Lean, J., 1997: The sun's variable radiation and its relevance for earth. *Annual Review of Astronomy and Astrophysics,* **35,** 33-67. http://dx.doi.org/10.1146/annurev.astro.35.1.33

Leibensperger, E.M., L.J. Mickley, D.J. Jacob, W.T. Chen, J.H. Seinfeld, A. Nenes, P.J. Adams, D.G. Streets, N. Kumar, and D. Rind, 2012: Climatic effects of 1950-2050 changes in US anthropogenic aerosols – Part 1: Aerosol trends and radiative forcing. *Atmospheric Chemistry and Physics* **12,** 3333-3348. http://dx.doi.org/10.5194/acp-12-3333-2012

Lelieveld, J. and P.J. Crutzen, 1992: Indirect chemical effects of methane on climate warming. *Nature,* **355,** 339-342. http://dx.doi.org/10.1038/355339a0

Li, F., J. Austin, and J. Wilson, 2008: The strength of the Brewer–Dobson circulation in a changing climate: Coupled chemistry–climate model simulations. *Journal of Climate,* **21,** 40-57. http://dx.doi.org/10.1175/2007jcli1663.1

Li, J., Z. Han, and Z. Xie, 2013: Model analysis of long-term trends of aerosol concentrations and direct radiative forcings over East Asia. *Tellus B: Chemical and Physical Meteorology,* **65,** 20410. http://dx.doi.org/10.3402/tellusb.v65i0.20410

Liao, H., Y. Zhang, W.-T. Chen, F. Raes, and J.H. Seinfeld, 2009: Effect of chemistry-aerosol-climate coupling on predictions of future climate and future levels of tropospheric ozone and aerosols. *Journal of Geophysical Research: Atmospheres,* **114,** D10306. http://dx.doi.org/10.1029/2008JD010984

Liljedahl, A.K., J. Boike, R.P. Daanen, A.N. Fedorov, G.V. Frost, G. Grosse, L.D. Hinzman, Y. Iijma, J.C. Jorgenson, N. Matveyeva, M. Necsoiu, M.K. Raynolds, V.E. Romanovsky, J. Schulla, K.D. Tape, D.A. Walker, C.J. Wilson, H. Yabuki, and D. Zona, 2016: Pan-Arctic ice-wedge degradation in warming permafrost and its influence on tundra hydrology. *Nature Geoscience,* **9,** 312-318. http://dx.doi.org/10.1038/ngeo2674

Lockwood, M., 2012: Solar influence on global and regional climates. *Surveys in Geophysics,* **33,** 503-534. http://dx.doi.org/10.1007/s10712-012-9181-3

Loeb, N. G., S. Kato and B. A. Wielicki, 2002: Defining Top-of-the-Atmosphere Flux Reference Level for Earth Radiation Budget Studies, *Journal of Climate*, 15, 3301-3309, http://dx.doi.org/10.1175/1520-0442(2002)015<3301:DTOTAF>2.0.CO;2

Loeb, N.G., B.A. Wielicki, D.R. Doelling, G.L. Smith, D.F. Keyes, S. Kato, N. Manalo-Smith, and T. Wong, 2009: Toward optimal closure of the Earth's top-of-atmosphere radiation budget. *Journal of Climate,* **22,** 748-766. http://dx.doi.org/10.1175/2008JCLI2637.1

Löffler, M., S. Brinkop, and P. Jöckel, 2016: Impact of major volcanic eruptions on stratospheric water vapour. *Atmospheric Chemistry and Physics,* **16,** 6547-6562. http://dx.doi.org/10.5194/acp-16-6547-2016

FINAL DRAFT

Lohmann, U. and J. Feichter, 2005: Global indirect aerosol effects: A review. *Atmospheric Chemistry and Physics,* **5,** 715-737. http://dx.doi.org/10.5194/acp-5-715-2005

