Summary sentence or paragraph that integrates the above information

Fundamental scientific understanding of the climate system provides a framework for considering potential pathways for achieving a target of preventing 3.6°F (2°C) of warming. There are uncertainties about cumulative CO_2 emissions compatible with this target, in large part because of uncertainties about the role of non-CO_2 species, but it appears, based on past emissions and future projections, that the cumulative carbon threshold for this target could be reached or exceeded in about two decades.

Key Finding 4

Successful implementation of the first round of Nationally Determined Contributions associated with the Paris Agreement will provide some likelihood of meeting the long-term temperature goal of limiting global warming to "well below" 3.6°F (2°C) above preindustrial levels; the likelihood depends strongly on the magnitude of global emission reductions after 2030. (*High confidence*)

Description of evidence base

The primary source supporting this key finding is Fawcett et al. (2015); it is also supported by Rogelj et al. (2016), Sanderson et al. (2016), and the Climate Action Tracker. Each of these analyses evaluated the global climate implications of the aggregation of the individual country contributions thus far put forward under the Paris Agreement.

Major uncertainties

The largest uncertainty lies in the assumption of "successful implementation" of the first round of NDCs; these are assumed to be fully successful but could either over- or underachieve. This in turn creates uncertainty about the extent of emission reductions that would be needed after the first round of NDCs in order to achieve the 2°C or any other target. The response of the climate system, the climate sensitivity, is also a source of uncertainty; the Fawcett et al. analysis used the IPCC AR5 range, 1.5° to 4.5°C.

Assessment of confidence based on evidence and agreement, including short description of nature of evidence and level of agreement

There is *high* confidence in this key finding because a number of analyses have examined the implications of the first round of NDCs under the Paris Agreement and have come to similar conclusions, as captured in this key finding.

Summary sentence or paragraph that integrates the above information

FINAL DRAFT

Different analyses have estimated the implications for global mean temperature of the first round of NDCs associated with the Paris Agreement and have reached similar conclusions. Assuming successful implementation of this first round of NDCs, along with a range of climate sensitivities, these contributions provide some likelihood of meeting the long-term goal of limiting global warming to well below 2°C about pre-industrial levels, but much depends on assumptions about what happens after 2030.

Key Finding 5

Climate intervention or geoengineering strategies such as solar radiation management are measures that attempt to limit or reduce global temperature increases. If interest in geoengineering increases with observed impacts and/or projected risks of climate change, interest will also increase in assessments of the technical feasibilities, costs, risks, co-benefits, and governance challenges of these additional measures, which are as yet unproven at scale. These assessments are a necessary step before judgments about the benefits and risks of these approaches can be made with high confidence. (*High confidence*)

Description of evidence base

Key Finding 5 contains qualitative statements based on the growing literature addressing this topic, including from such bodies as the National Academy of Sciences and the Royal Society, coupled with judgment by the authors about the future interest level in this topic.

Major uncertainties

The major uncertainty is how public perception and interest among policymakers in climate intervention may change over time, even independently from the perceived level of progress made towards reducing CO_2 and other GHG emissions over time.

Assessment of confidence based on evidence and agreement, including short description of nature of evidence and level of agreement

There is *high* confidence that climate intervention strategies may gain greater attention, especially if efforts to slow the buildup of atmospheric CO_2 and other GHGs are considered inadequate by many in the scientific and policy communities.

Summary sentence or paragraph that integrates the above information

The key finding is a qualitative statement based on the growing literature on this topic. The uncertainty moving forward is the comfort level and desire among numerous stakeholders to research and potentially carry out these climate intervention strategies, particularly in light of how progress by the global community to reduce GHG emissions is perceived.

FINAL DRAFT

FIGURES

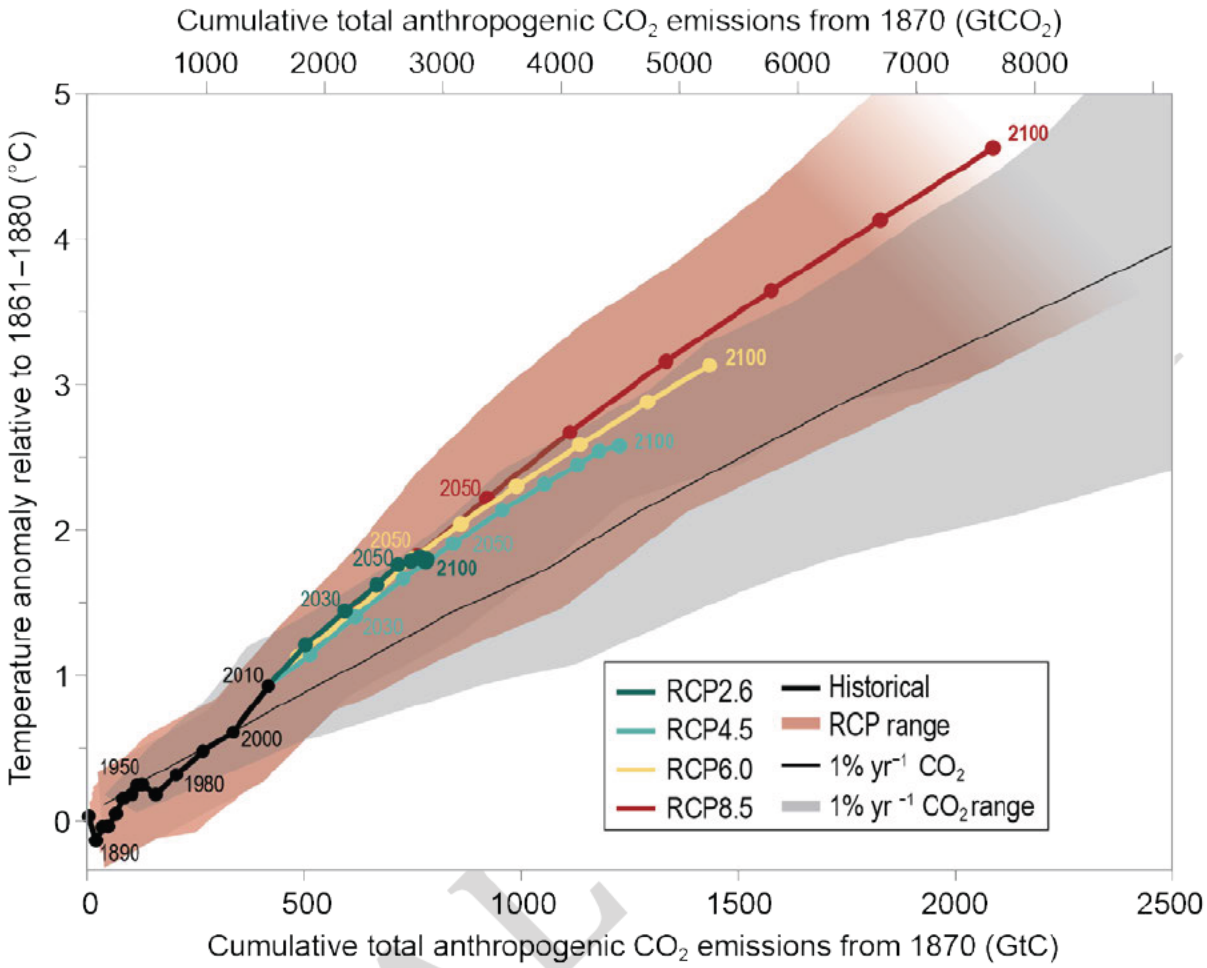

Figure 14.1: Global mean temperature change for a number of scenarios as a function of cumulative CO_2 emissions from preindustrial conditions, with time progressing along each individual line for each scenario. (Figure source: IPCC 2013; ©IPCC. Used with permission).

FINAL

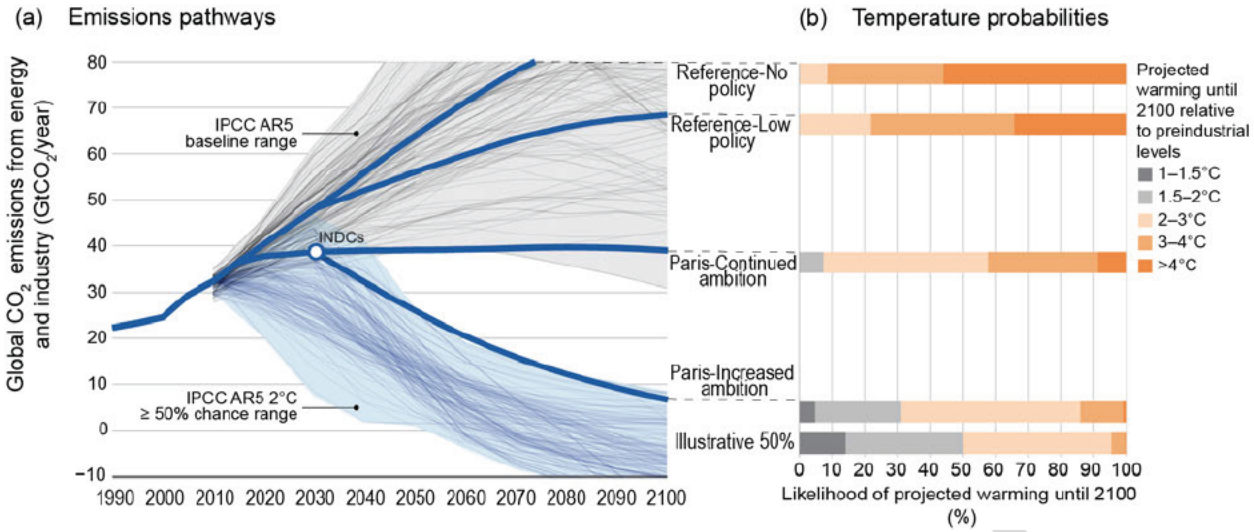

Figure 14.2: Global CO_2 emissions and probabilistic temperature outcomes of Paris. (a) Global CO_2 emissions from energy and industry (includes CO_2 emissions from all fossil fuel production and use and industrial processes such as cement manufacture that also produce CO_2 as a byproduct) for emissions scenarios following no policy, current policy, meeting the NDCs with no increased future ambition and meeting the NDCs with continually increasing ambition. (b) Likelihoods of different levels of increase in global mean surface temperature during the 21st century relative to preindustrial levels for the four scenarios. Although (a) shows only CO_2 emissions from energy and industry, temperature outcomes are based on the full suite of GHG, aerosol, and short-lived species emissions across the full set of human activities and physical Earth systems. (Figure source: Fawcett et al. 2015).

FINAL DRAFT

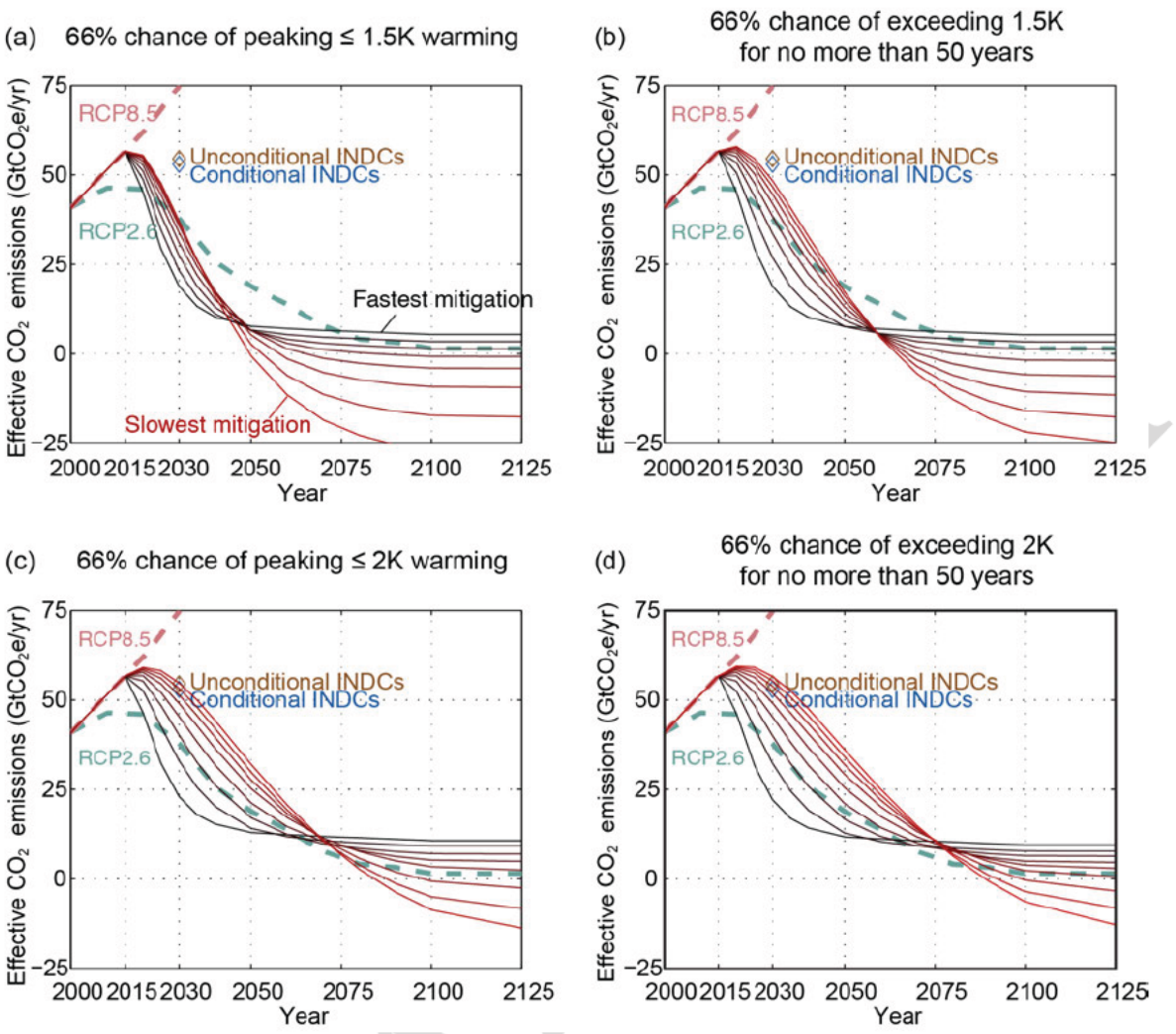

Figure 14.3: Global emission pathways for GHGs, expressed as CO_2-equivalent emissions, which would be consistent with different temperature targets (relative to preindustrial temperatures). (a) shows a set of pathways where global mean temperatures would likely (66%) not exceed 2.7°F (1.5°C). A number of pathways are consistent with the target, ranging from the red curve (slowest near-term mitigation with large negative emission requirements in the future) to the black curve with rapid near-term mitigation and less future negative emissions. (b) shows similar pathways with a 66% chance of exceeding 2.7°F (1.5°C) for only 50 years, where (c) and (d) show similar emission pathways for 3.6°F (2°C). (Figure source: Sanderson et al. 2016).

FINAL

	Dates by when cumulative carbon emissions (GtC) since 1870 reach amount commensurate with 3.6F (2C), when accounting for non-CO2 forcings:		
	>66% = 790 GtC	>50% = 820 GtC	>33% = 900 GtC
RCP4.5	2037	2040	2047
RCP8.5	2033	2035	2040

	Dates by when cumulative carbon emissions (GtC) since 1870 reach amount commensurate with 2.7F (1.5C), when accounting for non-CO2 forcings:		
	>66% = 593 GtC	>50% = 615 GtC	>33% = 675 GtC
RCP4.5	2019	2021	2027
RCP8.5	2019	2021	2025

Table 14.1: Dates illustrating when cumulative CO_2 emission thresholds associated with eventual warming of 3.6°F or 2.7°F above preindustrial levels might be reached. RCP4.5 and RCP8.5 refer, respectively, to the low and high emission scenarios used throughout this report. The estimated cumulative CO_2 emissions (measured in Gigatons (Gt) of carbon) associated with different probabilities (e.g., >66%) of preventing 3.6°F (2°C) of warming are from the IPCC (Collins et al. 2013). The cumulative emissions compatible with 2.7°F (1.5°C) are linearly derived from the estimates associated with 3.6°F (2°C). The cumulative CO_2 estimates take into account the additional net warming effects associated with past and future non-CO_2 emissions according to the RCP scenarios. Historic CO_2 emissions from 1870–2015 (including fossil fuel combustion, land use change, and cement manufacturing) are from Le Quéré et al. 2016. See Traceable Accounts for further details.

FINAL DRAFT

REFERENCES

Allen, M.R., D.J. Frame, C. Huntingford, C.D. Jones, J.A. Lowe, M. Meinshausen, and N. Meinshausen, 2009: Warming caused by cumulative carbon emissions towards the trillionth tonne. *Nature,* **458,** 1163-1166. http://dx.doi.org/10.1038/nature08019

Anenberg, S.C., J. Schwartz, D. Shindell, M. Amann, G. Faluvegi, Z. Klimont, G. Janssens-Maenhout, L. Pozzoli, R. Van Dingenen, E. Vignati, L. Emberson, N.Z. Muller, J.J. West, M. Williams, V. Demkine, W.K. Hicks, J. Kuylenstierna, F. Raes, and V. Ramanathan, 2012: Global air quality and health co-benefits of mitigating near-term climate change through methane and black carbon emission controls. *Environmental Health Perspectives,* **120,** 831-839. http://dx.doi.org/10.1289/ehp.1104301

Bond, T.C., S.J. Doherty, D.W. Fahey, P.M. Forster, T. Berntsen, B.J. DeAngelo, M.G. Flanner, S. Ghan, B. Kärcher, D. Koch, S. Kinne, Y. Kondo, P.K. Quinn, M.C. Sarofim, M.G. Schultz, M. Schulz, C. Venkataraman, H. Zhang, S. Zhang, N. Bellouin, S.K. Guttikunda, P.K. Hopke, M.Z. Jacobson, J.W. Kaiser, Z. Klimont, U. Lohmann, J.P. Schwarz, D. Shindell, T. Storelvmo, S.G. Warren, and C.S. Zender, 2013: Bounding the role of black carbon in the climate system: A scientific assessment. *Journal of Geophysical Research: Atmospheres,* **118,** 5380-5552. http://dx.doi.org/10.1002/jgrd.50171

Ciais, P., C. Sabine, G. Bala, L. Bopp, V. Brovkin, J. Canadell, A. Chhabra, R. DeFries, J. Galloway, M. Heimann, C. Jones, C. Le Quéré, R.B. Myneni, S. Piao, and P. Thornton, 2013: Carbon and other biogeochemical cycles. *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, 465–570. http://www.climatechange2013.org/report/full-report/

Climate Action Tracker, 2016: Climate Action Tracker. http://climateactiontracker.org/global.html

Collins, M., R. Knutti, J. Arblaster, J.-L. Dufresne, T. Fichefet, P. Friedlingstein, X. Gao, W.J. Gutowski, T. Johns, G. Krinner, M. Shongwe, C. Tebaldi, A.J. Weaver, and M. Wehner, 2013: Long-term climate change: Projections, commitments and irreversibility. *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, 1029–1136. http://www.climatechange2013.org/report/full-report/

FINAL DRAFT

Fawcett, A.A., G.C. Iyer, L.E. Clarke, J.A. Edmonds, N.E. Hultman, H.C. McJeon, J. Rogelj, R. Schuler, J. Alsalam, G.R. Asrar, J. Creason, M. Jeong, J. McFarland, A. Mundra, and W. Shi, 2015: Can Paris pledges avert severe climate change? *Science,* **350,** 1168-1169. http://dx.doi.org/10.1126/science.aad5761

Hayhoe, K.A.S., H.S. Kheshgi, A.K. Jain, and D.J. Wuebbles, 1998: Tradeoffs in fossil fuel use: The effects of CO2, CH4, and SO2 aerosol emissions on climate. *World Resources Review,* **10**.

