S. Emori, V. Eyring, C. Forest, P. Gleckler, E. Guilyardi, C. Jakob, V. Kattsov, C. Reason and M. Rummukainen, 2013: Evaluation of Climate Models. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. https://www.ipcc.ch/pdf/assessment-report/ar5/.../WG1AR5_Chapter09_FINAL.pdf

Florian, Aleš. "An efficient sampling scheme: updated Latin Hypercube Sampling." Probabilistic engineering mechanics 7.2 (1992): 123-130.

Ghosh, Subimal, and P. P. Mujumdar. "Climate change impact assessment: Uncertainty modeling with imprecise probability." Journal of Geophysical Research: Atmospheres 114.D18 (2009).

Gottschalk, Lars, and Rolf Weingartner. "Distribution of peak flow derived from a distribution of rainfall volume and runoff coefficient, and a unit hydrograph." Journal of hydrology 208.3 (1998): 148-162. https://www.researchgate.net/profile/Lars_Gottschalk/publication/223020819_Distribution_of_Peak_Flow_Derived_From_a_Distribution_of_Rainfall_Volume_and_Runoff_Coefficient_and_a_Unit_Hydrograph/links/0a85e531f0642da0c8000000.pdf

Guo, Donglin, and Huijun Wang. "CMIP5 permafrost degradation projection: A comparison among different regions." Journal of Geophysical Research: Atmospheres 121.9 (2016): 4499-4517.

Hadley Centre for Climate Prediction and Research (Exeter). *ENSEMBLES: climate change and its impacts at seasonal, decadal and centennial timescales: summary of research and results from the ENSEMBLES project*. Ed. Paul Van der Linden. Hadley Centre for Climate Prediction and Research, 2009. http://ensembles-eu.metoffice.com/docs/Ensembles_final_report_Nov09.pdf

Haerter, J. O., et al. "Climate model bias correction and the role of timescales." *Hydrology and Earth System Sciences* 15.3 (2011): 1065-1079. http://www.hydrol-earth-syst-sci.net/15/1065/2011/hess-15-1065-2011.pdf

Hallegatte, Stephane, et al. "Future flood losses in major coastal cities." Nature climate change 3.9 (2013): 802-806.

Hansen, James, et al. "Ice melt, sea level rise and superstorms: evidence from paleoclimate data, climate modeling, and modern observations that 2◦ C global warming is highly dangerous." Atmospheric Chemistry and Physics Discussions 15.14 (2015): 20059-20179. http://www.atmos-chem-phys.net/16/3761/2016/

Helton, Jon C., and Freddie Joe Davis. "Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems." Reliability Engineering & System Safety 81.1 (2003): 23-69.

Hawkins, E, Osborne, TM, Ho, CK and Challinor, AJ (2013) Calibration and bias correction of climate projections for crop modelling: An idealised case study over Europe. Agricultural and Forest Meteorology, 170. 19 - 31. http://eprints.whiterose.ac.uk/77973/10/challinor14.pdf

Howard, William, et al. Report of the Defense Science Board Task Force on Trends and Implications of Climate Change on National and International Security. Defense Science Board, Washington DC, 2011. https://www.hsdl.org/?view&did=692151

Hsiang, Solomon M., and Marshall Burke. "Climate, conflict, and social stability: what does the evidence say?" Climatic Change 123.1 (2014): 39-55. http://link.springer.com/article/10.1007/s10584-013-0868-3

Hsiang, Solomon M., Marshall Burke, and Edward Miguel. "Quantifying the influence of climate on human conflict." Science 341.6151 (2013): 1235367.

IPCC, 2014: Summary for policymakers. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1-32. http://www.ipcc.ch/pdf/assessment-report/ar5/wg2/ar5_wgII_spm_en.pdf

Jevrejeva, Svetlana, Aslak Grinsted, and J. C. Moore. "Upper limit for sea level projections by 2100." Environmental Research Letters 9, no. 10 (2014): 104008.