Lynch, P., J.S. Reid, D.L. Westphal, J. Zhang, T.F. Hogan, E.J. Hyer, C.A. Curtis, D.A. Hegg, Y. Shi, J.R. Campbell, J.I. Rubin, W.R. Sessions, F.J. Turk, and A.L. Walker, 2016: An 11-year global gridded aerosol optical thickness reanalysis (v1.0) for atmospheric and climate sciences. *Geoscientific Model Development,* **9,** 1489-1522. http://dx.doi.org/10.5194/gmd-9-1489-2016

Mahajan, S., K.J. Evans, J.J. Hack, and J.E. Truesdale, 2013: Linearity of climate response to increases in black carbon aerosols. *Journal of Climate,* **26,** 8223-8237. http://dx.doi.org/10.1175/JCLI-D-12-00715.1

Mao, J., A. Ribes, B. Yan, X. Shi, P.E. Thornton, R. Seferian, P. Ciais, R.B. Myneni, H. Douville, S. Piao, Z. Zhu, R.E. Dickinson, Y. Dai, D.M. Ricciuto, M. Jin, F.M. Hoffman, B. Wang, M. Huang, and X. Lian, 2016: Human-induced greening of the northern extratropical land surface. *Nature Climate Change,* **6,** 959-963. http://dx.doi.org/10.1038/nclimate3056

Mao, K.B., Y. Ma, L. Xia, W.Y. Chen, X.Y. Shen, T.J. He, and T.R. Xu, 2014: Global aerosol change in the last decade: An analysis based on MODIS data. *Atmospheric Environment,* **94,** 680-686. http://dx.doi.org/10.1016/j.atmosenv.2014.04.053

Marmer, E., B. Langmann, H. Fagerli, and V. Vestreng, 2007: Direct shortwave radiative forcing of sulfate aerosol over Europe from 1900 to 2000. *Journal of Geophysical Research,* **112,** D23S17. http://dx.doi.org/10.1029/2006JD008037

Masson-Delmotte, V., M. Schulz, A. Abe-Ouchi, J. Beer, A. Ganopolski, J.F. González Rouco, E. Jansen, K. Lambeck, J. Luterbacher, T. Naish, T. Osborn, B. Otto-Bliesner, T. Quinn, R. Ramesh, M. Rojas, X. Shao, and A. Timmermann, 2013: Information from paleoclimate archives. *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, 383–464. http://www.climatechange2013.org/report/full-report/

Matthews, H.D., A.J. Weaver, K.J. Meissner, N.P. Gillett, and M. Eby, 2004: Natural and anthropogenic climate change: Incorporating historical land cover change, vegetation dynamics and the global carbon cycle. *Climate Dynamics,* **22,** 461-479. http://dx.doi.org/10.1007/s00382-004-0392-2

McLandress, C., T.G. Shepherd, M.C. Reader, D.A. Plummer, and K.P. Shine, 2014: The climate impact of past changes in halocarbons and CO_2 in the tropical UTLS region. *Journal of Climate,* **27,** 8646-8660. http://dx.doi.org/10.1175/jcli-d-14-00232.1

FINAL DRAFT

Meehl, G.A., W.M. Washington, C.M. Ammann, J.M. Arblaster, T.M.L. Wigley, and C. Tebaldi, 2004: Combinations of natural and anthropogenic forcings in twentieth-century climate. *Journal of Climate,* **17,** 3721-3727. http://dx.doi.org/10.1175/1520-0442(2004)017<3721:CONAAF>2.0.CO;2

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

Morgenstern, O., G. Zeng, N. Luke Abraham, P.J. Telford, P. Braesicke, J.A. Pyle, S.C. Hardiman, F.M. O'Connor, and C.E. Johnson, 2013: Impacts of climate change, ozone recovery, and increasing methane on surface ozone and the tropospheric oxidizing capacity. *Journal of Geophysical Research: Atmospheres,* **118,** 1028-1041. http://dx.doi.org/10.1029/2012JD018382