IPCC, 2013: Summary for policymakers. *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, UK and New York, NY, 1-30. http://www.climatechange2013.org/report/

Joos, F., R. Roth, J.S. Fuglestvedt, G.P. Peters, I.G. Enting, W. von Bloh, V. Brovkin, E.J. Burke, M. Eby, N.R. Edwards, T. Friedrich, T.L. Frölicher, P.R. Halloran, P.B. Holden, C. Jones, T. Kleinen, F.T. Mackenzie, K. Matsumoto, M. Meinshausen, G.K. Plattner, A. Reisinger, J. Segschneider, G. Shaffer, M. Steinacher, K. Strassmann, K. Tanaka, A. Timmermann, and A.J. Weaver, 2013: Carbon dioxide and climate impulse response functions for the computation of greenhouse gas metrics: A multi-model analysis. *Atmospheric Chemistry and Physics,* **13,** 2793-2825. http://dx.doi.org/10.5194/acp-13-2793-2013

Keith, D.W. and D.G. MacMartin, 2015: A temporary, moderate and responsive scenario for solar geoengineering. *Nature Climate Change,* **5,** 201-206. http://dx.doi.org/10.1038/nclimate2493

Keith, D.W., R. Duren, and D.G. MacMartin, 2014: Field experiments on solar geoengineering: Report of a workshop exploring a representative research portfolio. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences,* **372**. http://dx.doi.org/10.1098/rsta.2014.0175

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. *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, UK and New York, NY, USA, 953–1028. http://www.climatechange2013.org/report/full-report/

FINAL DRAFT

Kravitz, B., K. Caldeira, O. Boucher, A. Robock, P.J. Rasch, K. Alterskjær, D.B. Karam, J.N.S. Cole, C.L. Curry, J.M. Haywood, P.J. Irvine, D. Ji, A. Jones, J.E. Kristjánsson, D.J. Lunt, J.C. Moore, U. Niemeier, H. Schmidt, M. Schulz, B. Singh, S. Tilmes, S. Watanabe, S. Yang, and J.-H. Yoon, 2013: Climate model response from the Geoengineering Model Intercomparison Project (GeoMIP). *Journal of Geophysical Research: Atmospheres,* **118,** 8320-8332. http://dx.doi.org/10.1002/jgrd.50646

Le Quéré, C., R.M. Andrew, J.G. Canadell, S. Sitch, J.I. Korsbakken, G.P. Peters, A.C. Manning, T.A. Boden, P.P. Tans, R.A. Houghton, R.F. Keeling, S. Alin, O.D. Andrews, P. Anthoni, L. Barbero, L. Bopp, F. Chevallier, L.P. Chini, P. Ciais, K. Currie, C. Delire, S.C. Doney, P. Friedlingstein, T. Gkritzalis, I. Harris, J. Hauck, V. Haverd, M. Hoppema, K. Klein Goldewijk, A.K. Jain, E. Kato, A. Körtzinger, P. Landschützer, N. Lefèvre, A. Lenton, S. Lienert, D. Lombardozzi, J.R. Melton, N. Metzl, F. Millero, P.M.S. Monteiro, D.R. Munro, J.E.M.S. Nabel, S.I. Nakaoka, K. O'Brien, A. Olsen, A.M. Omar, T. Ono, D. Pierrot, B. Poulter, C. Rödenbeck, J. Salisbury, U. Schuster, J. Schwinger, R. Séférian, I. Skjelvan, B.D. Stocker, A.J. Sutton, T. Takahashi, H. Tian, B. Tilbrook, I.T. van der Laan-Luijkx, G.R. van der Werf, N. Viovy, A.P. Walker, A.J. Wiltshire, and S. Zaehle, 2016: Global carbon budget 2016. *Earth System Science Data,* **8,** 605-649. http://dx.doi.org/10.5194/essd-8-605-2016

MacCracken, M.C., 2016: The rationale for accelerating regionally focused climate intervention research. *Earth's Future,* **4,** 649-657. http://dx.doi.org/10.1002/2016EF000450

MacMartin, D.G., D.W. Keith, B. Kravitz, and K. Caldeira, 2013: Management of trade-offs in geoengineering through optimal choice of non-uniform radiative forcing. *Nature Climate Change,* **3,** 365-368. http://dx.doi.org/10.1038/nclimate1722

Myhre, G., D. Shindell, F.-M. Bréon, W. Collins, J. Fuglestvedt, J. Huang, D. Koch, J.-F. Lamarque, D. Lee, B. Mendoza, T. Nakajima, A. Robock, G. Stephens, T. Takemura, and H. Zhang, 2013: Anthropogenic and natural radiative forcing. *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, 659–740. http://www.climatechange2013.org/report/full-report/

NAS, 2015: *Climate Intervention: Carbon Dioxide Removal and Reliable Sequestration*. The National Academies Press, Washington, DC, 154 pp. http://dx.doi.org/10.17226/18805

NAS, 2015: *Climate Intervention: Reflecting Sunlight to Cool Earth*. The National Academies Press, Washington, DC, 260 pp. http://dx.doi.org/10.17226/18988

FINAL DRAFT

NRC, 2011: *Climate Stabilization Targets: Emissions, Concentrations, and Impacts over Decades to Millennia*. National Research Council. The National Academies Press, Washington, D.C., 298 pp. http://dx.doi.org/10.17226/12877

Paltsev, S., E. Monier, J. Scott, A. Sokolov, and J. Reilly, 2015: Integrated economic and climate projections for impact assessment. *Climatic Change,* **131,** 21-33. http://dx.doi.org/10.1007/s10584-013-0892-3

Pierce, J.R., D.K. Weisenstein, P. Heckendorn, T. Peter, and D.W. Keith, 2010: Efficient formation of stratospheric aerosol for climate engineering by emission of condensible vapor from aircraft. *Geophysical Research Letters,* **37,** L18805. http://dx.doi.org/10.1029/2010GL043975

Prather, M.J., J.E. Penner, J.S. Fuglestvedt, A. Kurosawa, J.A. Lowe, N. Höhne, A.K. Jain, N. Andronova, L. Pinguelli, C. Pires de Campos, S.C.B. Raper, R.B. Skeie, P.A. Stott, J. van Aardenne, and F. Wagner, 2009: Tracking uncertainties in the causal chain from human activities to climate. *Geophysical Research Letters,* **36,** L05707. http://dx.doi.org/10.1029/2008GL036474

Rao, S., Z. Klimont, J. Leitao, K. Riahi, R. van Dingenen, L.A. Reis, K. Calvin, F. Dentener, L. Drouet, S. Fujimori, M. Harmsen, G. Luderer, C. Heyes, J. Strefler, M. Tavoni, and D.P. van Vuuren, 2016: A multi-model assessment of the co-benefits of climate mitigation for global air quality. *Environmental Research Letters,* **11,** 124013. http://dx.doi.org/10.1088/1748-9326/11/12/124013

Ricke, K.L., M.G. Morgan, and M.R. Allen, 2010: Regional climate response to solar-radiation management. *Nature Geoscience,* **3,** 537-541. http://dx.doi.org/10.1038/ngeo915

Rogelj, J., M. Meinshausen, M. Schaeffer, R. Knutti, and K. Riahi, 2015: Impact of short-lived non-CO_2 mitigation on carbon budgets for stabilizing global warming. *Environmental Research Letters,* **10,** 075001. http://dx.doi.org/10.1088/1748-9326/10/7/075001

Rogelj, J., M. den Elzen, N. Höhne, T. Fransen, H. Fekete, H. Winkler, R. Schaeffer, F. Sha, K. Riahi, and M. Meinshausen, 2016: Paris Agreement climate proposals need a boost to keep warming well below 2 °C. *Nature,* **534,** 631-639. http://dx.doi.org/10.1038/nature18307

Sanderson, B.M., B.C. O'Neill, and C. Tebaldi, 2016: What would it take to achieve the Paris temperature targets? *Geophysical Research Letters,* **43,** 7133-7142. http://dx.doi.org/10.1002/2016GL069563

FINAL DRAFT

Shah, N., M. Wei, E.L. Virginie, and A.A. Phadke, 2015: Benefits of Leapfrogging to Superefficiency and Low Global Warming Potential Refrigerants in Room Air Conditioning. LBNL-1003671. Lawrence Berkeley National Laboratory, Energy Technology Area, Berkeley, CA. 39 pp. https://eetd.lbl.gov/publications/benefits-of-leapfrogging-to-superef-0

Shepherd, J.G., K. Caldeira, P. Cox, J. Haigh, D. Keith, B. Launder, G. Mace, G. MacKerron, J. Pyle, S. Rayner, C. Redgwell, and A. Watson, 2009: *Geoengineering the Climate: Science, Governance and Uncertainty*. Royal Society, 82 pp. http://eprints.soton.ac.uk/156647/1/Geoengineering_the_climate.pdf

Shindell, D., J.C.I. Kuylenstierna, E. Vignati, R. van Dingenen, M. Amann, Z. Klimont, S.C. Anenberg, N. Muller, G. Janssens-Maenhout, F. Raes, J. Schwartz, G. Faluvegi, L. Pozzoli, K. Kupiainen, L. Hoglund-Isaksson, L. Emberson, D. Streets, V. Ramanathan, K. Hicks, N.T.K. Oanh, G. Milly, M. Williams, V. Demkine, and D. Fowler, 2012: Simultaneously mitigating near-term climate change and improving human health and food security. *Science,* **335,** 183-189. http://dx.doi.org/10.1126/science.1210026

Solomon, S., G.K. Plattner, R. Knutti, and P. Friedlingstein, 2009: Irreversible climate change due to carbon dioxide emissions. *Proceedings of the National Academy of Sciences of the United States of America,* **106,** 1704-1709. http://dx.doi.org/10.1073/pnas.0812721106

Tebaldi, C. and P. Friedlingstein, 2013: Delayed detection of climate mitigation benefits due to climate inertia and variability. *Proceedings of the National Academy of Sciences,* **110,** 17229-17234. http://dx.doi.org/10.1073/pnas.1300005110

Tebaldi, C. and M.F. Wehner, 2016: Benefits of mitigation for future heat extremes under RCP4.5 compared to RCP8.5. *Climatic Change,* **First online,** 1-13. http://dx.doi.org/10.1007/s10584-016-1605-5

Tilmes, S., B.M. Sanderson, and B.C. O'Neill, 2016: Climate impacts of geoengineering in a delayed mitigation scenario. *Geophysical Research Letters,* **43,** 8222-8229. http://dx.doi.org/10.1002/2016GL070122

UNFCCC, 2015: Paris Agreement. United Nations Framework Convention on Climate Change, [Bonn, Germany]. 25 pp. http://unfccc.int/files/essential_background/convention/application/pdf/english_paris_agreement.pdf

Zaelke, D. and N. Borgford-Parnell, 2015: The importance of phasing down hydrofluorocarbons and other short-lived climate pollutants. *Journal of Environmental Studies and Sciences,* **5,** 169-175. http://dx.doi.org/10.1007/s13412-014-0215-7

FINAL DRAFT

15. Potential Surprises: Compound Extremes and Tipping Elements

KEY FINDINGS

1. Positive feedbacks (self-reinforcing cycles) within the climate system have the potential to accelerate human-induced climate change and even shift the Earth's climate system, in part or in whole, into new states that are very different from those experienced in the recent past (for example, ones with greatly diminished ice sheets or different large-scale patterns of atmosphere or ocean circulation). Some feedbacks and potential state shifts can be modeled and quantified; others can be modeled or identified but not quantified; and some are probably still unknown. (*Very high confidence* in the potential for state shifts and in the incompleteness of knowledge about feedbacks and potential state shifts).

2. The physical and socioeconomic impacts of compound extreme events (such as simultaneous heat and drought, wildfires associated with hot and dry conditions, or flooding associated with high precipitation on top of snow or waterlogged ground) can be greater than the sum of the parts (*very high confidence*). Few analyses consider the spatial or temporal correlation between extreme events.

3. While climate models incorporate important climate processes that can be well quantified, they do not include all of the processes that can contribute to feedbacks, compound extreme events, and abrupt and/or irreversible changes. For this reason, future changes outside the range projected by climate models cannot be ruled out (*very high confidence*). Moreover, the systematic tendency of climate models to underestimate temperature change during warm paleoclimates suggests that climate models are more likely to underestimate than to overestimate the amount of long-term future change (*medium confidence*).

15.1 Introduction

The Earth system is made up of many components that interact in complex ways across a broad range of temporal and spatial scales. As a result of these interactions the behavior of the system cannot be predicted by looking at individual components in isolation. Negative feedbacks, or self-stabilizing cycles, within and between components of the Earth system can dampen changes (Ch. 2: Physical Drivers of Climate Change). However, their stabilizing effects render such feedbacks of less concern from a risk perspective than positive feedbacks, or self-reinforcing cycles. Positive feedbacks magnify both natural and anthropogenic changes. Some Earth system components, such as arctic sea ice and the polar ice sheets, may exhibit thresholds beyond which these self-reinforcing cycles can drive the component, or the entire system, into a radically different state. Although the probabilities of these state shifts may be difficult to assess, their consequences could be high, potentially exceeding anything anticipated by climate model projections for the coming century.

FINAL DRAFT

Humanity is conducting an unprecedented experiment with the Earth system through the large-scale combustion of fossil fuels and widespread deforestation and the resulting release of carbon dioxide (CO_2) into the atmosphere, as well as through emissions of other greenhouse gases and radiatively active substances from human activities (Ch. 2: Physical Drivers of Climate Change). These forcings are driving changes in temperature and other climate variables. Previous chapters have covered a variety of observed and projected changes in such variables, including averages and extremes of temperature, precipitation, sea level, and storm events (see Chapters 1, 4–13).

While the distribution of climate model projections provides insight into the range of possible future changes, this range is limited by the fact that models do not include or fully represent all of the known processes and components of the Earth system (e.g., ice sheets or arctic carbon reservoirs) (Flato et al. 2013), nor do they include all of the interactions between these components that contribute to the self-stabilizing and self-reinforcing cycles mentioned above (e.g., the dynamics of the interactions between ice sheets, the ocean, and the atmosphere). They also do not include currently unknown processes that may become increasingly relevant under increasingly large climate forcings. This limitation is emphasized by the systematic tendency of climate models to underestimate temperature change during warm paleoclimates (Section 15.5). Therefore, there is significant potential for our planetary experiment to result in unanticipated surprises and a broad consensus that the further and faster the Earth system is pushed towards warming, the greater the risk of such surprises.

Scientists have been surprised by the Earth system many times in the past. The discovery of the ozone hole is a clear example. Prior to groundbreaking work by Molina and Rowland (1974), chlorofluorocarbons (CFCs) were viewed as chemically inert; the chemistry by which they catalyzed stratospheric ozone depletion was unknown. Within eleven years of Molina and Rowland's work, British Antarctic Survey scientists reported ground observations showing that spring ozone concentrations in the Antarctic, driven by chlorine from human-emitted CFCs, had fallen by about one-third since the late 1960s (Farman et al. 1985). The problem quickly moved from being an "unknown unknown" to a "known known," and by 1987, the Montreal Protocol was adopted to phase out these ozone-depleting substances.

Another surprise has come from arctic sea ice. While the potential for powerful positive ice-albedo feedbacks has been understood since the late 19th century, climate models have struggled to capture the magnitude of these feedbacks and to include all the relevant dynamics that affect sea ice extent. As of 2007, the observed decline in arctic sea ice from the start of the satellite era in 1979 outpaced that projected by almost all the models used by the Intergovernmental Panel on Climate Change's Fourth Assessment Report (AR4) (Stroeve et al. 2007), and it was not until AR4 that the IPCC first raised the prospect of an ice-free summer Arctic during this century (Meehl et al. 2007). More recent studies are more consistent with observations and have moved the date of an ice-free summer Arctic up to approximately mid-century (Stroeve et al. 2012; see Ch. 11: Artic Changes). But continued rapid declines—2016 featured the lowest annually

FINAL DRAFT

averaged arctic sea ice extent on record, and the 2017 winter maximum was also the lowest on record—suggest that climate models may still be underestimating or missing relevant feedback processes. These processes could include, for example, effects of melt ponds, changes in storminess and ocean wave impacts, and warming of near surface waters (Schröder et al. 2014; Asplin et al. 2012; Perovich et al. 2008).

This chapter focuses primarily on two types of potential surprises. The first arises from changing correlations in extreme events which may not be surprising on their own but together can increase the likelihood of compound extremes, in which multiple events occur simultaneously or in rapid sequence. Increasingly frequent compound extremes—either of multiple types of events (such as paired extremes of droughts and intense rainfall) or over greater spatial or temporal scales (such as a drought occurring in multiple major agricultural regions around the world or lasting for multiple decades)—are often not captured by analyses that focus solely on one type of extreme.

The second type of surprise arises from self-reinforcing cycles, which can give rise to "tipping elements"—subcomponents of the Earth system that can be stable in multiple different states and can be "tipped" between these states by small changes in forcing, amplified by positive feedbacks. Examples of potential tipping elements include ice sheets, modes of atmosphere–ocean circulation like the El Niño–Southern Oscillation, patterns of ocean circulation like the Atlantic Meridional Overturning Circulation, and large-scale ecosystems like the Amazon rainforest (Lenton et al. 2008; Kopp et al. 2016). While compound extremes and tipping elements constitute at least partially "known unknowns," the paleoclimate record also suggests the possibility of "unknown unknowns." These possibilities arise in part from the tendency of current climate models to underestimate past responses to forcing, for reasons that may or may not be explained by current hypotheses (e.g., hypotheses related to positive feedbacks that are unrepresented or poorly represented in existing models).

15.2 Risk Quantification and Its Limits

Quantifying the risk of low-probability, high-impact events, based on models or observations, usually involves examining the tails of a probability distribution function (PDF). Robust detection, attribution, and projection of such events into the future is challenged by multiple factors, including an observational record that often does not represent the full range of physical possibilities in the climate system, as well as the limitations of the statistical tools, scientific understanding, and models used to describe these processes (Zwiers et al. 2013).

The 2013 Boulder, Colorado floods and the Dust Bowl of the 1930s in the central United States are two examples of extreme events whose magnitude and/or extent are unprecedented in the observational record. Statistical approaches such as Extreme Value Theory can be used to model and estimate the magnitude of rare events that may not have occurred in the observational record, such as the "1,000-year flood event" (i.e., a flood event with a 0.1% chance of occurrence in any

FINAL DRAFT

given year) (e.g., Smith 1987). While useful for many applications, these are not physical models: they are statistical models that are typically based on the assumption that observed patterns of natural variability (that is, the sample from which the models derive their statistics) are both valid and stationary beyond the observational period. Extremely rare events can also be assessed based upon paleoclimate records and physical modeling. In the paleoclimatic record, numerous abrupt changes have occurred since the last deglaciation, many larger than those recorded in the instrumental record. For example, tree ring records of drought in the western United States show abrupt, long-lasting megadroughts that were similar to but more intense and longer-lasting than the 1930s Dust Bowl (Woodhouse and Overpeck 1998).

Since models are based on physics rather than observational data, they are not inherently constrained to any given time period or set of physical conditions. They have been used to study the Earth in the distant past and even the climate of other planets (e.g., Lunt et al. 2012; Navarro et al. 2014). Looking to the future, thousands of years' worth of simulations can be generated and explored to characterize small-probability, high-risk extreme events, as well as correlated extremes (see Section 15.4). However, the likelihood that such model events represent real risks is limited by well-known uncertainties in climate modeling related to parameterizations, model resolution, and limits to scientific understanding (Ch. 4: Projections). For example, conventional convective parameterizations in global climate models systematically underestimate extreme precipitation (Kang et al. 2015). In addition, models often do not accurately capture or even include the processes, such as permafrost feedbacks, by which abrupt, non-reversible change may occur (see Section 15.4). An analysis focusing on physical climate predictions over the last 20 years found a tendency for scientific assessments such as those of the IPCC to under-predict rather than over-predict changes that were subsequently observed (Brysse et al. 2013).

15.3 Compound Extremes

An important aspect of surprise is the potential for compound extreme events. These can be events that occur at the same time or in sequence (such as consecutive floods in the same region) and in the same geographic location or at multiple locations within a given country or around the world (such as the 2009 Australian floods and wildfires). They may consist of multiple extreme events or of events that by themselves may not be extreme but together produce a multi-event occurrence (such as a heat wave accompanied by drought [Quarantelli 1986]). It is possible for the net impact of these events to be less than the sum of the individual events if their effects cancel each other out. For example, increasing CO_2 concentrations and acceleration of the hydrological cycle may mitigate the future impact of extremes in gross primary productivity that currently impact the carbon cycle (Zscheischler et al. 2014). However, from a risk perspective, the primary concern relates to compound extremes with additive or even multiplicative effects.

Some areas are susceptible to multiple types of extreme events that can occur simultaneously. For example, certain regions are susceptible to both flooding from coastal storms and riverine flooding from snow melt, and a compound event would be the occurrence of both

FINAL DRAFT

simultaneously. Compound events can also result from shared forcing factors, including natural cycles like the El Niño–Southern Oscillation (ENSO); large-scale circulation patterns, such as the ridge observed during the current California drought (e.g., Swain et al. 2016; see also Ch. 8: Droughts, Floods, and Wildfires); or relatively greater regional sensitivity to global change, as may occur in "hot spots" such as the western United States (Diffenbaugh and Giorgi 2012). Finally, compound events can result from mutually-reinforcing cycles between individual events, such as the relationship between drought and heat, linked through soil moisture and evaporation, in water-limited areas (IPCC 2012).

In a changing climate, the probability of compound events can be altered if there is an underlying trend in conditions such as mean temperature, precipitation, or sea level that alters the baseline conditions or vulnerability of a region. It can also be altered if there is a change in the frequency or intensity of individual extreme events relative to the changing mean (for example, stronger storm surges, more frequent heat waves, or heavier precipitation events).

The occurrence of warm/dry and warm/wet conditions is discussed extensively in the literature; at the global scale, these conditions have increased since the 1950s (Hao et al. 2013), and analysis of NOAA's billion-dollar disasters illustrates the correlation between temperature and precipitation extremes during the costliest climate and weather events since 1980 (Figure 15.1, right). In the future, hot summers will become more frequent, and although it is not always clear for every region whether drought frequency will change, droughts in already dry regions, such as the southwestern United States, are likely to be more intense in a warmer world due to faster evaporation and associated surface drying (Collins et al. 2013; Trenberth et al. 2014; Cook et al. 2015). For other regions, however, the picture is not as clear. Recent examples of heat/drought events (in the southern Great Plains in 2011 or in California, 2012–2015) have highlighted the inadequacy of traditional univariate risk assessment methods (AghaKouchak et al. 2014). Yet a bivariate analysis for the contiguous United States of precipitation deficits and positive temperature anomalies finds no significant trend in the last 30 years (Serinaldi 2016).