Jevrejeva, Svetlana, Luke P. Jackson, Riccardo E. M. Riva, Aslak Grinsted, and John C. Moore, Coastal sea level rise with warming above 2 °C PNAS 2016;

King, David, et al. "Climate change–a risk assessment." Centre for Science Policy, University of Cambridge. (2015).

http://www.csap.cam.ac.uk/media/uploads/files/1/climate-change--a-risk-assessment-v11.pdf

Kirtman, B., S.B. Power, J.A. Adedoyin, G.J. Boer, R. Bojariu, I. Camilloni, F.J. Doblas-Reyes, A.M. Fiore, M. Kimoto, G.A. Meehl, M. Prather, A. Sarr, C. Schär, R. Sutton, G.J. van Oldenborgh, G. Vecchi and H.J. Wang, 2013: Near-term Climate Change: Projections and Predictability. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Sve, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. https://www.ipcc.ch/pdf/assessment-report/ar5/wg1/WG1AR5_Chapter11_FINAL.pdf
Koven, Charles D., William J. Riley, and Alex Stern. "Analysis of permafrost thermal dynamics and response to climate change in the CMIP5 Earth System Models." Journal of Climate 26.6 (2013): 1877-1900.

Lipscomb, William H., et al. "Ridging, strength, and stability in high-resolution sea ice models." Journal of Geophysical Research: Oceans 112.C3 (2007).

Mårtensson, Sebastian, et al. "Ridged sea ice characteristics in the Arctic from a coupled multicategory sea ice model." Journal of Geophysical Research: Oceans 117.C8 (2012).

Mastrandrea, Michael D., et al. "The IPCC AR5 guidance note on consistent treatment of uncertainties: a common approach across the working groups." Climatic Change 108.4 (2011): 675-691. http://link.springer.com/article/10.1007/s10584-011-0178-6

McKay, Michael D., Richard J. Beckman, and William J. Conover. "A comparison of three methods for selecting values of input variables in the analysis of output from a computer code." Technometrics 42.1 (2000): 55-61.

National Intelligence Council, Implications for US National Security of Anticipated Climate Change, September 21, 2016. Report: NIC WP 2016-01, Washington, DC. http://www.eenews.net/assets/2016/09/21/document_pm_02.pdf

Neumann, J. E., Emanuel, K., Ravela, S., Ludwig, L., Kirshen, P., Bosma, K., & Martinich, J. (2015). Joint effects of storm surge and sea-level rise on US Coasts: new economic estimates of impacts, adaptation, and benefits of mitigation policy. Climatic Change, 129(1-2), 337-349.

Nicholls, Robert J., and Anny Cazenave. "Sea-level rise and its impact on coastal zones." science 328.5985 (2010): 1517-1520. http://science.sciencemag.org/content/328/5985/1517

Niu, Guo-Yue, et al. "A simple TOPMODEL-based runoff parameterization (SIMTOP) for use in global climate models." Journal of Geophysical Research: Atmospheres 110.D21 (2005).

NOAA, Global sea level rise scenarios for the United States National Climate Assessment. US Department of Commerce, National Oceanic and Atmospheric Administration, Oceanic and Atmospheric Research, Climate Program Office, 2012.

Paul Van der Linden (Ed.). ENSEMBLES: climate change and its impacts at seasonal, decadal and centennial timescales: summary of research and results from the ENSEMBLES project. Hadley Centre for Climate Prediction and Research, (Exeter). 2009. http://ensembles-eu.metoffice.com/docs/Ensembles_final_report_Nov09.pdf

Reerink, T. J., M. Kliphuis, and R. S. W. Van de Wal. "Mapping technique of climate fields between GCM's and ice models." Geoscientific model development 3.1 (2009): 13-41.

Sanderson, Benjamin M., Reto Knutti, and Peter Caldwell. "Addressing interdependency in a multimodel ensemble by interpolation of model properties." Journal of Climate 28.13 (2015): 5150-5170.

Shoutilin, Sergey V., et al. "Dynamic-thermodynamic sea ice model: ridging and its application to climate study and navigation." Journal of climate 18.18 (2005): 3840-3855.

Shu, Qi, Zhenya Song, and Fangli Qiao. "Assessment of sea ice simulations in the CMIP5 models." *The Cryosphere* 9.1 (2015): 399-409.

Slangen, A. B. A., et al. "Projecting twenty-first century regional sea-level changes." Climatic Change 124.1-2 (2014): 317-332.
http://pordlabs.ucsd.edu/ltalley/sio219/winter_2015/slangen_etal_climchange2014.pdf

Slater, Andrew G., and David M. Lawrence. "Diagnosing present and future permafrost from climate models." Journal of Climate 26.15 (2013): 5608-5623.