Morris, G.A., J.E. Rosenfield, M.R. Schoeberl, and C.H. Jackman, 2003: Potential impact of subsonic and supersonic aircraft exhaust on water vapor in the lower stratosphere assessed via a trajectory model. *Journal of Geophysical Research: Atmospheres,* **108,** 4103. http://dx.doi.org/10.1029/2002JD002614

Munk, W. and C. Wunsch, 1998: Abyssal recipes II: Energetics of tidal and wind mixing. *Deep Sea Research Part I: Oceanographic Research Papers,* **45,** 1977-2010. http://dx.doi.org/10.1016/S0967-0637(98)00070-3

Murphy, D.M., J.C. Chow, E.M. Leibensperger, W.C. Malm, M. Pitchford, B.A. Schichtel, J.G. Watson, and W.H. White, 2011: Decreases in elemental carbon and fine particle mass in the United States. *Atmospheric Chemistry and Physics,* **11,** 4679-4686. http://dx.doi.org/10.5194/acp-11-4679-2011

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, G., W. Aas, R. Cherian, W. Collins, G. Faluvegi, M. Flanner, P. Forster, Ø. Hodnebrog, Z. Klimont, M.T. Lund, J. Mülmenstädt, C. Lund Myhre, D. Olivié, M. Prather, J. Quaas, B.H. Samset, J.L. Schnell, M. Schulz, D. Shindell, R.B. Skeie, T. Takemura, and S. Tsyro, 2017: Multi-model simulations of aerosol and ozone radiative forcing due to anthropogenic

FINAL DRAFT

emission changes during the period 1990–2015. *Atmospheric Chemistry and Physics,* **17,** 2709-2720. http://dx.doi.org/10.5194/acp-17-2709-2017

Naik, V., A. Voulgarakis, A.M. Fiore, L.W. Horowitz, J.F. Lamarque, M. Lin, M.J. Prather, P.J. Young, D. Bergmann, P.J. Cameron-Smith, I. Cionni, W.J. Collins, S.B. Dalsøren, R. Doherty, V. Eyring, G. Faluvegi, G.A. Folberth, B. Josse, Y.H. Lee, I.A. MacKenzie, T. Nagashima, T.P.C. van Noije, D.A. Plummer, M. Righi, S.T. Rumbold, R. Skeie, D.T. Shindell, D.S. Stevenson, S. Strode, K. Sudo, S. Szopa, and G. Zeng, 2013: Preindustrial to present-day changes in tropospheric hydroxyl radical and methane lifetime from the Atmospheric Chemistry and Climate Model Intercomparison Project (ACCMIP). *Atmospheric Chemistry and Physics,* **13,** 5277-5298. http://dx.doi.org/10.5194/acp-13-5277-2013

Nisbet, E.G., E.J. Dlugokencky, M.R. Manning, D. Lowry, R.E. Fisher, J.L. France, S.E. Michel, J.B. Miller, J.W.C. White, B. Vaughn, P. Bousquet, J.A. Pyle, N.J. Warwick, M. Cain, R. Brownlow, G. Zazzeri, M. Lanoisellé, A.C. Manning, E. Gloor, D.E.J. Worthy, E.G. Brunke, C. Labuschagne, E.W. Wolff, and A.L. Ganesan, 2016: Rising atmospheric methane: 2007–2014 growth and isotopic shift. *Global Biogeochemical Cycles,* **30,** 1356-1370. http://dx.doi.org/10.1002/2016GB005406

Nowack, P.J., N. Luke Abraham, A.C. Maycock, P. Braesicke, J.M. Gregory, M.M. Joshi, A. Osprey, and J.A. Pyle, 2015: A large ozone-circulation feedback and its implications for global warming assessments. *Nature Climate Change,* **5,** 41-45. http://dx.doi.org/10.1038/nclimate2451

Otterå, O.H., M. Bentsen, H. Drange, and L. Suo, 2010: External forcing as a metronome for Atlantic multidecadal variability. *Nature Geoscience,* **3,** 688-694. http://dx.doi.org/10.1038/ngeo955