Another compound event frequently discussed in the literature is the increase in wildfire risk resulting from the combined effects of high precipitation variability (wet seasons followed by dry), elevated temperature, and low humidity. If followed by heavy rain, wildfires can in turn increase the risk of landslides and erosion. They can also radically increase emissions of greenhouse gases, as demonstrated by the amount of carbon dioxide produced by the Fort McMurray fires of May 2016—more than 10% of Canada's annual emissions.

A third example of a compound event involves flooding arising from wet conditions due to precipitation or to snowmelt, which could be exacerbated by warm temperatures. These wet conditions lead to high groundwater levels, saturated soils, and/or elevated river flows, which can increase the risk of flooding associated with a given storm days or even months later (IPCC 2012).

FINAL DRAFT

Compound events may surprise in two ways. The first is if known types of compound events recur, but are stronger, longer-lasting, and/or more widespread than those experienced in the observational record or projected by model simulations for the future. One example would be simultaneous drought events in different agricultural regions across the country, or even around the world, that challenge the ability of human systems to provide adequate affordable food. Regions that lack the ability to adapt would be most vulnerable to this risk (e.g., Fraser et al. 2013). Another example would be the concurrent and more severe heavy precipitation events that have occurred in the U.S. Midwest in recent years. After record insurance payouts following the events, in 2014 several insurance companies, led by Farmers Insurance, sued the city of Chicago and surrounding counties for failing to adequately prepare for the impacts of a changing climate. Although the suit was dropped later that same year, their point was made: in some regions of the United States, the insurance industry is not able to cope with the increasing frequency and/or concurrence of certain types of extreme events.

The second way in which compound events could surprise would be the emergence of new types of compound events not observed in the historical record or predicted by model simulations, due to model limitations (in terms of both their spatial resolution as well as their ability to explicitly resolve the physical processes that would result in such compound events), an increase in the frequency of such events from human-induced climate change, or both. An example is Hurricane Sandy, where sea level rise, anomalously high ocean temperatures, and high tides combined to strengthen both the storm and the magnitude of the associated storm surge (Reed et al. 2015). At the same time, a blocking ridge over Greenland—a feature whose strength and frequency may be related to both Greenland surface melt and reduced summer sea ice in the Arctic (Liu et al. 2016; see also Ch. 11: Arctic Changes)—redirected the storm inland to what was, coincidentally, an exceptionally high-exposure location.

[INSERT FIGURE 15.1 HERE]

15.4 Climatic Tipping Elements

Different parts of the Earth system exhibit *critical thresholds*, sometimes called "tipping points" (e.g., Lenton et al. 2008; Collins et al. 2013; NRC 2013; Kopp et al. 2016). These parts, known as *tipping elements*, have the potential to enter into self-amplifying cycles that commit them to shifting from their current state into a new state: for example, from one in which the summer Arctic Ocean is covered by ice, to one in which it is ice-free. In some potential tipping elements, these state shifts occur abruptly; in others, the commitment to a state shift may occur rapidly, but the state shift itself may take decades, centuries, or even millennia to play out. Often the forcing that commits a tipping element to a shift in state is unknown. Sometimes, it is even unclear whether a proposed tipping element actually exhibits tipping behavior. Through a combination of physical modeling, paleoclimate observations, and expert elicitations, scientists have identified a number of possible tipping elements in atmosphere–ocean circulation, the cryosphere, the carbon cycle, and ecosystems (Figure 15.1, left; Table 15.1).

FINAL DRAFT

[INSERT TABLE 15.1 HERE]

One important tipping element is the Atlantic Meridional Overturning Circulation (AMOC), a major component of global ocean circulation. Driven by the sinking of cold, dense water in the North Atlantic near Greenland, its strength is projected to decrease with warming due to freshwater input from increased precipitation, glacial melt, and melt of the Greenland Ice Sheet (Rahmstorf et al. 2015; see also discussion in Ch. 11: Arctic Changes). A decrease in AMOC strength is probable and may already be culpable for the "warming hole" observed in the North Atlantic (Drijfhout et al. 2012; Rahmstorf et al. 2015), although it is still unclear whether this decrease represents a forced change or internal variability (Cheng et al. 2016). Given sufficient freshwater input, there is even the possibility of complete AMOC collapse. Most models do not predict such a collapse in the 21st century (NRC 2013), although one study that used observations to bias-correct climate model simulations found that CO_2 concentrations of 700 ppm led to a AMOC collapse within 300 years (Liu et al. 2017).

A slowing or collapse of the AMOC would have several consequences for the United States. A decrease in AMOC strength would accelerate sea level rise off the northeastern United States (Yin and Goddard 2013), while a full collapse could result in as much as approximately 1.6 feet (0.5 m) of regional sea level rise (Gregory and Lowe 2000; Levermann et al. 2005), as well as a cooling of approximately 0°F–4°F (0°C–2°C) over the country (Jackson et al. 2015; Liu et al. 2017). These changes would occur in addition to preexisting global and regional sea level and temperature change. A slowdown of the AMOC would also lead to a reduction of ocean carbon dioxide uptake, and thus an acceleration of global-scale warming (Pérez et al. 2013).

Another tipping element is the atmospheric–oceanic circulation of the equatorial Pacific that, through a set of feedbacks, drives the state shifts of the El Niño–Southern Oscillation. This is an example of a tipping element that already shifts on a sub-decadal, interannual timescale, primarily in response to internal noise. Climate model experiments suggest that warming will reduce the threshold needed to trigger extremely strong El Niño and La Niña events (Cai et al. 2014, 2015). As evident from recent El Niño and La Niña events, such a shift would negatively impact many regions and sectors across the United States (for more on ENSO impacts, see Ch. 5: Circulation and Variability).

A third potential tipping element is arctic sea ice, which may exhibit abrupt state shifts into summer ice-free or year-round ice-free states (Lindsay and Zhang 2005; Eisenman and Wetlauffer 2013). As discussed above, climate models have historically underestimated the rate of arctic sea ice loss. This is likely due to insufficient representation of critical positive feedbacks in models. Such feedbacks could include: greater high-latitude storminess and ocean wave penetration as sea ice declines; more northerly incursions of warm air and water; melting associated with increasing water vapor; loss of multiyear ice; and albedo decreases on the sea ice surface (e.g., Schroder et al. 2014; Asplin et al. 2012; Perovich et al. 2008). At the same time, however, the point at which the threshold for an abrupt shift would be crossed also depends on

FINAL DRAFT

the role of natural variability in a changing system; the relative importance of potential stabilizing negative feedbacks, such as more efficient heat transfer from the ocean to the atmosphere in fall and winter as sea declines; and how sea ice in other seasons, as well as the climate system more generally, responds once the first "ice-free" summer occurs (e.g., Ding et al. 2017). It is also possible that summer sea ice may not abruptly collapse, but instead respond in a manner proportional to the increase in temperature (Armour et al. 2011; Ridley et al. 2012; Li et al. 2013; Wagner and Eisenman 2015). Moreover, an abrupt decrease in winter sea ice may result simply as the gradual warming of Arctic Ocean causes it to cross a critical temperature for ice formation, rather than from self-reinforcing cycles (Bathiany et al. 2016).

Two possible tipping elements in the carbon cycle also lie in the Arctic. The first is buried in the permafrost, which contains an estimated 1,300–1,600 Gt C (Schuur et al. 2015; see also Ch. 11: Arctic Changes). As the Arctic warms, about 5–15% is estimated to be vulnerable to release in this century (Schuur et al., 2015). Locally, the heat produced by the decomposition of organic carbon could serve as a positive feedback, accelerating carbon release (Hollesen et al. 2015). However, the release of permafrost carbon, as well as whether that carbon is initially released as CO_2 or as the more potent greenhouse gas CH_4, is limited by many factors, including the freeze–thaw cycle, the rate with which heat diffuses into the permafrost, the potential for organisms to cycle permafrost carbon into new biomass, and oxygen availability. Though the release of permafrost carbon would probably not be fast enough to trigger a runaway self-amplifying cycle leading to a permafrost-free Arctic (Schuur et al. 2015), it still has the potential to significantly amplify both local and global warming, reduce the budget of human-caused CO_2 emissions consistent with global temperature targets, and drive continued warming even if human-caused emissions stopped altogether (MacDougall et al. 2012, 2015).

The second possible arctic carbon cycle tipping element is the reservoir of methane hydrates frozen into the sediments of continental shelves of the Arctic Ocean (see also Ch. 11: Arctic Changes). There is an estimated 500 to 3,000 Gt C in methane hydrates (Archer 2007; Ruppel 2011; Piñero et al. 2013), with a most recent estimate of 1,800 Gt C (equivalently, 2,400 Gt CH_4) (Ruppel and Kessler 2017). If released as methane rather than CO_2, this would be equivalent to about 82,000 Gt CO_2 using a global warming potential of 34 (Myhre et al. 2013). While the existence of this reservoir has been known and discussed for several decades (e.g., Kvenvolden 1988), only recently has it been hypothesized that warming bottom water temperatures may destabilize the hydrates over timescales shorter than millennia, leading to their release into the water column and eventually the atmosphere (e.g., Archer 2007; Kretschmer et al. 2015). Recent measurements of the release of methane from these sediments in summer find that, while methane hydrates on the continental shelf and upper slope are undergoing dissociation, the resulting emissions are not reaching the ocean surface in sufficient quantity to affect the atmospheric methane budget significantly, if at all (Myhre et al. 2016; Ruppel and Kessler 2017). Estimates of plausible hydrate releases to the atmosphere over the next century are only a

FINAL DRAFT

fraction of present-day anthropogenic methane emissions (Kretschmer et al. 2015; Stranne et al. 2016; Ruppel and Kessler 2017).

These estimates of future emissions from permafrost and hydrates, however, neglect the possibility that humans may insert themselves into the physical feedback systems. With an estimated 53% of global fossil fuel reserves in the Arctic becoming increasingly accessible in a warmer world (Lee and Holder 2001), the risks associated with this carbon being extracted and burned, further exacerbating the influence of humans on global climate, are evident (Jakob and Hilaire 2015; McGlade and Elkins 2015). Of less concern but still relevant, arctic ocean waters themselves are a source of methane, which could increase as sea ice decreases (Kort et al. 2012).

The Antarctic and Greenland Ice Sheets are clear tipping elements. The Greenland Ice Sheet exhibits multiple stable states as a result of feedbacks involving the elevation of the ice sheet, atmosphere-ocean-sea ice dynamics, and albedo (Ridley et al. 2010; Robinson et al. 2012; Levermann et al. 2013; Koenig et al. 2014). At least one study suggests that warming of 2.9ºF (1.6°C) above a preindustrial baseline could commit Greenland to an 85% reduction in ice volume and a 20 ft (6 m) contribution to global mean sea level over millennia (Robinson et al. 2012). One 10,000-year modeling study (Clark et al. 2016) suggests that following the higher RCP8.5 pathway (see Ch. 4: Projections) over the 21st century would lead to complete loss of the Greenland Ice Sheet over 6,000 years.

In Antarctica, the amount of ice that sits on bedrock below sea level is enough to raise global mean sea level by 75.5 feet (23 m) (Fretwell et al. 2013). This ice is vulnerable to collapse over centuries to millennia due to a range of feedbacks involving ocean-ice sheet-bedrock interactions (Schoof 2007; Gomez et al. 2010; Ritz et al. 2015; Mengel and Levermann et al. 2014; Pollard et al. 2015; Clark et al. 2016). Observational evidence suggests that ice dynamics already in progress have committed the planet to as much as 3.9 feet (1.2 m) worth of sea level rise from the West Antarctic Ice Sheet alone, although that amount is projected to occur over the course of many centuries (Joughin et al. 2014; Rignot et al. 2014). Plausible physical modeling indicates that, under the higher RCP8.5 scenario, Antarctic ice could contribute 3.3 feet (1 m) or more to global mean sea level over the remainder of this century (DeConto and Pollard 2016), with some authors arguing that rates of change could be even faster (Hansen et al. 2016). Over 10,000 years, one modeling study suggests that 3.6°F (2°C) of sustained warming could lead to about 70 feet (25 m) of global mean sea level rise from Antarctica alone (Clark et al. 2016).

Finally, tipping elements also exist in large-scale ecosystems. For example, boreal forests such as those in southern Alaska may expand northward in response to arctic warming. Because forests are darker than the tundra they replace, their expansion amplifies regional warming, which in turn accelerates their expansion (Jones et al. 2009). As another example, coral reef ecosystems, such as those in Florida, are maintained by stabilizing ecological feedbacks among corals, coralline red algae, and grazing fish and invertebrates. However, these stabilizing feedbacks can be undermined by warming, increased risk of bleaching events, spread of disease, and ocean

FINAL DRAFT

acidification, leading to abrupt reef collapse (Hoegh-Guldberg et al. 2007). More generally, many ecosystems can undergo rapid regime shifts in response to a range of stressors, including climate change (e.g., Scheffer et al. 2001; Folke et al. 2004).

15.5 Paleoclimatic Hints of Additional Potential Surprises

The paleoclimatic record provides evidence for additional state shifts whose driving mechanisms are as yet poorly understood. As mentioned, global climate models tend to underestimate both the magnitude of global mean warming in response to higher CO_2 levels as well as its amplification at high latitudes, compared to reconstructions of temperature and CO_2 from the geological record. Three case studies—all periods well predating the first appearance of *Homo sapiens* around 200,000 years ago (Tattersall 2009)—illustrate the limitations of current scientific understanding in capturing the full range of self-reinforcing cycles that operate within the Earth system, particularly over millennial time scales.

The first of these, the late Pliocene, occurred about 3.6 to 2.6 million years ago. Climate model simulations for this period systematically underestimate warming north of 30°N (Salzmann et al. 2013). Similarly, during the middle Miocene (about 17–14.5 million years ago), models also fail to simultaneously replicate global mean temperature—estimated from proxies to be approximately 14°F ± 4°F (8°C ± 2°C) warmer than preindustrial—and the approximately 40% reduction in the pole-to-equator temperature gradient relative to today (Goldner et al. 2014). Although about one-third of the global mean temperature increase during the Miocene can be attributed to changes in geography and vegetation, geological proxies indicate CO_2 concentrations of around 400 ppm (Goldner et al. 2014; Foster et al. 2012), similar to today. This suggests the possibility of as yet unmodeled feedbacks, perhaps related to a significant change in the vertical distribution of heat in the tropical ocean (LaRiviere et al. 2012).

The last of these case studies, the early Eocene, occurred about 56–48 million years ago. This period is characterized by the absence of permanent land ice, CO_2 concentrations peaking around 1,400 ± 470 ppm (Anagnostu et al. 2016), and global temperatures about 25°F ± 5°F (14°C ± 3°C) warmer than the preindustrial (Caballero and Huber 2013). Like the late Pliocene and the middle Miocene, this period also exhibits about half the pole-to-equator temperature gradient of today (Huber and Caballero 2011; Lunt et al. 2012). About one-third of the temperature difference is attributable to changes in geography, vegetation, and ice sheet coverage (Caballero and Huber 2013). However, to reproduce both the elevated global mean temperature and the reduced pole-to-equator temperature gradient, climate models would require CO_2 concentrations that exceed those indicated by the proxy record by two to five times (Lunt et al. 2012) — suggesting once again the presence of as yet poorly understood processes and feedbacks.

One possible explanation for this discrepancy is a planetary state shift that, above a particular CO_2 threshold, leads to a significant increase in the sensitivity of the climate to CO_2. Paleo-data for the last 800,000 years suggest a gradual increase in climate sensitivity with global mean

FINAL DRAFT

temperature over glacial-interglacial cycles (von der Heydt et al. 2014; Friedrich et al. 2016), although these results are based on a time period with CO_2 concentrations lower than today. At higher CO_2 levels, one modeling study (Caballero and Huber 2013) suggests that an abrupt change in atmospheric circulation (the onset of equatorial atmospheric superrotation) between 1,120 and 2,240 ppm CO_2 that could lead to a reduction in cloudiness and an approximate doubling of climate sensitivity. However, the critical threshold for such a transition is poorly constrained. If it occurred in the past at a lower CO_2 level, it might explain the Eocene discrepancy and potentially also the Miocene discrepancy: but in that case, it could also pose a plausible threat within the 21st century under the higher RCP8.5 pathway.

Regardless of the particular mechanism, the systematic paleoclimatic model-data mismatch for past warm climates suggests that climate models are omitting at least one, and probably more, processes crucial to future warming, especially in polar regions. For this reason, future changes outside the range projected by climate models cannot be ruled out, and climate models are more likely to underestimate than to overestimate the amount of long-term future change.

FINAL DRAFT

TRACEABLE ACCOUNTS

Key Finding 1

Positive feedbacks (self-reinforcing cycles) within the climate system have the potential to accelerate human-induced climate change and even shift the Earth's climate system, in part or in whole, into new states that are very different from those experienced in the recent past (for example, ones with greatly diminished ice sheets or different large-scale patterns of atmosphere or ocean circulation). Some feedbacks and potential state shifts can be modeled and quantified; others can be modeled or identified but not quantified; and some are probably still unknown. (*Very high confidence* in the potential for state shifts and in the incompleteness of knowledge about feedbacks and potential state shifts).

Description of evidence base

This key finding is based on a large body of scientific literature recently summarized by Lenton et al. (2008), NRC (2013), and Kopp et al. (2016). As NRC (2013, page vii) states, "A study of Earth's climate history suggests the inevitability of 'tipping points'—thresholds beyond which major and rapid changes occur when crossed—that lead to abrupt changes in the climate system" and (page xi), "Can all tipping points be foreseen? Probably not. Some will have no precursors, or may be triggered by naturally occurring variability in the climate system. Some will be difficult to detect, clearly visible only after they have been crossed and an abrupt change becomes inevitable." As IPCC AR5 WG1 Chapter 12, section 12.5.5 (Collins et al. 2013) further states, "A number of components or phenomena within the Earth system have been proposed as potentially possessing critical thresholds (sometimes referred to as tipping points) beyond which abrupt or nonlinear transitions to a different state ensues." Collins et al. (2013) further summarizes critical thresholds that can be modeled and others that can only be identified.

Major uncertainties

The largest uncertainties are 1) whether proposed tipping elements actually undergo critical transitions; 2) the magnitude and timing of forcing that will be required to initiate critical transitions in tipping elements; 3) the speed of the transition once it has been triggered; 4) the characteristics of the new state that results from such transition; and 5) the potential for new tipping elements to exist that are yet unknown.

Assessment of confidence based on evidence and agreement, including short description of nature of evidence and level of agreement

There is *very high confidence* in the likelihood of the existence of positive feedbacks and tipping elements statement is based on a large body of literature published over the last 25 years that draws from basic physics, observations, paleoclimate data, and modeling.

FINAL DRAFT

There is *very high confidence* that some feedbacks can be quantified, others are known but cannot be quantified, and others may yet exist that are currently unknown.

Summary sentence or paragraph that integrates the above information

The key finding is based on NRC (2013) and IPCC AR4 WG1 Chapter 12 section 12.5.5 (IPCC 2007), which made a thorough assessment of the relevant literature.

Key Finding 2

The physical and socioeconomic impacts of compound extreme events (such as simultaneous heat and drought, wildfires associated with hot and dry conditions, or flooding associated with high precipitation on top of snow or waterlogged ground) can be greater than the sum of the parts (*very high confidence*). Few analyses consider the spatial or temporal correlation between extreme events.

Description of evidence base

This key finding is based on a large body of scientific literature summarized in the 2012 IPCC Special Report on Extremes (IPCC 2012). The report's Summary for Policymakers (page 6) states, "exposure and vulnerability are key determinants of disaster risk and of impacts when risk is realized... extreme impacts on human, ecological, or physical systems can result from individual extreme weather or climate events. Extreme impacts can also result from non-extreme events where exposure and vulnerability are high or from a compounding of events or their impacts. For example, drought, coupled with extreme heat and low humidity, can increase the risk of wildfire."

Major uncertainties

The largest uncertainties are in the temporal congruence of the events and the compounding nature of their impacts.

Assessment of confidence based on evidence and agreement, including short description of nature of evidence and level of agreement

There is *very high confidence* that the impacts of multiple events could exceed the sum of the impacts of events occurring individually.

Summary sentence or paragraph that integrates the above information

The key finding is based on the 2012 IPCC SREX report, particularly section 3.1.3 on compound or multiple events, which presents a thorough assessment of the relevant literature.

FINAL DRAFT

Key Finding 3

While climate models incorporate important climate processes that can be well quantified, they do not include all of the processes that can contribute to feedbacks, compound extreme events, and abrupt and/or irreversible changes. For this reason, future changes outside the range projected by climate models cannot be ruled out (*very high confidence*). Moreover, the systematic tendency of climate models to underestimate temperature change during warm paleoclimates suggests that climate models are more likely to underestimate than to overestimate the amount of long-term future change (*medium confidence*).

Description of evidence base

This key finding is based on the conclusions of IPCC AR5 WG1 (IPCC 2013), specifically Chapter 7 (Flato et al. 2013); the state of the art of global models is briefly summarized in Chapter 4: Projections of this report. The second half of this key finding is based upon the tendency of global climate models to underestimate, relative to geological reconstructions, the magnitude of both long-term global mean warming and the amplification of warming at high latitudes in past warm climates (e.g., Salzmann et al. 2013; Goldner et al. 2014; Caballeo and Huber 2013; Lunt et al. 2012).

Major uncertainties

The largest uncertainties are structural: are the models including all the important components and relationships necessary to model the feedbacks and if so, are these correctly represented in the models?