Strauss, B. H., S. Kulp, and A. Levermann. "Mapping choices: carbon, climate, and rising seas, our global legacy." Princeton, NJ: Climate Central (2015).
http://sealevel.climatecentral.org/uploads/research/Global-Mapping-Choices-Report.pdf

Stocker, T.F., D. Qin, G.-K. Plattner, L.V. Alexander, S.K. Allen, N.L. Bindoff, F.-M. Bréon, J.A. Church, U. Cubasch, S. Emori, P. Forster, P. Friedlingstein, N. Gillett, J.M. Gregory, D.L. Hartmann, E. Jansen, B. Kirtman, R. Knutti, K. Krishna Kumar, P. Lemke, J. Marotzke, V. Masson-Delmotte, G.A. Meehl, I.I. Mokhov, S. Piao, V. Ramaswamy, D.Randall, M. Rhein, M. Rojas, C. Sabine, D. Shindell, L.D. Talley, D.G. Vaughan and S.-P. Xie, 2013: Technical Summary. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
http://www.climatechange2013.org/images/report/WG1AR5_TS_FINAL.pdf

Stroeve, J. C., and A. P. Barrett. "Assessment of Arctic Sea Ice in the CMIP5 Climate Models." *AGU Fall Meeting*. Vol. 1. 2011. http://www.cesm.ucar.edu/working_groups/Polar/presentations/2012/stroeve.pdf

Taylor, Karl E., Ronald J. Stouffer, and Gerald A. Meehl. "An overview of CMIP5 and the experiment design." *Bulletin of the American Meteorological Society* 93.4 (2012): 485-498. https://e-reports-ext.llnl.gov/pdf/482749.pdf

Tebaldi, C., & Sansó, B. (2009). Joint projections of temperature and precipitation change from multiple climate models: a hierarchical Bayesian approach. Journal of the Royal Statistical Society: Series A (Statistics in Society), 172(1), 83-106.

Tebaldi, Claudia, Benjamin H. Strauss, and Chris E. Zervas. "Modelling sea level rise impacts on storm surges along US coasts." Environmental Research Letters 7.1 (2012): 014032.

Teutschbein, Claudia, and Jan Seibert. "Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods." Journal of Hydrology 456 (2012): 12-29. https://www.researchgate.net/profile/Jan_Seibert/publication/256756594_Bias_correction_of_regional_climate_model_simulations_for_hydrological_climate-change_impact_studies_Review_and_evaluation_of_different_methods/links/02e7e523f6473149d1000000.pdf

Van Vuuren, Detlef P., et al. "The representative concentration pathways: an overview." *Climatic change* 109 (2011): 5-31. http://link.springer.com/article/10.1007/s10584-011-0148-z%20/fulltext.html

Wang, Chunzai, et al. "A global perspective on CMIP5 climate model biases." *Nature Climate Change* 4.3 (2014): 201-205.

Weiss, Jeremy L., Jonathan T. Overpeck, and Ben Strauss. "Implications of recent sea level rise science for low-elevation areas in coastal cities of the conterminous USA." *Climatic Change* 105.3-4 (2011): 635-645.

Werner, Adrian D., and Craig T. Simmons. "Impact of sea-level rise on sea water intrusion in coastal aquifers." Ground Water 47.2 (2009): 197-204. https://www.researchgate.net/profile/Craig_Simmons2/publication/23976090_Impact_of_Sea-Level_Rise_on_Sea_Water_Intrusion_in_Coastal_Aquifers/links/55a02b8508ae032ef0545700.pdf

Wibig, Joanna, et al. "Projected Change—Models and Methodology." *Second Assessment of Climate Change for the Baltic Sea Basin*. Springer International Publishing, 2015. 189-

215. http://link.springer.com/chapter/10.1007/978-3-319-16006-1_10
http://climate4impact.eu/impactportal/help/howto.jsp

Yin, Jianjun, Michael E. Schlesinger, and Ronald J. Stouffer. "Model projections of rapid sea-level rise on the northeast coast of the United States." *Nature Geoscience* 2.4 (2009): 262-266.

Zubler, Elias M., et al. "Climate change signals of CMIP5 general circulation models over the Alps–impact of model selection." *International Journal of Climatology* (2015).

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