Pacifico, F., G.A. Folberth, C.D. Jones, S.P. Harrison, and W.J. Collins, 2012: Sensitivity of biogenic isoprene emissions to past, present, and future environmental conditions and implications for atmospheric chemistry. *Journal of Geophysical Research,* **117,** D22302. http://dx.doi.org/10.1029/2012JD018276

Passow, U. and C.A. Carlson, 2012: The biological pump in a high CO2 world. *Marine Ecology Progress Series,* **470,** 249-271. http://dx.doi.org/10.3354/meps09985

Philipona, R., K. Behrens, and C. Ruckstuhl, 2009: How declining aerosols and rising greenhouse gases forced rapid warming in Europe since the 1980s. *Geophysical Research Letters,* **36,** L02806. http://dx.doi.org/10.1029/2008GL036350

Pietikäinen, J.P., K. Kupiainen, Z. Klimont, R. Makkonen, H. Korhonen, R. Karinkanta, A.P. Hyvärinen, N. Karvosenoja, A. Laaksonen, H. Lihavainen, and V.M. Kerminen, 2015:

FINAL DRAFT

Impacts of emission reductions on aerosol radiative effects. *Atmospheric Chemistry and Physics,* **15,** 5501-5519. http://dx.doi.org/10.5194/acp-15-5501-2015

Pistone, K., I. Eisenman, and V. Ramanathan, 2014: Observational determination of albedo decrease caused by vanishing Arctic sea ice. *Proceedings of the National Academy of Sciences,* **111,** 3322-3326. http://dx.doi.org/10.1073/pnas.1318201111

Quaas, J., Y. Ming, S. Menon, T. Takemura, M. Wang, J.E. Penner, A. Gettelman, U. Lohmann, N. Bellouin, O. Boucher, A.M. Sayer, G.E. Thomas, A. McComiskey, G. Feingold, C. Hoose, J.E. Kristjánsson, X. Liu, Y. Balkanski, L.J. Donner, P.A. Ginoux, P. Stier, B. Grandey, J. Feichter, I. Sednev, S.E. Bauer, D. Koch, R.G. Grainger, Kirkev, aring, A. g, T. Iversen, Ø. Seland, R. Easter, S.J. Ghan, P.J. Rasch, H. Morrison, J.F. Lamarque, M.J. Iacono, S. Kinne, and M. Schulz, 2009: Aerosol indirect effects – general circulation model intercomparison and evaluation with satellite data. *Atmospheric Chemistry and Physics,* **9,** 8697-8717. http://dx.doi.org/10.5194/acp-9-8697-2009

Rädel, G., T. Mauritsen, B. Stevens, D. Dommenget, D. Matei, K. Bellomo, and A. Clement, 2016: Amplification of El Niño by cloud longwave coupling to atmospheric circulation. *Nature Geoscience,* **9,** 106-110. http://dx.doi.org/10.1038/ngeo2630

Raes, F., H. Liao, W.-T. Chen, and J.H. Seinfeld, 2010: Atmospheric chemistry-climate feedbacks. *Journal of Geophysical Research,* **115,** D12121. http://dx.doi.org/10.1029/2009JD013300

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

Raible, C.C., S. Brönnimann, R. Auchmann, P. Brohan, T.L. Frölicher, H.-F. Graf, P. Jones, J. Luterbacher, S. Muthers, R. Neukom, A. Robock, S. Self, A. Sudrajat, C. Timmreck, and M. Wegmann, 2016: Tambora 1815 as a test case for high impact volcanic eruptions: Earth system effects. *Wiley Interdisciplinary Reviews: Climate Change,* **7,** 569-589. http://dx.doi.org/10.1002/wcc.407