Assessment of confidence based on evidence and agreement, including short description of nature of evidence and level of agreement

There is *very high confidence* that the models are incomplete representations of the real world; and there is *medium confidence* that their tendency is to under- rather than over-estimate the amount of long-term future change.

Summary sentence or paragraph that integrates the above information

The key finding is based on the IPCC AR5 WG1 Chapter 9 (IPCC 2013), as well as systematic paleoclimatic model/data comparisons.

FINAL DRAFT

1 **TABLE**

2 **Table 15.1**: Potential tipping elements (adapted from Kopp et al. 2016).

Candidate Climatic Tipping Element	State Shift	Main impact pathways
Atmosphere–ocean circulation		
Atlantic meridional overturning circulation	Major reduction in strength	regional temperature and precipitation; global mean temperature; regional sea level
El Niño-Southern Oscillation	Increase in amplitude	regional temperature and precipitation
Equatorial atmospheric superrotation	Initiation	cloud cover; climate sensitivity
Regional North Atlantic Ocean convection	Major reduction in strength	regional temperature and precipitation
Cryosphere		
Antarctic Ice Sheet	Major decrease in ice volume	sea level; albedo; freshwater forcing on ocean circulation
Arctic sea ice	Major decrease in summertime and/or perennial area	regional temperature and precipitation; albedo
Greenland Ice Sheet	Major decrease in ice volume	sea level; albedo; freshwater forcing on ocean circulation
Carbon cycle		

FINAL DRAFT

Methane hydrates	Massive release of carbon	greenhouse gas emissions
Permafrost carbon	Massive release of carbon	greenhouse gas emissions
Ecosystem		
Amazon rainforest	Dieback, transition to grasslands	greenhouse gas emissions; biodiversity
Boreal forest	Dieback, transition to grasslands	greenhouse gas emissions; albedo; biodiversity
Coral reefs	Die-off	biodiversity

1

FINAL DRAFT

FIGURE

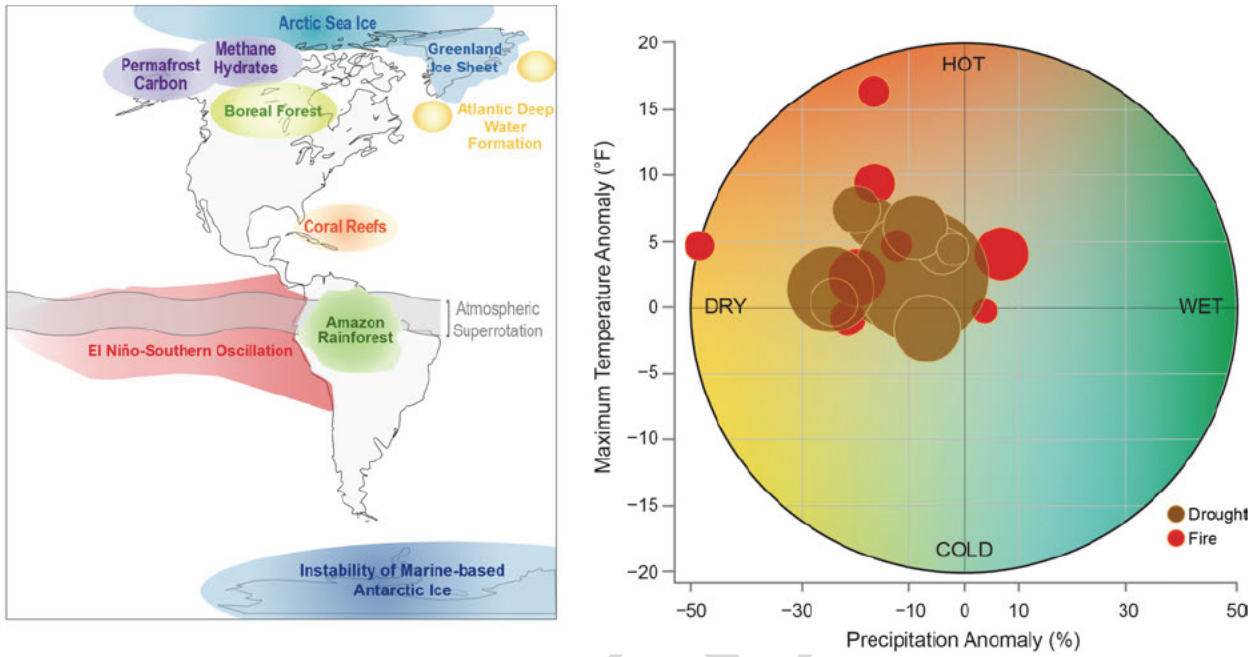

Figure 15.1: (left) Potential climatic tipping elements affecting the Americas (Figure source: adapted from Lenton et al. 2008). (right) Wildfire and drought events from the NOAA Billion Dollar Weather Events list (1980–2016), and associated temperature and precipitation anomalies. Dot size scales with the magnitude of impact, as reflected by the cost of the event. These high-impact events occur preferentially under hot, dry conditions.

FINAL

REFERENCES

AghaKouchak, A., L. Cheng, O. Mazdiyasni, and A. Farahmand, 2014: Global warming and changes in risk of concurrent climate extremes: Insights from the 2014 California drought. *Geophysical Research Letters,* **41,** 8847-8852. http://dx.doi.org/10.1002/2014GL062308

Anagnostou, E., E.H. John, K.M. Edgar, G.L. Foster, A. Ridgwell, G.N. Inglis, R.D. Pancost, D.J. Lunt, and P.N. Pearson, 2016: Changing atmospheric CO2 concentration was the primary driver of early Cenozoic climate. *Nature,* **533,** 380-384. http://dx.doi.org/10.1038/nature17423

Archer, D., 2007: Methane hydrate stability and anthropogenic climate change. *Biogeosciences,* **4,** 521-544. http://dx.doi.org/10.5194/bg-4-521-2007

Armour, K.C., I. Eisenman, E. Blanchard-Wrigglesworth, K.E. McCusker, and C.M. Bitz, 2011: The reversibility of sea ice loss in a state-of-the-art climate model. *Geophysical Research Letters,* **38,** L16705. http://dx.doi.org/10.1029/2011GL048739

Asplin, M.G., R. Galley, D.G. Barber, and S. Prinsenberg, 2012: Fracture of summer perennial sea ice by ocean swell as a result of Arctic storms. *Journal of Geophysical Research: Oceans,* **117,** C06025. http://dx.doi.org/10.1029/2011JC007221

Bathiany, S., D. Notz, T. Mauritsen, G. Raedel, and V. Brovkin, 2016: On the potential for abrupt Arctic winter sea ice loss. *Journal of Climate,* **29,** 2703-2719. http://dx.doi.org/10.1175/JCLI-D-15-0466.1

Brysse, K., N. Oreskes, J. O'Reilly, and M. Oppenheimer, 2013: Climate change prediction: Erring on the side of least drama? *Global Environmental Change,* **23,** 327-337. http://dx.doi.org/10.1016/j.gloenvcha.2012.10.008

Caballero, R. and M. Huber, 2013: State-dependent climate sensitivity in past warm climates and its implications for future climate projections. *Proceedings of the National Academy of Sciences,* **110,** 14162-14167. http://dx.doi.org/10.1073/pnas.1303365110

Cai, W., S. Borlace, M. Lengaigne, P. van Rensch, M. Collins, G. Vecchi, A. Timmermann, A. Santoso, M.J. McPhaden, L. Wu, M.H. England, G. Wang, E. Guilyardi, and F.-F. Jin, 2014: Increasing frequency of extreme El Niño events due to greenhouse warming. *Nature Climate Change,* **4,** 111-116. http://dx.doi.org/10.1038/nclimate2100

Cai, W., G. Wang, A. Santoso, M.J. McPhaden, L. Wu, F.-F. Jin, A. Timmermann, M. Collins, G. Vecchi, M. Lengaigne, M.H. England, D. Dommenget, K. Takahashi, and E. Guilyardi, 2015: Increased frequency of extreme La Niña events under greenhouse warming. *Nature Climate Change,* **5,** 132-137. http://dx.doi.org/10.1038/nclimate2492

FINAL DRAFT

Cheng, J., Z. Liu, S. Zhang, W. Liu, L. Dong, P. Liu, and H. Li, 2016: Reduced interdecadal variability of Atlantic Meridional Overturning Circulation under global warming. *Proceedings of the National Academy of Sciences,* **113,** 3175-3178. http://dx.doi.org/10.1073/pnas.1519827113

Clark, P.U., J.D. Shakun, S.A. Marcott, A.C. Mix, M. Eby, S. Kulp, A. Levermann, G.A. Milne, P.L. Pfister, B.D. Santer, D.P. Schrag, S. Solomon, T.F. Stocker, B.H. Strauss, A.J. Weaver, R. Winkelmann, D. Archer, E. Bard, A. Goldner, K. Lambeck, R.T. Pierrehumbert, and G.-K. Plattner, 2016: Consequences of twenty-first-century policy for multi-millennial climate and sea-level change. *Nature Climate Change,* **6,** 360-369. http://dx.doi.org/10.1038/nclimate2923

Collins, M., R. Knutti, J. Arblaster, J.-L. Dufresne, T. Fichefet, P. Friedlingstein, X. Gao, W.J. Gutowski, T. Johns, G. Krinner, M. Shongwe, C. Tebaldi, A.J. Weaver, and M. Wehner, 2013: Long-term climate change: Projections, commitments and irreversibility. *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, 1029–1136. http://www.climatechange2013.org/report/full-report/

Cook, B.I., T.R. Ault, and J.E. Smerdon, 2015: Unprecedented 21st century drought risk in the American Southwest and Central Plains. *Science Advances,* **1**. http://dx.doi.org/10.1126/sciadv.1400082

DeConto, R.M. and D. Pollard, 2016: Contribution of Antarctica to past and future sea-level rise. *Nature,* **531,** 591-597. http://dx.doi.org/10.1038/nature17145

Diffenbaugh, N.S. and F. Giorgi, 2012: Climate change hotspots in the CMIP5 global climate model ensemble. *Climatic Change,* **114,** 813-822. http://dx.doi.org/10.1007/s10584-012-0570-x

Ding, Q., A. Schweiger, M. Lheureux, D.S. Battisti, S. Po-Chedley, N.C. Johnson, E. Blanchard-Wrigglesworth, K. Harnos, Q. Zhang, R. Eastman, and E.J. Steig, 2017: Influence of high-latitude atmospheric circulation changes on summertime Arctic sea ice. *Nature Climate Change,* **7,** 289-295. http://dx.doi.org/10.1038/nclimate3241

Drijfhout, S., G.J.v. Oldenborgh, and A. Cimatoribus, 2012: Is a decline of AMOC causing the warming hole above the North Atlantic in observed and modeled warming patterns? *Journal of Climate,* **25,** 8373-8379. http://dx.doi.org/10.1175/jcli-d-12-00490.1

FINAL DRAFT

Eisenman, I. and J.S. Wettlaufer, 2009: Nonlinear threshold behavior during the loss of Arctic sea ice. *Proceedings of the National Academy of Sciences,* **106,** 28-32. http://dx.doi.org/10.1073/pnas.0806887106

Farman, J.C., B.G. Gardiner, and J.D. Shanklin, 1985: Large losses of total ozone in Antarctica reveal seasonal ClOx/NOx interaction. *Nature,* **315,** 207-210. http://dx.doi.org/10.1038/315207a0

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. *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, 741–866. http://www.climatechange2013.org/report/full-report/

Folke, C., Carpenter, S., Walker, B., Scheffer, M., Elmqvist, T., Gunderson, L., & Holling, C. S. (2004). Regime shifts, resilience, and biodiversity in ecosystem management. *Annu. Rev. Ecol. Evol. Syst.*, *35*, 557-581.

Foster, G.L., C.H. Lear, and J.W.B. Rae, 2012: The evolution of pCO2, ice volume and climate during the middle Miocene. *Earth and Planetary Science Letters,* **341–344,** 243-254. http://dx.doi.org/10.1016/j.epsl.2012.06.007

Fraser, E.D.G., E. Simelton, M. Termansen, S.N. Gosling, and A. South, 2013: "Vulnerability hotspots": Integrating socio-economic and hydrological models to identify where cereal production may decline in the future due to climate change induced drought. *Agricultural and Forest Meteorology,* **170,** 195-205. http://dx.doi.org/10.1016/j.agrformet.2012.04.008

Fretwell, P., H.D. Pritchard, D.G. Vaughan, J.L. Bamber, N.E. Barrand, R. Bell, C. Bianchi, R.G. Bingham, D.D. Blankenship, G. Casassa, G. Catania, D. Callens, H. Conway, A.J. Cook, H.F.J. Corr, D. Damaske, V. Damm, F. Ferraccioli, R. Forsberg, S. Fujita, Y. Gim, P. Gogineni, J.A. Griggs, R.C.A. Hindmarsh, P. Holmlund, J.W. Holt, R.W. Jacobel, A. Jenkins, W. Jokat, T. Jordan, E.C. King, J. Kohler, W. Krabill, M. Riger-Kusk, K.A. Langley, G. Leitchenkov, C. Leuschen, B.P. Luyendyk, K. Matsuoka, J. Mouginot, F.O. Nitsche, Y. Nogi, O.A. Nost, S.V. Popov, E. Rignot, D.M. Rippin, A. Rivera, J. Roberts, N. Ross, M.J. Siegert, A.M. Smith, D. Steinhage, M. Studinger, B. Sun, B.K. Tinto, B.C. Welch, D. Wilson, D.A. Young, C. Xiangbin, and A. Zirizzotti, 2013: Bedmap2: Improved ice bed, surface and thickness datasets for Antarctica. *The Cryosphere,* **7,** 375-393. http://dx.doi.org/10.5194/tc-7-375-2013

FINAL DRAFT

Friedrich, T., A. Timmermann, M. Tigchelaar, O. Elison Timm, and A. Ganopolski, 2016: Nonlinear climate sensitivity and its implications for future greenhouse warming. *Science Advances,* **2**. http://dx.doi.org/10.1126/sciadv.1501923

Goldner, A., N. Herold, and M. Huber, 2014: The challenge of simulating the warmth of the mid-Miocene climatic optimum in CESM1. *Climate of the Past,* **10,** 523-536. http://dx.doi.org/10.5194/cp-10-523-2014

Gomez, N., J.X. Mitrovica, P. Huybers, and P.U. Clark, 2010: Sea level as a stabilizing factor for marine-ice-sheet grounding lines. *Nature Geoscience,* **3,** 850-853. http://dx.doi.org/10.1038/ngeo1012

Gregory, J.M. and J.A. Lowe, 2000: Predictions of global and regional sea-level rise using AOGCMs with and without flux adjustment. *Geophysical Research Letters,* **27,** 3069-3072. http://dx.doi.org/10.1029/1999GL011228

Hansen, J., M. Sato, P. Hearty, R. Ruedy, M. Kelley, V. Masson-Delmotte, G. Russell, G. Tselioudis, J. Cao, E. Rignot, I. Velicogna, B. Tormey, B. Donovan, E. Kandiano, K. von Schuckmann, P. Kharecha, A.N. Legrande, M. Bauer, and K.W. Lo, 2016: 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,** 3761-3812. http://dx.doi.org/10.5194/acp-16-3761-2016

Hao, Z., A. AghaKouchak, and T.J. Phillips, 2013: Changes in concurrent monthly precipitation and temperature extremes. *Environmental Research Letters,* **8,** 034014. http://dx.doi.org/10.1088/1748-9326/8/3/034014

Hollesen, J., H. Matthiesen, A.B. Møller, and B. Elberling, 2015: Permafrost thawing in organic Arctic soils accelerated by ground heat production. *Nature Climate Change,* **5,** 574-578. http://dx.doi.org/10.1038/nclimate2590

Hoegh-Guldberg, O., P.J. Mumby, A.J. Hooten, R.S. Steneck, P. Greenfield, E. Gomez, C.D. Harvell, P.F. Sale, A.J. Edwards, K. Caldeira, N. Knowlton, C.M. Eakin, R. Iglesias-Prieto, N. Muthiga, R.H. Bradbury, A. Dubi, and M.E. Hatziolos, 2007: Coral reefs under rapid climate change and ocean acidification. *Science,* **318,** 1737-1742. http://dx.doi.org/10.1126/science.1152509

Huber, M. and R. Caballero, 2011: The early Eocene equable climate problem revisited. *Climate of the Past,* **7,** 603-633. http://dx.doi.org/10.5194/cp-7-603-2011

IPCC, 2007: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor, and H.L. Miller, Eds. Cambridge University Press, Cambridge. U.K, New York, NY, USA, 996 pp.

FINAL DRAFT

www.ipcc.ch/publications_and_data/publications_ipcc_fourth_assessment_report_wg1_report_the_physical_science_basis.htm

IPCC, 2012: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (Eds.). Cambridge University Press, Cambridge, UK and New York, NY. 582 pp. http://ipcc-wg2.gov/SREX/images/uploads/SREX-All_FINAL.pdf

IPCC, 2013: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK and New York, NY, 1535 pp. http://www.climatechange2013.org/report/

Jackson, L.C., R. Kahana, T. Graham, M.A. Ringer, T. Woollings, J.V. Mecking, and R.A. Wood, 2015: Global and European climate impacts of a slowdown of the AMOC in a high resolution GCM. *Climate Dynamics,* **45,** 3299-3316. http://dx.doi.org/10.1007/s00382-015-2540-2

Jakob, M. and J. Hilaire, 2015: Climate science: Unburnable fossil-fuel reserves. *Nature,* **517,** 150-152. http://dx.doi.org/10.1038/517150a

Jones, C., J. Lowe, S. Liddicoat, and R. Betts, 2009: Committed terrestrial ecosystem changes due to climate change. *Nature Geoscience,* **2,** 484-487. http://dx.doi.org/10.1038/ngeo555

Joughin, I., B.E. Smith, and B. Medley, 2014: Marine ice sheet collapse potentially under way for the Thwaites Glacier Basin, West Antarctica. *Science,* **344,** 735-738. http://dx.doi.org/10.1126/science.1249055

Kang, I.-S., Y.-M. Yang, and W.-K. Tao, 2015: GCMs with implicit and explicit representation of cloud microphysics for simulation of extreme precipitation frequency. *Climate Dynamics,* **45,** 325-335. http://dx.doi.org/10.1007/s00382-014-2376-1

Koenig, S.J., R.M. DeConto, and D. Pollard, 2014: Impact of reduced Arctic sea ice on Greenland ice sheet variability in a warmer than present climate. *Geophysical Research Letters,* **41,** 3933-3942. http://dx.doi.org/10.1002/2014GL059770

Kopp, R.E., R.L. Shwom, G. Wagner, and J. Yuan, 2016: Tipping elements and climate–economic shocks: Pathways toward integrated assessment. *Earth's Future,* **4,** 346-372. http://dx.doi.org/10.1002/2016EF000362

Kort, E.A., S.C. Wofsy, B.C. Daube, M. Diao, J.W. Elkins, R.S. Gao, E.J. Hintsa, D.F. Hurst, R. Jimenez, F.L. Moore, J.R. Spackman, and M.A. Zondlo, 2012: Atmospheric observations of

FINAL DRAFT

Arctic Ocean methane emissions up to 82° north. *Nature Geoscience,* **5,** 318-321. http://dx.doi.org/10.1038/ngeo1452

Kretschmer, K., A. Biastoch, L. Rüpke, and E. Burwicz, 2015: Modeling the fate of methane hydrates under global warming. *Global Biogeochemical Cycles,* **29,** 610-625. http://dx.doi.org/10.1002/2014GB005011

Kvenvolden, K.A., 1988: Methane hydrate — A major reservoir of carbon in the shallow geosphere? *Chemical Geology,* **71,** 41-51. http://dx.doi.org/10.1016/0009-2541(88)90104-0

LaRiviere, J.P., A.C. Ravelo, A. Crimmins, P.S. Dekens, H.L. Ford, M. Lyle, and M.W. Wara, 2012: Late Miocene decoupling of oceanic warmth and atmospheric carbon dioxide forcing. *Nature,* **486,** 97-100. http://dx.doi.org/10.1038/nature11200

Lee, S.-Y. and G.D. Holder, 2001: Methane hydrates potential as a future energy source. *Fuel Processing Technology,* **71,** 181-186. http://dx.doi.org/10.1016/S0378-3820(01)00145-X

Lenton, T.M., H. Held, E. Kriegler, J.W. Hall, W. Lucht, S. Rahmstorf, and H.J. Schellnhuber, 2008: Tipping elements in the Earth's climate system. *Proceedings of the National Academy of Sciences,* **105,** 1786-1793. http://dx.doi.org/10.1073/pnas.0705414105

Levermann, A., A. Griesel, M. Hofmann, M. Montoya, and S. Rahmstorf, 2005: Dynamic sea level changes following changes in the thermohaline circulation. *Climate Dynamics,* **24,** 347-354. http://dx.doi.org/10.1007/s00382-004-0505-y

Levermann, A., P.U. Clark, B. Marzeion, G.A. Milne, D. Pollard, V. Radic, and A. Robinson, 2013: The multimillennial sea-level commitment of global warming. *Proceedings of the National Academy of Sciences,* **110,** 13745-13750. http://dx.doi.org/10.1073/pnas.1219414110

Li, C., D. Notz, S. Tietsche, and J. Marotzke, 2013: The transient versus the equilibrium response of sea ice to global warming. *Journal of Climate,* **26,** 5624-5636. http://dx.doi.org/10.1175/JCLI-D-12-00492.1

Lindsay, R.W. and J. Zhang, 2005: The thinning of Arctic sea ice, 1988–2003: Have we passed a tipping point? *Journal of Climate,* **18,** 4879-4894. http://dx.doi.org/10.1175/jcli3587.1

Liu, J., Z. Chen, J. Francis, M. Song, T. Mote, and Y. Hu, 2016: Has Arctic sea ice loss contributed to increased surface melting of the Greenland Ice Sheet? *Journal of Climate,* **29,** 3373-3386. http://dx.doi.org/10.1175/JCLI-D-15-0391.1

Liu, W., S.-P. Xie, Z. Liu, and J. Zhu, 2017: Overlooked possibility of a collapsed Atlantic Meridional Overturning Circulation in warming climate. *Science Advances,* **3**. http://dx.doi.org/10.1126/sciadv.1601666

FINAL DRAFT

Lunt, D.J., T. Dunkley Jones, M. Heinemann, M. Huber, A. LeGrande, A. Winguth, C. Loptson, J. Marotzke, C.D. Roberts, J. Tindall, P. Valdes, and C. Winguth, 2012: A model–data comparison for a multi-model ensemble of early Eocene atmosphere–ocean simulations: EoMIP. *Climate of the Past,* **8,** 1717-1736. http://dx.doi.org/10.5194/cp-8-1717-2012

MacDougall, A.H., C.A. Avis, and A.J. Weaver, 2012: Significant contribution to climate warming from the permafrost carbon feedback. *Nature Geoscience,* **5,** 719-721. http://dx.doi.org/10.1038/ngeo1573

MacDougall, A.H., K. Zickfeld, R. Knutti, and H.D. Matthews, 2015: Sensitivity of carbon budgets to permafrost carbon feedbacks and non-CO 2 forcings. *Environmental Research Letters,* **10,** 125003. http://dx.doi.org/10.1088/1748-9326/10/12/125003

McGlade, C. and P. Ekins, 2015: The geographical distribution of fossil fuels unused when limiting global warming to 2°C. *Nature,* **517,** 187-190. http://dx.doi.org/10.1038/nature14016

Meehl, G.A., T.F. Stocker, W.D. Collins, P. Friedlingstein, A.T. Gaye, J.M. Gregory, A. Kitoh, R. Knutti, J.M. Murphy, A. Noda, S.C.B. Raper, I.G. Watterson, A.J. Weaver, and Z.-C. Zhao, 2007: Global Climate Projections. *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor, and H.L. Miller, Eds. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 747-845.

Mengel, M. and A. Levermann, 2014: Ice plug prevents irreversible discharge from East Antarctica. *Nature Climate Change,* **4,** 451-455. http://dx.doi.org/10.1038/nclimate2226

Molina, M.J. and F.S. Rowland, 1974: Stratospheric sink for chlorofluoromethanes: Chlorine atomc-atalysed destruction of ozone. *Nature,* **249,** 810-812. http://dx.doi.org/10.1038/249810a0

Myhre, G., D. Shindell, F.-M. Bréon, W. Collins, J. Fuglestvedt, J. Huang, D. Koch, J.-F. Lamarque, D. Lee, B. Mendoza, T. Nakajima, A. Robock, G. Stephens, T. Takemura, and H. Zhang, 2013: Anthropogenic and natural radiative forcing. *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, 659–740. http://www.climatechange2013.org/report/full-report/

Myhre, C.L., B. Ferré, S.M. Platt, A. Silyakova, O. Hermansen, G. Allen, I. Pisso, N. Schmidbauer, A. Stohl, J. Pitt, P. Jansson, J. Greinert, C. Percival, A.M. Fjaeraa, S.J. O'Shea, M. Gallagher, M. Le Breton, K.N. Bower, S.J.B. Bauguitte, S. Dalsøren, S.

FINAL DRAFT

Vadakkepuliyambatta, R.E. Fisher, E.G. Nisbet, D. Lowry, G. Myhre, J.A. Pyle, M. Cain, and J. Mienert, 2016: Extensive release of methane from Arctic seabed west of Svalbard during summer 2014 does not influence the atmosphere. *Geophysical Research Letters,* **43,** 4624-4631. http://dx.doi.org/10.1002/2016GL068999

Navarro, T., J.B. Madeleine, F. Forget, A. Spiga, E. Millour, F. Montmessin, and A. Määttänen, 2014: Global climate modeling of the Martian water cycle with improved microphysics and radiatively active water ice clouds. *Journal of Geophysical Research: Planets,* **119,** 1479-1495. http://dx.doi.org/10.1002/2013JE004550

NRC, 2013: *Abrupt Impacts of Climate Change: Anticipating Surprises*. The National Academies Press, Washington, DC, 222 pp. http://dx.doi.org/10.17226/18373

Pérez, F.F., H. Mercier, M. Vazquez-Rodriguez, P. Lherminier, A. Velo, P.C. Pardo, G. Roson, and A.F. Rios, 2013: Atlantic Ocean CO2 uptake reduced by weakening of the meridional overturning circulation. *Nature Geoscience,* **6,** 146-152. http://dx.doi.org/10.1038/ngeo1680

Perovich, D.K., J.A. Richter-Menge, K.F. Jones, and B. Light, 2008: Sunlight, water, and ice: Extreme Arctic sea ice melt during the summer of 2007. *Geophysical Research Letters,* **35,** L11501. http://dx.doi.org/10.1029/2008GL034007

Piñero, E., M. Marquardt, C. Hensen, M. Haeckel, and K. Wallmann, 2013: Estimation of the global inventory of methane hydrates in marine sediments using transfer functions. *Biogeosciences,* **10,** 959-975. http://dx.doi.org/10.5194/bg-10-959-2013

Pollard, D., R.M. DeConto, and R.B. Alley, 2015: Potential Antarctic Ice Sheet retreat driven by hydrofracturing and ice cliff failure. *Earth and Planetary Science Letters,* **412,** 112-121. http://dx.doi.org/10.1016/j.epsl.2014.12.035

Quarantelli, E.L., 1986: Disaster Crisis Management. 113. University of Delaware, Newark, DE. 10 pp. http://udspace.udel.edu/handle/19716/487

Rahmstorf, S., J.E. Box, G. Feulner, M.E. Mann, A. Robinson, S. Rutherford, and E.J. Schaffernicht, 2015: Exceptional twentieth-century slowdown in Atlantic Ocean overturning circulation. *Nature Climate Change,* **5,** 475-480. http://dx.doi.org/10.1038/nclimate2554

Reed, A.J., M.E. Mann, K.A. Emanuel, N. Lin, B.P. Horton, A.C. Kemp, and J.P. Donnelly, 2015: Increased threat of tropical cyclones and coastal flooding to New York City during the anthropogenic era. *Proceedings of the National Academy of Sciences,* **112,** 12610-12615. http://dx.doi.org/10.1073/pnas.1513127112

Ridley, J., J.M. Gregory, P. Huybrechts, and J. Lowe, 2010: Thresholds for irreversible decline of the Greenland ice sheet. *Climate Dynamics,* **35,** 1049-1057. http://dx.doi.org/10.1007/s00382-009-0646-0

FINAL DRAFT

Ridley, J.K., J.A. Lowe, and H.T. Hewitt, 2012: How reversible is sea ice loss? *The Cryosphere,* **6,** 193-198. http://dx.doi.org/10.5194/tc-6-193-2012

Rignot, E., J. Mouginot, M. Morlighem, H. Seroussi, and B. Scheuchl, 2014: Widespread, rapid grounding line retreat of Pine Island, Thwaites, Smith, and Kohler Glaciers, West Antarctica, from 1992 to 2011. *Geophysical Research Letters,* **41,** 3502-3509. http://dx.doi.org/10.1002/2014GL060140

Ritz, C., T.L. Edwards, G. Durand, A.J. Payne, V. Peyaud, and R.C.A. Hindmarsh, 2015: Potential sea-level rise from Antarctic ice-sheet instability constrained by observations. *Nature,* **528,** 115-118. http://dx.doi.org/10.1038/nature16147

Robinson, A., R. Calov, and A. Ganopolski, 2012: Multistability and critical thresholds of the Greenland ice sheet. *Nature Climate Change,* **2,** 429-432. http://dx.doi.org/10.1038/nclimate1449

Ruppel, C.D. *Methane hydrates and contemporary climate change*. Nature Education Knowledge, 2011. **3**.

Ruppel, C.D. and J.D. Kessler, 2017: The interaction of climate change and methane hydrates. *Reviews of Geophysics,* **55,** 126-168. http://dx.doi.org/10.1002/2016RG000534

Salzmann, U., A.M. Dolan, A.M. Haywood, W.-L. Chan, J. Voss, D.J. Hill, A. Abe-Ouchi, B. Otto-Bliesner, F.J. Bragg, M.A. Chandler, C. Contoux, H.J. Dowsett, A. Jost, Y. Kamae, G. Lohmann, D.J. Lunt, S.J. Pickering, M.J. Pound, G. Ramstein, N.A. Rosenbloom, L. Sohl, C. Stepanek, H. Ueda, and Z. Zhang, 2013: Challenges in quantifying Pliocene terrestrial warming revealed by data-model discord. *Nature Climate Change,* **3,** 969-974. http://dx.doi.org/10.1038/nclimate2008

Scheffer, M., Carpenter, S., Foley, J. A., Folke, C., & Walker, B. (2001). Catastrophic shifts in ecosystems. *Nature*, *413*(6856), 591-596.

Schoof, C., 2007: Ice sheet grounding line dynamics: Steady states, stability, and hysteresis. *Journal of Geophysical Research,* **112,** F03S28. http://dx.doi.org/10.1029/2006JF000664

Schröder, D., D.L. Feltham, D. Flocco, and M. Tsamados, 2014: September Arctic sea-ice minimum predicted by spring melt-pond fraction. *Nature Climate Change,* **4,** 353-357. http://dx.doi.org/10.1038/nclimate2203

Schuur, E.A.G., A.D. McGuire, C. Schadel, G. Grosse, J.W. Harden, D.J. Hayes, G. Hugelius, C.D. Koven, P. Kuhry, D.M. Lawrence, S.M. Natali, D. Olefeldt, V.E. Romanovsky, K. Schaefer, M.R. Turetsky, C.C. Treat, and J.E. Vonk, 2015: Climate change and the permafrost carbon feedback. *Nature,* **520,** 171-179. http://dx.doi.org/10.1038/nature14338

FINAL DRAFT

Serinaldi, F., 2016: Can we tell more than we can know? The limits of bivariate drought analyses in the United States. *Stochastic Environmental Research and Risk Assessment,* **30,** 1691-1704. http://dx.doi.org/10.1007/s00477-015-1124-3

Smith, J.A., 1987: Estimating the upper tail of flood frequency distributions. *Water Resources Research,* **23,** 1657-1666. http://dx.doi.org/10.1029/WR023i008p01657

Stranne, C., M. O'Regan, G.R. Dickens, P. Crill, C. Miller, P. Preto, and M. Jakobsson, 2016: Dynamic simulations of potential methane release from East Siberian continental slope sediments. *Geochemistry, Geophysics, Geosystems,* **17,** 872-886. http://dx.doi.org/10.1002/2015GC006119

Stroeve, J., M.M. Holland, W. Meier, T. Scambos, and M. Serreze, 2007: Arctic sea ice decline: Faster than forecast. *Geophysical Research Letters,* **34,** L09501. http://dx.doi.org/10.1029/2007GL029703

Stroeve, J.C., V. Kattsov, A. Barrett, M. Serreze, T. Pavlova, M. Holland, and W.N. Meier, 2012: Trends in Arctic sea ice extent from CMIP5, CMIP3 and observations. *Geophysical Research Letters,* **39,** L16502. http://dx.doi.org/10.1029/2012GL052676

Swain, D.L., D.E. Horton, D. Singh, and N.S. Diffenbaugh, 2016: Trends in atmospheric patterns conducive to seasonal precipitation and temperature extremes in California. *Science Advances,* **2**. http://dx.doi.org/10.1126/sciadv.1501344

Tattersall, I., 2009: Human origins: Out of Africa. *Proceedings of the National Academy of Sciences,* **106,** 16018-16021. http://dx.doi.org/10.1073/pnas.0903207106

Trenberth, K.E., A. Dai, G. van der Schrier, P.D. Jones, J. Barichivich, K.R. Briffa, and J. Sheffield, 2014: Global warming and changes in drought. *Nature Climate Change,* **4,** 17-22. http://dx.doi.org/10.1038/nclimate2067

von der Heydt, A.S., P. Köhler, R.S.W. van de Wal, and H.A. Dijkstra, 2014: On the state dependency of fast feedback processes in (paleo) climate sensitivity. *Geophysical Research Letters,* **41,** 6484-6492. http://dx.doi.org/10.1002/2014GL061121

Wagner, T.J.W. and I. Eisenman, 2015: How climate model complexity influences sea ice stability. *Journal of Climate,* **28,** 3998-4014. http://dx.doi.org/10.1175/JCLI-D-14-00654.1

Woodhouse, C.A. and J.T. Overpeck, 1998: 2000 years of drought variability in the central United States. *Bulletin of the American Meteorological Society,* **79,** 2693-2714. http://dx.doi.org/10.1175/1520-0477(1998)079<2693:YODVIT>2.0.CO;2

FINAL DRAFT

Yin, J. and P.B. Goddard, 2013: Oceanic control of sea level rise patterns along the East Coast of the United States. *Geophysical Research Letters,* **40,** 5514-5520. http://dx.doi.org/10.1002/2013GL057992

Zscheischler, J., M. Reichstein, J. von Buttlar, M. Mu, J.T. Randerson, and M.D. Mahecha, 2014: Carbon cycle extremes during the 21st century in CMIP5 models: Future evolution and attribution to climatic drivers. *Geophysical Research Letters,* **41,** 8853-8861. http://dx.doi.org/10.1002/2014GL062409

Zwiers, F.W., L.V. Alexander, G.C. Hegerl, T.R. Knutson, J.P. Kossin, P. Naveau, N. Nicholls, C. Schär, S.I. Seneviratne, and X. Zhang, 2013: Climate extremes: Challenges in estimating and understanding recent changes in the frequency and intensity of extreme climate and weather events. *Climate Science for Serving Society: Research, Modeling and Prediction Priorities*. Asrar, G.R. and J.W. Hurrell, Eds. Springer Netherlands, Dordrecht, 339-389. http://dx.doi.org/10.1007/978-94-007-6692-1_13

FINAL DRAFT

Appendix A. Observational Datasets Used in Climate Studies

Climate Datasets

Observations, including those from satellites, mobile platforms, field campaigns and ground-based networks, provide the basis of knowledge on many temporal and spatial scales for understanding the changes occurring in Earth's climate system. These observations also inform the development, calibration, and evaluation of numerical models of the physics, chemistry, and biology being used in analyzing the past changes in climate and for making future projections. As all observational data collected by support from Federal agencies are required to be made available free of charge with machine readable metadata, everyone can access these products for their personal analysis and research and for informing decisions. Many of these datasets are accessible through web services.

Many long-running observations worldwide have provided us with long-term records necessary for investigating climate change and its impacts. These include important climate variables such as surface temperature, sea ice extent, sea level rise, and streamflow. Perhaps one of the most iconic climatic datasets, that of atmospheric carbon dioxide measured at Mauna Loa, HI, has been recorded since the 1950s. The U.S. and Global Historical Climatology Networks have been used as authoritative sources of recorded surface temperature increases, with some stations having continuous records going back many decades. Satellite radar altimetry data (for example, TOPEX/JASON1, 2 satellite data) have informed the development of the University of Colorado's 20+ year record of global sea level changes. In the United States, the USGS (U.S. Geological Survey) National Water Information System contains, in some instances, decades of daily streamflow records which inform not only climate but land-use studies as well. The U.S. Bureau of Reclamation and U.S. Army Corp of Engineers have maintained data about reservoir levels for decades where applicable. Of course, datasets based on shorter-term observations are used in conjunction with longer-term records for climate study, and the U.S. programs are aimed at providing continuous data records. Methods have been developed and applied to process these data so as to account for biases, collection method, earth surface geometry, the urban heat island effect, station relocations, and uncertainty (e.g., see Vose et al. 2012; Rennie et al. 2014; Karl et al. 2015).

Even observations not designed for climate have informed climate research. These include ship logs containing descriptions of ice extent, readings of temperature and precipitation provided in newspapers, and harvest records. Today, observations recorded both manually and in automated fashions inform research and are used in climate studies.

The U.S Global Change Research Program (USGCRP) has established the Global Change Information System (GCIS) to better coordinate and integrate the use of federal information products on changes in the global environment and the implications of those changes for society. The GCIS is an open-source, web-based resource for traceable global change data, information,

FINAL DRAFT

and products. Designed for use by scientists, decision makers, and the public, the GCIS provides coordinated links to a select group of information products produced, maintained, and disseminated by government agencies and organizations. Currently the GCIS is aimed at the datasets used in Third National Climate Assessment (NCA3) and the USGCRP Climate and Health Assessment. It is to be updated for the datasets used in this report (The Climate Science Special Report, CSSR).

Satellite Temperature Datasets

A special look is given to the satellite temperature datasets because of controversies associated with these datasets. Satellite-borne microwave sounders such as the Microwave Sounding Unit (MSU) and Advanced Microwave Sounding Unit (AMSU) instruments operating on NOAA polar-orbiting platforms make measurements of the temperature of thick layers of the atmosphere with near global coverage. Because the long-term data record requires the piecing together of measurements made by 16 different satellites, accurate instrument intercalibration is of critical importance. Over the mission lifetime of most satellites, the instruments drift in both calibration and local measurement time. Adjustments to counter the effects of these drifts need to be developed and applied before a long-term record can be assembled. For tropospheric measurements, the most challenging of these adjustments is the adjustment for drifting measurement time, which requires knowledge of the diurnal cycle in both atmospheric and surface temperature. Current versions of the sounder-based datasets account for the diurnal cycle by either using diurnal cycles deduced from model output (Mears and Wentz 2009; Zou et al. 2009) or by attempting to derive the diurnal cycle from the satellite measurements themselves (an approach plagued by sampling issues and possible calibration drifts) (Christy et al. 2003; Po-Chedley et al. 2015). Recently a hybrid approach has been developed, RSS Version 4.0 (Mears and Wentz 2016), that results in an increased warming signal relative to the other approaches, particularly since 2000. Each of these methods has strengths and weaknesses, but neither has sufficient accuracy to construct an unassailable long-term record of atmospheric temperature change. The resulting datasets show a greater spread in decadal-scale trends than do the surface temperature datasets for the same period, suggesting that they may be less reliable. In Figure A.1 shows annual time series for the global mean tropospheric temperature for some recent versions of the satellite datasets. These data have been adjusted to remove the influence of stratospheric cooling (Fu and Johanson 2005). Linear trend values are shown in Table A.1.

[INSERT FIGURE A.1 AND TABLE A.1 HERE]

FINAL DRAFT

TABLE

Table A.1. Global Trends in Temperature Total Troposphere (TTT) since 1979 and 2000 (in °F per decade).

Dataset	Trend (1979–2015) (°F/Decade)	Trend (2000–2015) (°F/Decade)
RSS V4.0	0.301	0.198
UAH V6Beta5	0.196	0.141
STAR V4.0	0.316	0.157
RSS V3.3	0.208	0.105
UAH V5.6	0.176	0.211
STAR V3.0	0.286	0.061

FIGURE

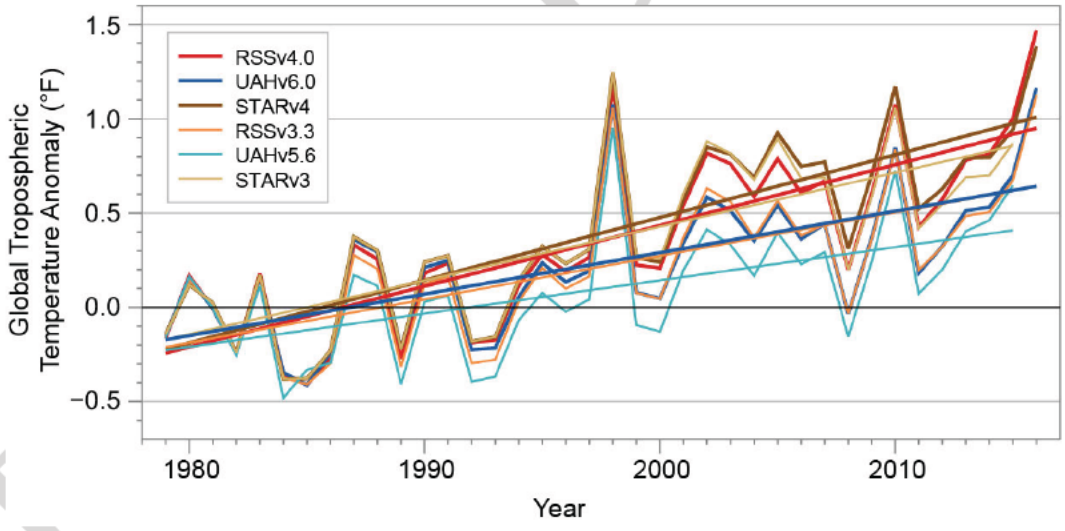

Figure A.1. Annual global (80°S–80°N) mean time series of tropospheric temperature for five recent datasets (see below). Each time series is adjusted so the mean value for the first three years is zero. This accentuates the differences in the long-term changes between the datasets. (Figure source: Remote Sensing Systems).

DRAFT

DATA SOURCES:

All Satellite Data are “Temperature Total Troposphere” time series calculated from TMT and TLS

(1.1*TMT) - (0.1*TLS). This combination reduces the effect of the lower stratosphere on the tropospheric temperature. (Fu, Qiang et al. "Contribution of stratospheric cooling to satellite-inferred tropospheric temperature trends." *Nature* 429.6987 (2004): 55-58.)

UAH. UAH Version 6.0Beta5. Yearly (yyyy) text files of TMT and TLS are available from

http://vortex.nsstc.uah.edu/data/msu/v6.0beta/tmt/tmtmonamg.yyyy_6.0beta5

http://vortex.nsstc.uah.edu/data/msu/v6.0beta/tls/tlsmonamg.yyyy_6.0beta5

Downloaded 5/15/2016.

UAH. UAH Version 5.6. Yearly (yyyy) text files of TMT and TLS are available from

http://vortex.nsstc.uah.edu/data/msu/t2/

http://vortex.nsstc.uah.edu/data/msu/t4/

Downloaded 5/15/2016.

RSS. RSS Version 4.0. ftp://ftp.remss.com/msu/data/netcdf/RSS_Tb_Anom_Maps_ch_TTT_V4_0.nc

Downloaded 5/15/2016

RSS. RSS Version 3.3. ftp://ftp.remss.com/msu/data/netcdf/RSS_Tb_Anom_Maps_ch_TTT_V3.3.nc

Downloaded 5/15/2016

NOAA STAR. Star Version 3.0.

ftp://ftp.star.nesdis.noaa.gov/pub/smcd/emb/mscat/data/MSU_AMSU_v3.0/Monthly_Atmospheric_Layer_Mean_Temperature/Merged_Deep-Layer_Temperature/NESDIS-STAR_TCDR_MSU-AMSUA_V03R00_TMT_S197811_E201604_C20160513.nc

ftp://ftp.star.nesdis.noaa.gov/pub/smcd/emb/mscat/data/MSU_AMSU_v3.0/Monthly_Atmospheric_Layer_Mean_Temperature/Merged_Deep-Layer_Temperature/NESDIS-STAR_TCDR_MSU-AMSUA_V03R00_TLS_S197811_E201604_C20160513.nc

Downloaded 5/18/2016.

FINAL DRAFT

REFERENCES

Christy, J.R., R.W. Spencer, W.B. Norris, W.D. Braswell, and D.E. Parker, 2003: Error estimates of version 5.0 of MSU–AMSU bulk atmospheric temperatures. *Journal of Atmospheric and Oceanic Technology,* **20,** 613-629. http://dx.doi.org/10.1175/1520-0426(2003)20<613:EEOVOM>2.0.CO;2

Fu, Q. and C.M. Johanson, 2005: Satellite-derived vertical dependence of tropical tropospheric temperature trends. *Geophysical Research Letters,* **32**. http://dx.doi.org/10.1029/2004GL022266

Karl, T.R., A. Arguez, B. Huang, J.H. Lawrimore, J.R. McMahon, M.J. Menne, T.C. Peterson, R.S. Vose, and H.-M. Zhang, 2015: Possible artifacts of data biases in the recent global surface warming hiatus. *Science,* **348,** 1469-1472. http://dx.doi.org/10.1126/science.aaa5632

Mears, C.A. and F.J. Wentz, 2009: Construction of the Remote Sensing Systems V3.2 atmospheric temperature records from the MSU and AMSU microwave sounders. *Journal of Atmospheric and Oceanic Technology,* **26,** 1040-1056. http://dx.doi.org/10.1175/2008JTECHA1176.1

Mears, C.A. and F.J. Wentz, 2016: Sensitivity of satellite-derived tropospheric temperature trends to the diurnal cycle adjustment. *Journal of Climate,* **29,** 3629-3646. http://dx.doi.org/10.1175/JCLI-D-15-0744.1

Po-Chedley, S., T.J. Thorsen, and Q. Fu, 2015: Removing diurnal cycle contamination in satellite-derived tropospheric temperatures: Understanding tropical tropospheric trend discrepancies. *Journal of Climate,* **28,** 2274-2290. http://dx.doi.org/10.1175/JCLI-D-13-00767.1

Rennie, J.J., J.H. Lawrimore, B.E. Gleason, P.W. Thorne, C.P. Morice, M.J. Menne, C.N. Williams, W.G. de Almeida, J.R. Christy, M. Flannery, M. Ishihara, K. Kamiguchi, A.M.G. Klein-Tank, A. Mhanda, D.H. Lister, V. Razuvaev, M. Renom, M. Rusticucci, J. Tandy, S.J. Worley, V. Venema, W. Angel, M. Brunet, B. Dattore, H. Diamond, M.A. Lazzara, F. Le Blancq, J. Luterbacher, H. Mächel, J. Revadekar, R.S. Vose, and X. Yin, 2014: The international surface temperature initiative global land surface databank: monthly temperature data release description and methods. *Geoscience Data Journal,* **1,** 75-102. http://dx.doi.org/10.1002/gdj3.8 http://dx.doi.org/10.1002/gdj3.8

Vose, R.S., D. Arndt, V.F. Banzon, D.R. Easterling, B. Gleason, B. Huang, E. Kearns, J.H. Lawrimore, M.J. Menne, T.C. Peterson, R.W. Reynolds, T.M. Smith, C.N. Williams, and D.L. Wuertz, 2012: NOAA's Merged Land-Ocean Surface Temperature Analysis. *Bulletin of the American Meteorological Society,* **93,** 1677-1685. http://dx.doi.org/10.1175/BAMS-D-11-00241.1

FINAL DRAFT

Zou, C.-Z., M. Gao, and M.D. Goldberg, 2009: Error structure and atmospheric temperature trends in observations from the microwave sounding unit. *Journal of Climate,* **22,** 1661-1681. http://dx.doi.org/10.1175/2008JCLI2233.1

FINAL DRAFT

Appendix B. Weighting Strategy for the Fourth National Climate Assessment

Introduction

This document briefly describes a weighting strategy for use with the Climate Model Intercomparison Project, Phase 5 (CMIP5) multimodel archive in the 4th National Climate Assessment. This approach considers both skill in the climatological performance of models over North America and the interdependency of models arising from common parameterizations or tuning practices. The method exploits information relating to the climatological mean state of a number of projection-relevant variables as well as long-term metrics representing long-term statistics of weather extremes. The weights, once computed, can be used to simply compute weighted mean and significance information from an ensemble containing multiple initial condition members from co-dependent models of varying skill.

Our methodology is based on the concepts outlined in Sanderson et al. (2015), and the specific application to the Fourth National Climate Assessment (NCA4) is also described in that paper. The approach produces a single set of model weights that can be used to combine projections into a weighted mean result, with significance estimates which also treat the weighting appropriately.

The method, ideally, would seek to have two fundamental characteristics:

- If a duplicate of one ensemble member is added to the archive, the resulting mean and significance estimate for future change computed from the ensemble should not change.
- If a demonstrably unphysical model is added to the archive, the resulting mean and significance estimates should also not change.

Method

The analysis requires an assessment of both model skill and an estimate of intermodel relationships— for which intermodel root mean square difference is taken as a proxy. The model and observational data used here is for the contiguous United States (CONUS), and most of Canada, using high-resolution data where available. Intermodel distances are computed as simple root mean square differences. Data is derived from a number of mean state fields and a number of fields that represent extreme behavior—these are listed in Table B.1. All fields are masked to only include information from CONUS/Canada.

FINAL DRAFT

The root mean square error (RMSE) between observations and each model can be used to produce an overall ranking for model simulations of the North American climate. Figure B.1 shows how this metric is influenced by different component variables.

[INSERT FIGURES B.1 AND B.2 HERE]

Models are downweighted for poor skill if their multivariate combined error is significantly greater than a "skill radius" term, which is a free parameter of the approach. The calibration of this parameter is determined through a perfect model study (Sanderson et al. 2016b). A pairwise distance matrix is computed to assess intermodel RMSE values for each model pair in the archive, and a model is downweighted for dependency if there exists another model with a pairwise distance to the original model significantly smaller than a "similarity radius." This is the second parameter of the approach, which is calibrated by considering known relationships within the archive. The resulting skill and independence weights are multiplied to give an overall "combined" weight—illustrated in Figure B.2 for the CMIP5 ensemble and listed in Table B.2.

The weights are used in the Climate Science Special Report (CSSR) to produce weighted mean and significance maps of future change, where the following protocol is used:

- Stippling—large changes, where the weighted multimodel average change is greater than double the standard deviation of the 20-year mean from control simulations runs, and 90% of the weight corresponds to changes of the same sign.
- Hatching—No significant change, where the weighted multimodel average change is less than the standard deviation of the 20-year means from control simulations runs.
- Whited out—Inconclusive, where the weighted multimodel average change is greater than double the standard deviation of the 20-year mean from control runs and less than 90% of the weight corresponds to changes of the same sign.

We illustrate the application of this method to future projections of precipitation change under RCP8.5 in Figure B.3. The weights used in the report are chosen to be conservative, minimizing the risk of overconfidence and maximizing out-of-sample predictive skill for future projections. This results (as in Figure B.3) in only modest differences in the weighted and unweighted maps. It is shown in Sanderson et al. (2016b) that a more aggressive weighting strategy, or one focused on a particular variable, tends to exhibit a stronger constraint on future change relative to the unweighted case. It is also notable that tradeoffs exist between skill and replication in the archive (evident in Figure B.2), such that the weighting for both skill and uniqueness has a compensating effect. As such, mean projections using the CMIP5 ensemble are not strongly influenced by the weighting. However, the establishment of the weighting strategy used in the CSSR

FINAL DRAFT

provides some insurance against a potential case in future assessments where there is a highly replicated, but poorly performing model.

[INSERT FIGURE B.3 HERE]

FINAL DRAFT

TABLES

Table B.1: Observational Datasets Used as Observations.

Field	Description	Source	Reference	Years
TS	Surface Temperature (seasonal)	Livneh,Hutchinson	(Hopkinson et al. 2012; Hutchinson et al. 2009; Livneh et al. 2013)	1950-2011
PR	Mean Precipitation (seasonal)	Livneh,Hutchinson	(Hopkinson et al. 2012; Hutchinson et al. 2009; Livneh et al. 2013)	1950-2011
RSUT	TOA Shortwave Flux (seasonal)	CERES-EBAF	(NASA 2011)	2000-2005
RLUT	TOA Longwave Flux (seasonal)	CERES-EBAF	(NASA 2011)	2000-2005
T	Vertical Temperature Profile (seasonal)	AIRS*	(Aumann et al. 2003)	2002-2010
RH	Vertical Humidity Profile (seasonal)	AIRS	(Aumann et al. 2003)	2002-2010
PSL	Surface Pressure (seasonal)	ERA-40	(Uppala et al. 2005)	1970-2000
Tnn	Coldest Night	Livneh,Hutchinson	(Hopkinson et al. 2012; Hutchinson et al. 2009; Livneh et al. 2013)	1950-2011
Txn	Coldest Day	Livneh,Hutchinson	(Hopkinson et al. 2012; Hutchinson et al. 2009; Livneh et al. 2013)	1950-2011
Tnx	Warmest Night	Livneh,Hutchinson	(Hopkinson et al. 2012; Hutchinson et al. 2009; Livneh et al. 2013)	1950-2011
Txx	Warmest day	Livneh,Hutchinson	(Hopkinson et al. 2012; Hutchinson et al. 2009; Livneh et al. 2013)	1950-2011
rx5day	seasonal max. 5-day total precip.	Livneh,Hutchinson	(Hopkinson et al. 2012; Hutchinson et al. 2009; Livneh et al. 2013)	1950-2011

FINAL DRAFT

1 **Table B.2:** Uniqueness, Skill and Combined weights for CMIP5

	Uniqueness weight	Skill Weight	Combined
ACCESS1-0	0.60	1.69	1.02
ACCESS1-3	0.78	1.40	1.09
BNU-ESM	0.88	0.77	0.68
CCSM4	0.43	1.57	0.68
CESM1-BGC	0.44	1.46	0.64
CESM1-CAM5	0.72	1.80	1.30
CESM1-FASTCHEM	0.76	0.50	0.38
CMCC-CESM	0.98	0.36	0.35
CMCC-CM	0.89	1.21	1.07
CMCC-CMS	0.59	1.23	0.73
CNRM-CM5	0.94	1.08	1.01
CSIRO-Mk3-6-0	0.95	0.77	0.74
CanESM2	0.97	0.65	0.63
FGOALS-g2	0.97	0.39	0.38
GFDL-CM3	0.81	1.18	0.95
GFDL-ESM2G	0.74	0.59	0.44
GFDL-ESM2M	0.72	0.60	0.43
GISS-E2-H-p1	0.38	0.74	0.28
GISS-E2-H-p2	0.38	0.69	0.26
GISS-E2-R-p1	0.38	0.97	0.37
GISS-E2-R-p2	0.37	0.89	0.33
HadCM3	0.98	0.89	0.87
HadGEM2-AO	0.52	1.19	0.62
HadGEM2-CC	0.50	1.21	0.60
HadGEM2-ES	0.43	1.40	0.61
IPSL-CM5A-LR	0.79	0.92	0.72
IPSL-CM5A-MR	0.83	0.99	0.82
IPSL-CM5B-LR	0.92	0.63	0.58
MIROC-ESM	0.54	0.28	0.15
MIROC-ESM-CHEM	0.54	0.32	0.17
MIROC4h	0.97	0.73	0.71
MIROC5	0.89	1.24	1.11
MPI-ESM-LR	0.35	1.38	0.49
MPI-ESM-MR	0.38	1.37	0.52
MPI-ESM-P	0.36	1.54	0.56
MRI-CGCM3	0.51	1.35	0.68
MRI-ESM1	0.51	1.31	0.67
NorESM1-M	0.83	1.06	0.88
bcc-csm1-1	0.88	0.62	0.55
bcc-csm1-1-m	0.90	0.89	0.80
inmcm4	0.95	1.13	1.08

2

FINAL DRAFT

FIGURES

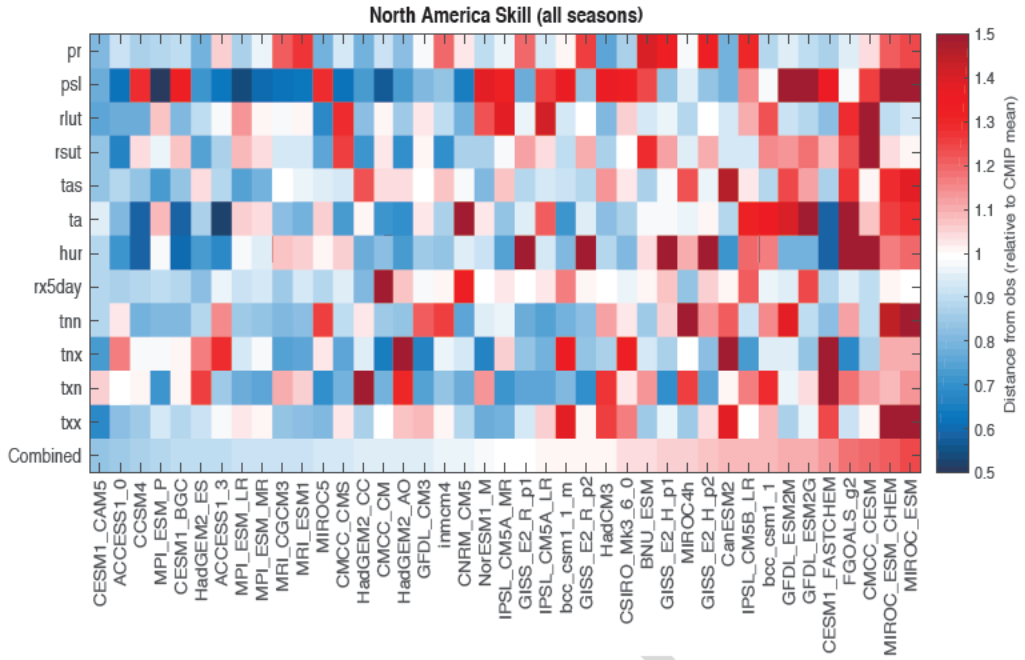

Figure B.1: A graphical representation of the intermodel distance matrix for CMIP5 and a set of observed values. Each row and column represents a single climate model (or observation). All scores are aggregated over seasons (individual seasons are not shown). Each box represents a pairwise distance, where warm (red) colors indicate a greater distance. Distances are measured as a fraction of the mean intermodel distance in the CMIP5 ensemble. (Figure source: Sanderson et al. 2016b).

FINAL DRAFT

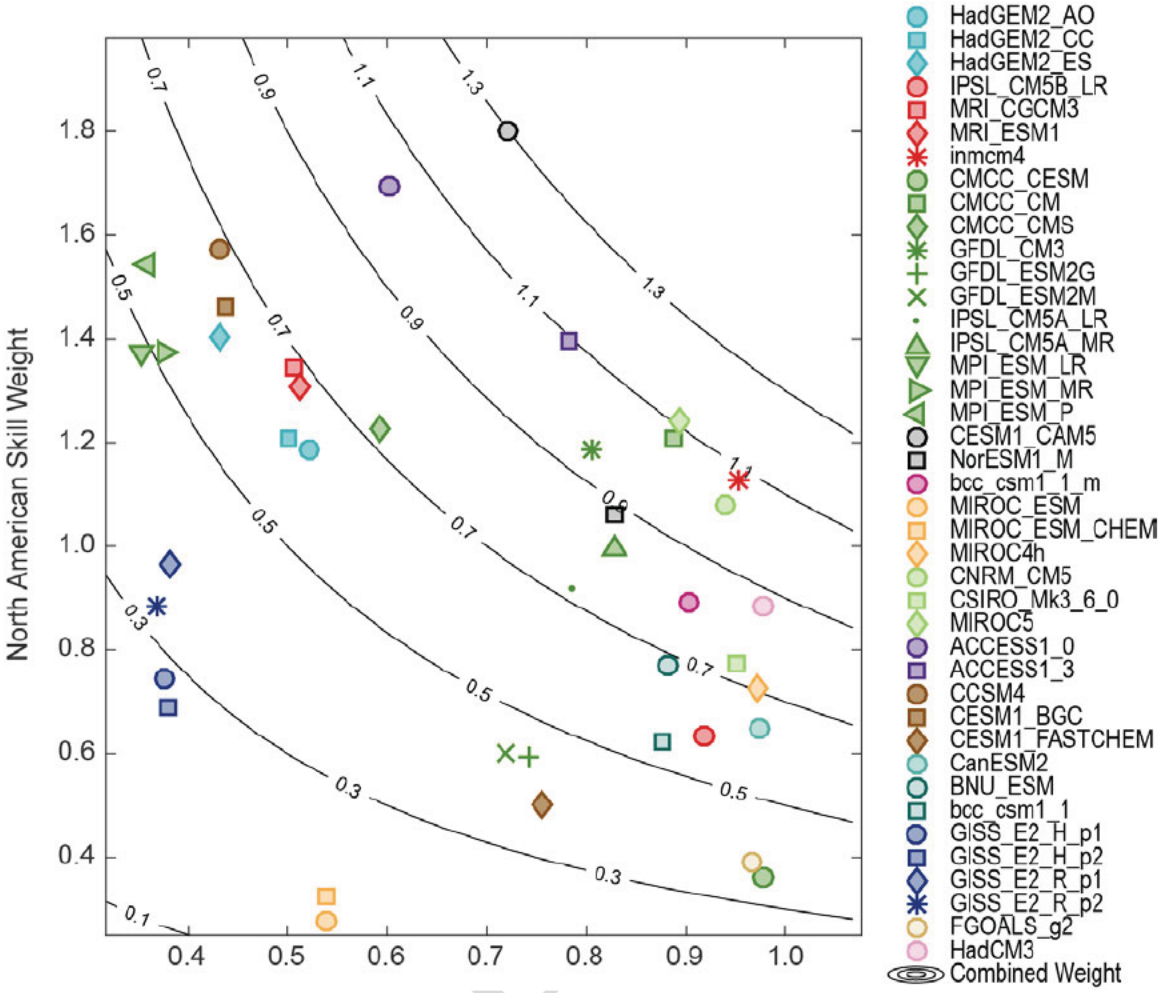

Figure B.2: Model skill and independence weights for the CMIP5 archive evaluated over the North American domain. Contours show the overall weighting, which is the product of the two individual weights. (Figure source: Sanderson et al. 2016b).

FINAL

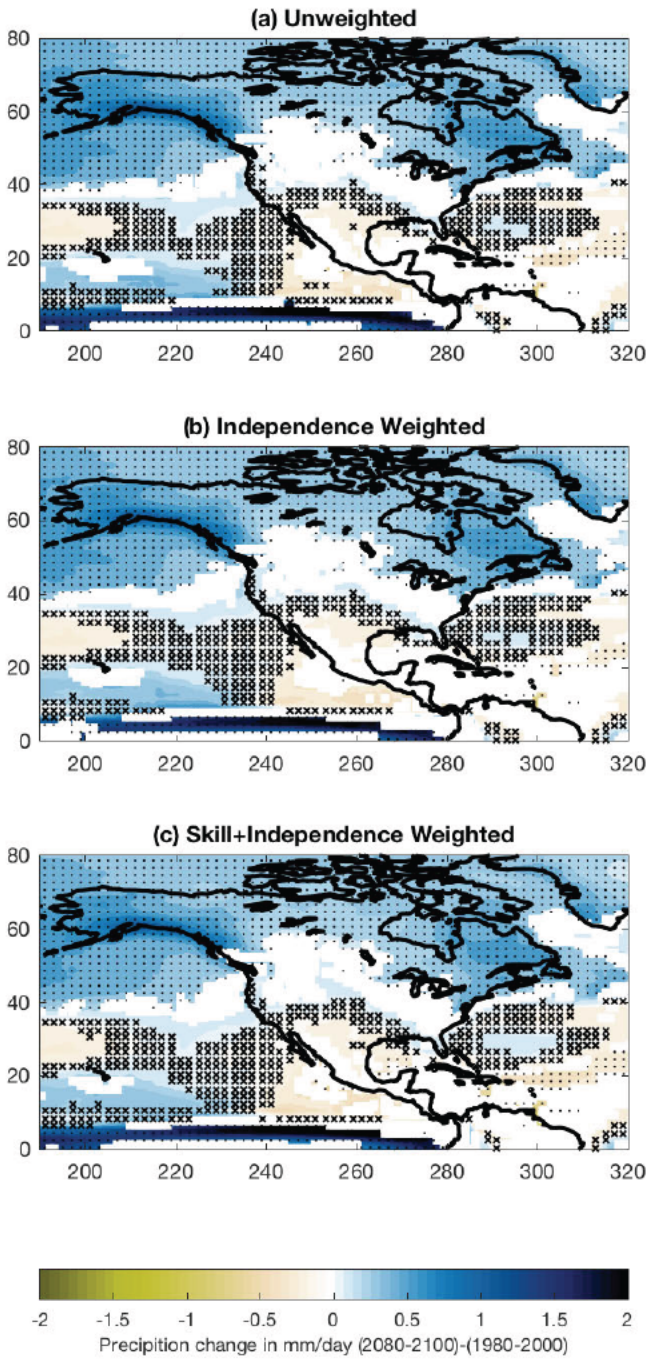

Figure B.3: Projections of precipitation change over North America in 2080–2100, relative to 1980–2000 under RCP8.5. (a) shows the simple unweighted CMIP5 multi-model average, using the significance methodology from (IPCC 2013), (b) Shows the weighted results as outlined in Section 3 for models weighted by uniqueness only, and (c) shows weighted results for models weighted by both uniqueness and skill. (Figure source: Sanderson et al. 2016b).

REFERENCES

Aumann, H.H., M.T. Chahine, C. Gautier, M.D. Goldberg, E. Kalnay, L.M. McMillin, H. Revercomb, P.W. Rosenkranz, W.L. Smith, D.H. Staelin, L.L. Strow, and J. Susskind, 2003: AIRS/AMSU/HSB on the Aqua mission: Design, science objectives, data products, and processing systems. *IEEE Transactions on Geoscience and Remote Sensing,* **41,** 253-264. http://dx.doi.org/10.1109/TGRS.2002.808356

Hopkinson, R.F., M.F. Hutchinson, D.W. McKenney, E.J. Milewska, and P. Papadopol, 2012: Optimizing Input Data for Gridding Climate Normals for Canada. *Journal of Applied Meteorology and Climatology,* **51,** 1508-1518. http://dx.doi.org/10.1175/JAMC-D-12-018.1

Hutchinson, M.F., D.W. McKenney, K. Lawrence, J.H. Pedlar, R.F. Hopkinson, E. Milewska, and P. Papadopol, 2009: Development and Testing of Canada-Wide Interpolated Spatial Models of Daily Minimum–Maximum Temperature and Precipitation for 1961–2003. *Journal of Applied Meteorology and Climatology,* **48,** 725-741. http://dx.doi.org/10.1175/2008JAMC1979.1

IPCC, 2013: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK and New York, NY, 1535 pp. http://dx.doi.org/10.1017/CBO9781107415324 www.climatechange2013.org

Livneh, B., E.A. Rosenberg, C. Lin, B. Nijssen, V. Mishra, K.M. Andreadis, E.P. Maurer, and D.P. Lettenmaier, 2013: A Long-Term Hydrologically Based Dataset of Land Surface Fluxes and States for the Conterminous United States: Update and Extensions. *Journal of Climate,* **26,** 9384-9392. http://dx.doi.org/10.1175/JCLI-D-12-00508.1

NASA, 2011: CERES EBAF Data Sets. https://ceres.larc.nasa.gov/products.php?product=EBAF-TOA

Sanderson, B.M., R. Knutti, and P. Caldwell, 2015: A Representative Democracy to Reduce Interdependency in a Multimodel Ensemble. *Journal of Climate,* **28,** 5171-5194. http://dx.doi.org/10.1175/JCLI-D-14-00362.1

Sanderson, B.M., M. Wehner, and R. Knutti, 2016b: Skill and Independence weighting for multi-model Assessment. *Geoscientific Model Development*. https://doi.org/10.5194/gmd-10-2379-2017

Uppala, S.M., P.W. KÅllberg, A.J. Simmons, U. Andrae, V.D.C. Bechtold, M. Fiorino, J.K. Gibson, J. Haseler, A. Hernandez, G.A. Kelly, X. Li, K. Onogi, S. Saarinen, N. Sokka, R.P. Allan, E. Andersson, K. Arpe, M.A. Balmaseda, A.C.M. Beljaars, L.V.D.

FINAL DRAFT

1 Berg, J. Bidlot, N. Bormann, S. Caires, F. Chevallier, A. Dethof, M. Dragosavac, M.
2 Fisher, M. Fuentes, S. Hagemann, E. Hólm, B.J. Hoskins, L. Isaksen, P.A.E.M.
3 Janssen, R. Jenne, A.P. McNally, J.F. Mahfouf, J.J. Morcrette, N.A. Rayner, R.W.
4 Saunders, P. Simon, A. Sterl, K.E. Trenberth, A. Untch, D. Vasiljevic, P. Viterbo, and
5 J. Woollen, 2005: The ERA-40 re-analysis. *Quarterly Journal of the Royal*
6 *Meteorological Society,* **131,** 2961-3012. http://dx.doi.org/10.1256/qj.04.176

FINAL DRAFT

Appendix C. Detection and Attribution Methodologies Overview

C.1 Introduction and Conceptual Framework

In this appendix, we present a brief overview of the methodologies and methodological issues for detection and attribution of climate change. Attributing an observed change or an event partly to a causal factor (such as anthropogenic climate forcing) normally requires that the change first be detectable (Hegerl et al. 2010). A *detectable* observed change is one which is determined to be highly unlikely to occur (less than about a 10% chance) due to internal variability alone, without necessarily being ascribed to a causal factor. An *attributable* change refers to a change in which the relative contribution of causal factors has been evaluated along with an assignment of statistical confidence (e.g., Bindoff et al. 2013; Hegerl et al. 2010).

As outlined in Bindoff et al. (2013), the conceptual framework for most detection and attribution studies consists of four elements: 1) relevant observations; 2) the estimated time history of relevant climate forcings (such as greenhouse gas concentrations or volcanic activity); 3) a modeled estimate of the impact of the climate forcings on the climate variables of interest; and 4) an estimate of the internal (unforced) variability of the climate variables of interest—that is, the changes that can occur due to natural unforced variations of the ocean, atmosphere, land, cryosphere, and other elements of the climate system in the absence of external forcings. The four elements above can be used together with a detection and attribution framework to assess possible causes of observed changes.

C.2 Fingerprint-Based Methods

A key methodological approach for detection and attribution is the regression-based "fingerprint" method (e.g., Hasselmann 1997; Allen and Stott 2003; Hegerl et al. 2007; Hegerl and Zwiers 2011; Bindoff et al. 2013), where observed changes are regressed onto a model-generated response pattern to a particular forcing (or set of forcings), and regression scaling factors are obtained. When a scaling factor for a forcing pattern is determined to be significantly different from zero, a detectable change has been identified. If the uncertainty bars on the scaling factor encompass unity, the observed change is consistent with the modeled response, and the observed change can be attributed, at least in part, to the associated forcing agent, according this methodology. Zwiers et al. (2011) showed how detection and attribution methods could be applied to the problem of changes in daily temperature extremes at the regional scale by using a generalized extreme value (GEV) approach. In their approach, a time-evolving pattern of GEV location parameters (i.e., "fingerprint") from models is fit to the observed extremes as a means of detecting and attributing changes in the extremes to certain forcing sets (for example, anthropogenic forcings).

A recent development in detection/attribution methodology (Ribes et al. 2017) uses hypothesis testing and an additive decomposition approach rather than linear regression of patterns. The new

FINAL DRAFT

approach makes use of the magnitudes of responses from the models rather than using the model patterns and deriving the scaling factors (magnitudes of responses) from regression. The new method, in a first application, gives very similar attributable anthropogenic warming estimates to the earlier methods as reported in Bindoff et al. (2013) and shown in Figure 3.2. Some further methodological developments for performing optimal fingerprint detection and attribution studies are proposed in Hannart (2016), who, for example, focuses on the possible use of raw data in analyses without the use of dimensional reductions, such as projecting the data onto a limited number of basis functions, such as spherical harmonics, before analysis.

C.3 Non-Fingerprint Based Methods

A simpler detection/attribution/consistency calculation, which does not involve regression and pattern scaling, compares observed and simulated time series to assess whether observations are consistent with natural variability simulations or with simulations forced by both natural and anthropogenic forcing agents (Knutson et al. 2013; van Oldenborgh et al. 2013). Cases where observations are inconsistent with model simulations using natural forcing only (a detectable change), while also being consistent with models that incorporate both anthropogenic and natural forcings, are interpreted as having an attributable anthropogenic contribution, subject to caveats regarding uncertainties in observations, climate forcings, modeled responses, and simulated internal climate variability. This simpler method is useful for assessing trends over smaller regions such as sub-regions of the United States (see the example given in Figure 6.5 for regional surface temperature trends).

Delsole et al. (2011) introduced a method of identifying internal (unforced) variability in climate data by decomposing variables by timescale, using a measure of their predictability. They found that while such internal variability could contribute to surface temperature trends of 30-years' duration or less, and could be responsible for the accelerated global warming during 1977–2008 compared to earlier decades, the strong (approximately 0.8°C, or 1.4°F) warming trend seen in observations over the past century was not explainable by such internal variability. Constructed circulation analogs (van den Dool et al. 2003; Deser et al. 2016) is a method used to identify the part of observed surface temperature changes that is due to atmospheric circulation changes alone.

The timescale by which climate change signals will become detectable in various regions is a question of interest in detection and attribution studies, and methods of estimating this have been developed and applied (e.g., Mahlstein et al. 2011; Deser et al. 2012b). These studies illustrate how natural variability can obscure forced climate signals for decades, particularly for smaller (less than continental) space scales.

Other examples of detection and attribution methods include the use of multiple linear regression with energy balance models (e.g., Canty et al. 2013) and Granger causality tests (e.g., Stern and Kaufmann 2014). These are typically attempting to relate forcing time series, such as the

FINAL DRAFT

historical record of atmospheric CO_2 since 1860, to a climate response measure, such as global mean temperature or ocean heat content, but without using a full coupled climate model to explicitly estimate the response of the climate system to forcing (or the spatial pattern of the response to forcing). Granger causality, for example, explores the lead–lag relationships between different variables to infer causal relationships between them, and attempts to control for any influence of a third variable that may be linked to the other two variables in question.

C.4. Multistep Attribution and Attribution without Detection

A growing number of climate change and extreme event attribution studies use a *multistep attribution* approach (Hegerl et al. 2010), based on attribution of a change in climate conditions that are closely related to the variable or event of interest. In the multistep approach, an observed change in the variable of interest is attributed to a change in climate or other environmental conditions, and then the changes in the climate or environmental conditions are separately attributed to an external forcing, such as anthropogenic emissions of greenhouse gases. As an example, some attribution statements for phenomena such as droughts or hurricane activity—where there are not necessarily detectable trends in occurrence of the phenomenon itself—are based on models and on detected changes in related variables such as surface temperature, as well as an understanding of the relevant physical processes linking surface temperatures to hurricanes or drought. For example, some studies of the recent California drought (e.g., Mao et al. 2015; Williams et al. 2015) attribute a fraction of the event to anthropogenic warming or to long-term warming based on modeling or statistical analysis, although without claiming that there was a detectable change in the drought frequency or magnitude.

The multistep approach and model simulations are both methods that, in principle, can allow for attribution of a climate change or a change in the likelihood of occurrence of an event to a causal factor without necessarily detecting a significant change in the occurrence rate of the phenomenon or event itself (though in some cases, there may also be a detectable change in the variable of interest). For example, Murakami et al. (2015) used model simulations to conclude that the very active hurricane season observed near Hawai‘i in 2014 was at least partially attributable to anthropogenic influence; they also show that there is no clear long-term detectable trend in historical hurricane occurrence near Hawai‘i in available observations. If an attribution statement is made where there is not a detectable change in the phenomenon itself (for example, hurricane frequency or drought frequency) then this statement is an example of *attribution without detection*. Such an attribution without detection can be distinguished from a conventional single-step attribution (for example, global mean surface temperature) where in the latter case there is a detectable change in the variable of interest (or the scaling factor for a forcing pattern is significantly different from zero in observations) and attribution of the changes in that variable to specific external forcing agents. Regardless of whether a single-step or multistep attribution approach is used, or whether there is a detectable change in the variable of interest, attribution

FINAL DRAFT

statements with relatively higher levels of confidence are underpinned by a thorough understanding of the physical processes involved.

There are reasons why attribution without detection statements can be appropriate, despite the lower confidence typically associated with such statements as compared to attribution statements that are supported by detection of a change in the phenomenon itself. For example, an event of interest may be so rare that a trend analysis for similar events is not practical. Including attribution without detection events in the analysis of climate change impacts reduces the chances of a false negative, that is, incorrectly concluding that climate change had no influence on a given extreme events (Anderegg et al. 2014) in a case where it did have an influence. However, avoiding this type of error through attribution without detection comes at the risk of increasing the rate of false positives, where one incorrectly concludes that anthropogenic climate change had a certain type of influence on an extreme event when in fact it did not have such an influence (see Box 3.1).

C.5 Extreme Event Attribution Methodologies

Since the release of the Intergovernmental Panel on Climate Change's Fifth Assessment Report (IPCC AR5) and the Third National Climate Assessment (NCA3; Melillo et al. 2014), there have been further advances in the science of detection and attribution of climate change. An emerging area in the science of detection and attribution is the attribution of extreme weather and climate events (NAS 2016; Stott 2016; Easterling et al. 2016). According to Hulme (2014), there are four general types of attribution methods that are applied in practice: physical reasoning, statistical analysis of time series, fraction of attributable risk (FAR) estimation, and the philosophical argument that there are no longer any purely natural weather events. As discussed in a recent National Academy of Sciences report (NAS 2016), possible anthropogenic influence on an extreme event can be assessed using a risk-based approach, which examines whether the odds of occurrence of a type of extreme event have changed, or through an ingredients-based or conditional attribution approach.

In the risk-based approach (Stott et al. 2004; Hulme 2014; NAS 2016), one typically uses a model to estimate the probability (p) of occurrence of a weather or climate event within two climate states: one state with anthropogenic influence (where the probability is p_1) and the other state without anthropogenic influence (where the probability is p_0). Then the ratio (p_1/p_0) describes how much more or less likely the event is in the modeled climate with anthropogenic influence compared to a modeled hypothetical climate without anthropogenic influences. Another common metric used with this approach is the fraction of attributable risk (FAR), defined as FAR = $1–(p_0/p_1)$. Further refinements on such an approach using causal theory are discussed in Hannart et al. (2016b).

In the conditional or ingredients-based approach (Trenberth et al. 2015; Shepherd 2016; Horton et al. 2016; NAS 2016), an investigator may look for changes in occurrence of atmospheric

FINAL DRAFT

circulation and weather patterns relevant to the extreme event, or at the impact of certain environmental changes (for example, greater atmospheric moisture) on the character of an extreme event. Conditional or ingredients-based attribution can be applied to extreme events or to climate changes in general. An example of the ingredients-based approach and more discussion of this type of attribution method is given in Box C.2.

Hannart et al. (2016b) have discussed how causal theory can also be applied to attribution studies in order to distinguish between necessary and sufficient causation. Hannart et al. (2016a) further propose methodologies to use data assimilation systems, which are now used operationally to update short-term numerical weather prediction models, for detection and attribution. They envision how such systems could be used in the future to implement near-real time systematic causal attribution of weather and climate-related events.

----- START BOX C.1 HERE -----

Box C.1. On the Use of Significance Levels and Significance Tests in Attribution Studies

In detection/attribution studies, a detectable observed change is one which is determined to be highly unlikely to occur (less than about a 10% chance) due to internal variability alone. Some frequently asked questions concern the use of such a high statistical threshold (significance level) in attribution studies. In this box, we respond to several such questions received in the public review period.

- Why is such a high degree of confidence (for example, statistical significance at *p* level of 0.05) typically required before concluding that an attributable anthropogenic component to a climate change or event has been detected? For example, could attribution studies be reframed to ask whether there is a 5% or more chance that anthropogenic climate change contributed to the event?

This question is partly related to the issue of risk avoidance. For example, if there is a particular climate change outcome that we wish to avoid (for example, global warming of 3°C, or 10°C, or a runaway greenhouse) then one can use the upper ranges of confidence intervals of climate model projections as guidance, based on available science, for avoiding such outcomes. Detection/attribution studies typically deal with smaller changes than climate projections over the next century or more. For detection/attribution studies, researchers are confronting models with historical data to explore whether or not observed climate change signals are emerging from the background of natural variability. Typically the emergent signal is just a small fraction of what is predicted by the models for the coming century under continued strong greenhouse gas emission scenarios. Detecting that a change has emerged from natural variability is not the same as approaching a threshold to be avoided, unless the goal is to ensure no detectable anthropogenic influence on climate. Consequently, use of a relative strong confidence level (or *p*-value of 0.05) for determining climate change detection seems justified for the particular case of climate change detection, since one can also separately use risk-avoidance strategies or

FINAL DRAFT

probability criteria to avoid reaching certain defined thresholds (for example, a 2°C global warming threshold).

A related question concerns ascribing blame for causing an extreme event. For example, if a damaging hurricane or typhoon strikes an area and causes much damage, affected residents may ask whether human-caused climate change was at least partially to blame for the event. In this case, climate scientists sometimes use the "Fraction of Attributable Risk" framework, where they examine whether the odds of some threshold event occurring have been increased due to anthropogenic climate change. This is typically a model-based calculation, where the probability distribution related to the event in question is modeled under preindustrial and present-day climate conditions, and the occurrence rates are compared for the two modeled distributions. Note that such an analysis can be done with or without the detection of a climate change signal for the occurrence of the event in question. In general, cases where there has been a detection and attribution of changes in the event in question to human causes, then the attribution of increased risk to anthropogenic forcing will be relatively more confident.

The question of whether it is more appropriate to use approaches that incorporate a high burden of statistical evidence before concluding that anthropogenic forcings contributed significantly (as in traditional detection/attribution studies) versus using models to estimate anthropogenic contributions when there may not even be a detectable signal present in the observations (as in some Fraction of Attributable Risk studies) may depend on what type of error or scenario one most wants to avoid. In the former case, one is attempting to avoid the error of concluding that anthropogenic forcing has contributed to some observed climate change, when in fact, it later turns out that anthropogenic forcing has not contributed to the change. In the second case, one is attempting to avoid the "error" of concluding that anthropogenic forcing has not contributed significantly to an observed climate change or event when (as it later comes to be known) anthropogenic forcing had evidently contributed to the change, just not at a level that was detectable at the time compared to natural variability.

- What is the tradeoff between false positives and false negatives in attribution statistical testing, and how is it decided which type of error one should focus on avoiding?

As discussed above, there are different types of errors or scenarios that we would ideally like to avoid. However, the decision of what type of analysis to do may involve a tradeoff where one decides that it is more important to avoid either falsely concluding that anthropogenic forcing *has* contributed, or to avoid falsely concluding that anthropogenic forcing had *not* made a detectable contribution to the event. Since there is no correct answer that can apply in all cases, it would be helpful if, in requesting scientific assessments, policymakers provide some guidance about which type of error or scenario they would most desire be avoided in the analyses and assessments in question.

FINAL DRAFT

- Since substantial anthropogenic climate change (increased surface temperatures, increased atmospheric water vapor, etc.) has already occurred, aren't all extreme events affected to some degree by anthropogenic climate change?

Climate scientists are aware from modeling experiments that very tiny changes to initial conditions in model simulations lead to very different realizations of internal climate variability "noise" in the model simulations. Comparing large samples of this random background noise from models against observed changes is one way to test whether the observed changes are statistically distinguishable from internal climate variability. In any case, this experience also teaches us that any anthropogenic influence on climate, no matter how tiny, has some effect on the future trajectory of climate variability, and thus could affect the timing and occurrence of extreme events. More meaningful questions are: 1) Has anthropogenic forcing produced a statistically significant change in the probability of occurrence of some class of extreme event? 2) Can we determine with confidence the net sign of influence of anthropogenic climate change on the frequency, intensity, etc., of a type of extreme event? 3) Can climate scientists quantify (with credible confidence intervals) the effect of climate change on the occurrence frequency, the intensity, or some other aspect of an observed extreme event?

----- END BOX C.1 HERE -----

----- START BOX C.2 HERE -----

Box C.2 Illustration of Ingredients-based Event Attribution: The Case of Hurricane Sandy

To illustrate some aspects of the conditional or ingredients-based attribution approach, the case of Hurricane Sandy can be considered. If one considers Hurricane Sandy's surge event, there is strong evidence that sea level rise, at least partly anthropogenic in origin (see Ch. 12: Sea Level Rise), made Sandy's surge event worse, all other factors being equal (Reed et al. 2015). The related question of whether anthropogenic climate change increased the risk of an event like Sandy involves not just the sea level ingredient to surge risk but also whether the frequency and/or intensity of Sandy-like storms has increased or decreased as a result of anthropogenic climate change. This latter question is more difficult and is briefly reviewed here.

A conditional or ingredients-based attribution approach, as applied to a hurricane event such as Sandy, may assume that the weather patterns in which the storm was embedded—and the storm itself—could have occurred in a preindustrial climate, and the event is re-simulated while changing only some aspects of the large-scale environment (for example, sea surface temperatures, atmospheric temperatures, and moisture) by an estimated anthropogenic climate change signal. Such an approach thus explores whether anthropogenic climate change to date has altered the odds of occurrence or intensity of a Hurricane Sandy-like event. Modeling studies show, as expected, that the anomalously warm sea surface temperatures off the U.S. East Coast during Sandy led to a substantially more intense simulated storm than under present-day climatological conditions (Magnusson et al. 2014). However, these anomalous sea surface

FINAL DRAFT

temperatures and other environmental changes are a mixture of anthropogenic and natural influences, and so it is not generally possible to infer the anthropogenic component from such experiments. Another study (Lackmann 2015) modeled the influence of just the anthropogenic changes to the thermodynamic environment (including sea surface temperatures, atmospheric temperatures, and moisture perturbations) and concluded that anthropogenic climate change to date had caused Hurricane Sandy to be about 5 hPa more intense, but that this modeled change was not statistically significant at the 95% confidence level. A third study used a statistical–dynamical model to compare simulated New York City-area tropical cyclones in pre-anthropogenic and anthropogenic time periods (Reed et al. 2015). It concluded that there have been anthropogenically induced increases in the types of tropical cyclones that cause extreme surge events in the region, apart from the effects of sea level rise, such as increased radius of maximum winds in the anthropogenic era. However, the statistical–dynamical model used in the study simulates an unusually large increase in global tropical cyclone activity in 21st century projections (Emanuel 2013) compared to other tropical cyclone modeling studies using dynamical models—a number of which simulate future decreases in late 21st century tropical storm frequency in the Atlantic basin (e.g., Christensen et al. 2013). This range of uncertainty among various model simulations of Atlantic tropical cyclone activity changes under climate change imply that there is low confidence in determining the net impact to date of anthropogenic climate change on the risk of Sandy-like events, though anthropogenic sea level rise, all other things equal, has increased the surge risk.

In summary, while there is agreement that sea level rise alone has caused greater storm surge risk in the New York City area, there is low confidence on whether a number of other important determinants of storm surge climate risk, such as the frequency, size, or intensity of Sandy-like storms in the New York region, have increased or decreased due to anthropogenic warming to date.

----- END BOX C.2 HERE -----

FINAL DRAFT

REFERENCES

Allen, M.R. and P.A. Stott, 2003: Estimating signal amplitudes in optimal fingerprinting, Part I: Theory. *Climate Dynamics,* **21,** 477-491. http://dx.doi.org/10.1007/s00382-003-0313-9

Anderegg, W.R.L., E.S. Callaway, M.T. Boykoff, G. Yohe, and T.y.L. Root, 2014: Awareness of both type 1 and 2 errors in climate science and assessment. *Bulletin of the American Meteorological Society,* **95,** 1445-1451. http://dx.doi.org/10.1175/BAMS-D-13-00115.1

Bindoff, N.L., P.A. Stott, K.M. AchutaRao, M.R. Allen, N. Gillett, D. Gutzler, K. Hansingo, G. Hegerl, Y. Hu, S. Jain, I.I. Mokhov, J. Overland, J. Perlwitz, R. Sebbari, and X. Zhang, 2013: Detection and attribution of climate change: From global to regional. *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, 867–952. http://www.climatechange2013.org/report/full-report/

Canty, T., N.R. Mascioli, M.D. Smarte, and R.J. Salawitch, 2013: An empirical model of global climate – Part 1: A critical evaluation of volcanic cooling. *Atmospheric Chemistry and Physics,* **13,** 3997-4031. http://dx.doi.org/10.5194/acp-13-3997-2013

Christensen, J.H., K. Krishna Kumar, E. Aldrian, S.-I. An, I.F.A. Cavalcanti, M. de Castro, W. Dong, P. Goswami, A. Hall, J.K. Kanyanga, A. Kitoh, J. Kossin, N.-C. Lau, J. Renwick, D.B. Stephenson, S.-P. Xie, and T. Zhou, 2013: Climate phenomena and their relevance for future regional climate change. *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, 1217–1308. http://www.climatechange2013.org/report/full-report/

DelSole, T., M.K. Tippett, and J. Shukla, 2011: A significant component of unforced multidecadal variability in the recent acceleration of global warming. *Journal of Climate,* **24,** 909-926. http://dx.doi.org/10.1175/2010jcli3659.1

Deser, C., R. Knutti, S. Solomon, and A.S. Phillips, 2012: Communication of the role of natural variability in future North American climate. *Nature Climate Change,* **2,** 775-779. http://dx.doi.org/10.1038/nclimate1562

Deser, C., L. Terray, and A.S. Phillips, 2016: Forced and internal components of winter air temperature trends over North America during the past 50 years: Mechanisms and

FINAL DRAFT

implications. *Journal of Climate,* **29,** 2237-2258. http://dx.doi.org/10.1175/JCLI-D-15-0304.1

Easterling, D.R., K.E. Kunkel, M.F. Wehner, and L. Sun, 2016: Detection and attribution of climate extremes in the observed record. *Weather and Climate Extremes,* **11,** 17-27. http://dx.doi.org/10.1016/j.wace.2016.01.001

Emanuel, K.A., 2013: Downscaling CMIP5 climate models shows increased tropical cyclone activity over the 21st century. *Proceedings of the National Academy of Sciences,* **110,** 12219-12224. http://dx.doi.org/10.1073/pnas.1301293110

Hannart, A., 2016: Integrated optimal fingerprinting: Method description and illustration. *Journal of Climate,* **29,** 1977-1998. http://dx.doi.org/10.1175/jcli-d-14-00124.1

Hannart, A., A. Carrassi, M. Bocquet, M. Ghil, P. Naveau, M. Pulido, J. Ruiz, and P. Tandeo, 2016a: DADA: Data assimilation for the detection and attribution of weather and climate-related events. *Climatic Change,* **136,** 155-174. http://dx.doi.org/10.1007/s10584-016-1595-3

Hannart, A., J. Pearl, F.E.L. Otto, P. Naveau, and M. Ghil, 2016b: Causal counterfactual theory for the attribution of weather and climate-related events. *Bulletin of the American Meteorological Society,* **97,** 99-110. http://dx.doi.org/10.1175/bams-d-14-00034.1

Hasselmann, K., 1997: Multi-pattern fingerprint method for detection and attribution of climate change. *Climate Dynamics,* **13,** 601-611. http://dx.doi.org/10.1007/s003820050185

Hegerl, G. and F. Zwiers, 2011: Use of models in detection and attribution of climate change. *Wiley Interdisciplinary Reviews: Climate Change,* **2,** 570-591. http://dx.doi.org/10.1002/wcc.121

Hegerl, G.C., F.W. Zwiers, P. Braconnot, N.P. Gillett, Y. Luo, J.A.M. Orsini, N. Nicholls, J.E. Penner, and P.A. Stott, 2007: Understanding and attributing climate change. *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor, and H.L. Miller, Eds. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 663-745. http://www.ipcc.ch/publications_and_data/ar4/wg1/en/ch9.html

Hegerl, G.C., O. Hoegh-Guldberg, G. Casassa, M.P. Hoerling, R.S. Kovats, C. Parmesan, D.W. Pierce, and P.A. Stott, 2010: Good practice guidance paper on detection and attribution related to anthropogenic climate change. *Meeting Report of the Intergovernmental Panel on Climate Change Expert Meeting on Detection and Attribution of Anthropogenic Climate Change*. Stocker, T.F., C.B. Field, D. Qin, V. Barros, G.-K. Plattner, M. Tignor, P.M. Midgley, and K.L. Ebi, Eds. IPCC Working Group I Technical Support Unit, University of

FINAL DRAFT

Bern, Bern, Switzerland, 1-8. http://www.ipcc.ch/pdf/supporting-material/ipcc_good_practice_guidance_paper_anthropogenic.pdf

Horton, R.M., J.S. Mankin, C. Lesk, E. Coffel, and C. Raymond, 2016: A review of recent advances in research on extreme heat events. *Current Climate Change Reports,* **2,** 242-259. http://dx.doi.org/10.1007/s40641-016-0042-x

Hulme, M., 2014: Attributing weather extremes to 'climate change'. *Progress in Physical Geography,* **38,** 499-511. http://dx.doi.org/10.1177/0309133314538644

Knutson, T.R., F. Zeng, and A.T. Wittenberg, 2013: Multimodel assessment of regional surface temperature trends: CMIP3 and CMIP5 twentieth-century simulations. *Journal of Climate,* **26,** 8709-8743. http://dx.doi.org/10.1175/JCLI-D-12-00567.1

Lackmann, G.M., 2015: Hurricane Sandy before 1900 and after 2100. *Bulletin of the American Meteorological Society,* **96 (12),** 547-560. http://dx.doi.org/10.1175/BAMS-D-14-00123.1

Magnusson, L., J.-R. Bidlot, S.T.K. Lang, A. Thorpe, N. Wedi, and M. Yamaguchi, 2014: Evaluation of medium-range forecasts for Hurricane Sandy. *Monthly Weather Review,* **142,** 1962-1981. http://dx.doi.org/10.1175/mwr-d-13-00228.1

Mahlstein, I., R. Knutti, S. Solomon, and R.W. Portmann, 2011: Early onset of significant local warming in low latitude countries. *Environmental Research Letters,* **6,** 034009. http://dx.doi.org/10.1088/1748-9326/6/3/034009

Mao, Y., B. Nijssen, and D.P. Lettenmaier, 2015: Is climate change implicated in the 2013–2014 California drought? A hydrologic perspective. *Geophysical Research Letters,* **42,** 2805-2813. http://dx.doi.org/10.1002/2015GL063456

Melillo, J.M., T.C. Richmond, and G.W. Yohe, eds., 2014: *Climate Change Impacts in the United States: The Third National Climate Assessment*. U.S. Global Change Research Program: Washington, D.C., 842 pp. http://dx.doi.org/10.7930/J0Z31WJ2

Murakami, H., G.A. Vecchi, T.L. Delworth, K. Paffendorf, L. Jia, R. Gudgel, and F. Zeng, 2015: Investigating the influence of anthropogenic forcing and natural variability on the 2014 Hawaiian hurricane season [in "Explaining Extreme Events of 2014 from a Climate Perspective"]. *Bulletin of the American Meteorological Society,* **96 (12),** S115-S119. http://dx.doi.org/10.1175/BAMS-D-15-00119.1

NAS, 2016: *Attribution of Extreme Weather Events in the Context of Climate Change*. The National Academies Press, Washington, DC, 186 pp. http://dx.doi.org/10.17226/21852

Reed, A.J., M.E. Mann, K.A. Emanuel, N. Lin, B.P. Horton, A.C. Kemp, and J.P. Donnelly, 2015: Increased threat of tropical cyclones and coastal flooding to New York City during the

FINAL DRAFT

anthropogenic era. *Proceedings of the National Academy of Sciences,* **112,** 12610-12615. http://dx.doi.org/10.1073/pnas.1513127112

Ribes, A., F.W. Zwiers, J.-M. Azaïs, and P. Naveau, 2017: A new statistical approach to climate change detection and attribution. *Climate Dynamics,* **48,** 367-386. http://dx.doi.org/10.1007/s00382-016-3079-6

Shepherd, T.G., 2016: A common framework for approaches to extreme event attribution. *Current Climate Change Reports,* **2,** 28-38. http://dx.doi.org/10.1007/s40641-016-0033-y

Stern, D.I. and R.K. Kaufmann, 2014: Anthropogenic and natural causes of climate change. *Climatic Change,* **122,** 257-269. http://dx.doi.org/10.1007/s10584-013-1007-x

Stott, P., 2016: How climate change affects extreme weather events. *Science,* **352,** 1517-1518. http://dx.doi.org/10.1126/science.aaf7271

Stott, P.A., D.A. Stone, and M.R. Allen, 2004: Human contribution to the European heatwave of 2003. *Nature,* **432,** 610-614. http://dx.doi.org/10.1038/nature03089

Trenberth, K.E., J.T. Fasullo, and T.G. Shepherd, 2015: Attribution of climate extreme events. *Nature Climate Change,* **5,** 725-730. http://dx.doi.org/10.1038/nclimate2657

van den Dool, H., J. Huang, and Y. Fan, 2003: Performance and analysis of the constructed analogue method applied to U.S. soil moisture over 1981–2001. *Journal of Geophysical Research,* **108,** 8617. http://dx.doi.org/10.1029/2002JD003114

van Oldenborgh, G.J., F.J. Doblas Reyes, S.S. Drijfhout, and E. Hawkins, 2013: Reliability of regional climate model trends. *Environmental Research Letters,* **8,** 014055. http://dx.doi.org/10.1088/1748-9326/8/1/014055

Williams, A.P., R. Seager, J.T. Abatzoglou, B.I. Cook, J.E. Smerdon, and E.R. Cook, 2015: Contribution of anthropogenic warming to California drought during 2012–2014. *Geophysical Research Letters,* **42,** 6819-6828. http://dx.doi.org/10.1002/2015GL064924

Zwiers, F.W., X.B. Zhang, and Y. Feng, 2011: Anthropogenic influence on long return period daily temperature extremes at regional scales. *Journal of Climate,* **24,** 881-892. http://dx.doi.org/10.1175/2010jcli3908.1

FINAL DRAFT

Appendix D. Acronyms and Units

AGCM	Atmospheric General Circulation Model
AIS	Antarctic Ice Sheet
AMO	Atlantic Multidecadal Oscillation
AMOC	Atlantic meridional overturning circulation
AMSU	Advanced Microwave Sounding Unit
AO	Arctic Oscillation
AOD	aerosol optical depth
AR	atmospheric river
AW	Atlantic Water
BAMS	Bulletin of the American Meteorological Society
BC	black carbon
BCE	Before Common Era
CAM5	Community Atmospheric Model, Version 5
CAPE	convective available potential energy
CCN	cloud condensation nuclei
CCSM3	Community Climate System Model, Version 3
CDR	carbon dioxide removal
CE	Common Era
CENRS	Committee on Environment, Natural Resources, and Sustainability (National Science and Technology Council, White House)
CESM-LE	Community Earth System Model Large Ensemble Project
CFCs	chlorofluorocarbons
CI	climate intervention
CMIP5	Coupled Model Intercomparison Project, Fifth Phase (also CMIP3 and CMIP6)
CONUS	contiguous United States
CP	Central Pacific
CSSR	Climate Science Special Report
DIC	dissolved inorganic carbon
DJF	December-January-February
DoD SERDP	U.S. Department of Defense, Strategic Environmental Research and Development Program
DOE	U.S. Department of Energy
EAIS	East Antarctic Ice Sheet
ECS	equilibrium climate sensitivity
ENSO	El Niño-Southern Oscillation
EOF analysis	empirical orthogonal function analysis
EP	Eastern Pacific

FINAL DRAFT

ERF	effective radiative forcing
ESD	empirical statistical downscaling
ESDM	empirical statistical downscaling model
ESM	Earth System Model
ESS	Earth system sensitivity
ETC	extratropical cyclone
ETCCDI	Expert Team on Climate Change Detection Indices
GBI	Greenland Blocking Index
GCIS	Global Change Information System
GCM	global climate model
GeoMIP	Geoengineering Model Intercomparison Project
GFDL HiRAM	Geophysical Fluid Dynamics Laboratory, global HIgh Resolution Atmospheric Model (NOAA)
GHCN	Global Historical Climatology Network (National Centers for Environmental Information, NOAA)
GHG	greenhouse gas
GMSL	global mean sea level
GMT	global mean temperature
GPS	global positioning system
GRACE	Gravity Recovery and Climate Experiment
GrIS	Greenland Ice Sheet
GWP	global warming potential
HadCM3	Hadley Centre Coupled Model, Version 3
HadCRUT4	Hadley Centre Climatic Research Unit Gridded Surface Temperature Data Set 4
HCFCs	hydrochlorofluorocarbons
HFCs	hydrofluorocarbons
HOT	Hawai‘i Ocean Time-series
HOT-DOGS	Hawai‘i Ocean Time-series Data Organization & Graphical System
HURDAT2	revised Atlantic Hurricane Database (National Hurricane Center, NOAA)
IAM	integrated assessment model
IAV	impacts, adaptation, and vulnerability
INMCM	Institute for Numerical Mathematics Climate Model
IPCC	Intergovernmental Panel on Climate Change
IPCC AR5	Fifth Assessment Report of the IPCC; also SPM – Summary for Policymakers, and WG1, WG2, WG3 – Working Groups 1-3
IPO	Interdecadal Pacific Oscillation
IVT	integrated vapor transport
JGOFS	U.S. Joint Global Ocean Flux Study

FINAL DRAFT

JJA	June-July-August
JTWC	Joint Typhoon Warning Center
LCC	land-cover changes
LULCC	land-use and land-cover change
MAM	March-April-May
MSU	Microwave Sounding Unit
NAM	Northern Annular Mode
NAO	North Atlantic Oscillation
NARCCAP	North American Regional Climate Change Assessment Program (World Meteorological Organization)
NAS	National Academy of Sciences
NASA	National Aeronautics and Space Administration
NCA	National Climate Assessment
NCA3	Third National Climate Assessment
NCA4	Fourth National Climate Assessment
NCEI	National Centers for Environmental Information (NOAA)
NDC	nationally determined contribution
NOAA	National Oceanic and Atmospheric Administration
NPI	North Pacific Index
NPO	North Pacific oscillation
NPP	net primary production
OMZs	oxygen minimum zones
OSTP	Office of Science and Technology Policy (White House)
PCA	principle component analysis
PDO	Pacific Decadal Oscillation
PDSI	Palmer Drought Severity Index
PETM	Paleo-Eocene Thermal Maximum
PFCs	perfluorocarbons
PGW	pseudo-global warming
PNA	Pacific North American Pattern
RCM	regional climate models
RCP	Representative Concentration Pathway
RF	radiative forcing
RFaci	aerosol–cloud interaction (effect on RF)
RFari	aerosol–radiation interaction (effect on RF)
RMSE	root mean square error
RSL	relative sea level
RSS	remote sensing systems
S06	surface-to-6 km layer
SCE	snow cover extent

FINAL DRAFT

SGCR	Subcommittee on Global Change Research (National Science and Technology Council, White House)
SLCF	short-lived climate forcer
SLCP	short-lived climate pollutant
SLR	sea level rise
SOC	soil organic carbon
SRES	IPCC Special Report on Emissions Scenarios
SREX	IPCC Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation
SRM	solar radiation management
SSC	Science Steering Committee
SSI	solar spectral irradiance
SSP	Shared Socioeconomic Pathway
SST	sea surface temperature
STAR	Center for Satellite Applications and Research (NOAA)
SWCRE	shortwave cloud radiative effect (on radiative fluxes)
LWCRE	longwave cloud radiative effect (on radiative fluxes)
TA	total alkalinity
TC	tropical cyclone
TCR	transient climate response
TCRE	transient climate response to cumulative carbon emissions
TOPEX/JASON1,2	Topography Experiment/Joint Altimetry Satellite Oceanography Network satellites (NASA)
TSI	total solar irradiance
TTT	temperature total troposphere
UAH	University of Alabama, Huntsville
UHI	urban heat island (effect)
UNFCCC	United Nations Framework Convention on Climate Change
USGCRP	U.S. Global Change Research Program
USGS	U.S. Geological Survey
UV	ultraviolet
VOCs	volatile organic compounds
WAIS	West Antarctic Ice Sheet
WCRP	World Climate Research Programme
WMGHG	well-mixed greenhouse gas
WOCE	World Ocean Circulation Experiment (JGOFS)

FINAL DRAFT

Abbreviations and Units

C	carbon
CO	carbon monoxide
CH_4	methane
cm	centimeters
CO_2	carbon dioxide
°C	degrees Celsius
°F	degrees Fahrenheit
GtC	gigatonnes of carbon
hPA	hectopascal
H_2S	hydrogen sulfide
H_2SO_4	sulfuric acid
km	kilometers
m	meters
mm	millimeters
Mt	megaton
µatm	microatmosphere
N	nitrogen
N_2O	nitrous oxide
NOx	nitrogen oxides
O_2	molecular oxygen
O_3	ozone
OH	hydroxyl radical
PgC	petagrams of carbon
ppb	parts per billion
ppm	parts per million
SF_6	sulfur hexafluoride
SO_2	sulfur dioxide
TgC	teragrams of carbon
W/m^2	Watts per meter squared

FINAL DRAFT

GLOSSARY TERMS

[relevant definitions to be linked from <globalchange.gov/glossary>]

FINAL DRAFT