Ramanathan, V., M.S. Lian, and R.D. Cess, 1979: Increased atmospheric CO2: Zonal and seasonal estimates of the effect on the radiation energy balance and surface temperature. *Journal of Geophysical Research: Oceans,* **84,** 4949-4958. http://dx.doi.org/10.1029/JC084iC08p04949

Randall, D.A., R.A. Wood, S. Bony, R. Colman, T. Fichefet, J. Fyfe, V. Kattsov, A. Pitman, J. Shukla, J. Srinivasan, R.J. Stouffer, A. Sumi, and K.E. Taylor, 2007: Ch. 8: Climate models and their evaluation. *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on*

FINAL DRAFT

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, 589-662. www.ipcc.ch/pdf/assessment-report/ar4/wg1/ar4-wg1-chapter8.pdf

Rhein, M., S.R. Rintoul, S. Aoki, E. Campos, D. Chambers, R.A. Feely, S. Gulev, G.C. Johnson, S.A. Josey, A. Kostianoy, C. Mauritzen, D. Roemmich, L.D. Talley, and F. Wang, 2013: Observations: Ocean. *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, 255–316. http://www.climatechange2013.org/report/full-report/

Rignot, E. and R.H. Thomas, 2002: Mass balance of polar ice sheets. *Science,* **297,** 1502-1506. http://dx.doi.org/10.1126/science.1073888

Rignot, E., M. Koppes, and I. Velicogna, 2010: Rapid submarine melting of the calving faces of West Greenland glaciers. *Nature Geoscience,* **3,** 187-191. http://dx.doi.org/10.1038/ngeo765

Robock, A., 2000: Volcanic eruptions and climate. *Reviews of Geophysics,* **38,** 191-219. http://dx.doi.org/10.1029/1998RG000054

Rosenfeld, D., M.O. Andreae, A. Asmi, M. Chin, G. de Leeuw, D.P. Donovan, R. Kahn, S. Kinne, N. Kivekäs, M. Kulmala, W. Lau, K.S. Schmidt, T. Suni, T. Wagner, M. Wild, and J. Quaas, 2014: Global observations of aerosol–cloud–precipitation–climate interactions. *Reviews of Geophysics,* **52,** 750-808. http://dx.doi.org/10.1002/2013RG000441

Rosenlof, K.H., S.J. Oltmans, D. Kley, J.M. Russell, E.W. Chiou, W.P. Chu, D.G. Johnson, K.K. Kelly, H.A. Michelsen, G.E. Nedoluha, E.E. Remsberg, G.C. Toon, and M.P. McCormick, 2001: Stratospheric water vapor increases over the past half-century. *Geophysical Research Letters,* **28,** 1195-1198. http://dx.doi.org/10.1029/2000GL012502

Rykaczewski, RR and JP Dunne. 2011. A measured look at ocean chlorophyll trends. *Nature*, 472:E5-E6, http://dx.doi.org/10.1038/nature09952

Saunois, M., R.B. Jackson, P. Bousquet, B. Poulter, and J.G. Canadell, 2016: The growing role of methane in anthropogenic climate change. *Environmental Research Letters,* **11,** 120207. http://dx.doi.org/10.1088/1748-9326/11/12/120207

Schaefer, K., H. Lantuit, E.R. Vladimir, E.A.G. Schuur, and R. Witt, 2014: The impact of the permafrost carbon feedback on global climate. *Environmental Research Letters,* **9,** 085003. http://dx.doi.org/10.1088/1748-9326/9/8/085003

FINAL DRAFT

Schanze, J.J., R.W. Schmitt, and L.L. Yu, 2010: The global oceanic freshwater cycle: A state-of-the-art quantification. *Journal of Marine Research,* **68,** 569-595. http://dx.doi.org/10.1357/002224010794657164

Schoof, C., 2010: Ice-sheet acceleration driven by melt supply variability. *Nature,* **468,** 803-806. http://dx.doi.org/10.1038/nature09618

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

Sejas, S.A., M. Cai, A. Hu, G.A. Meehl, W. Washington, and P.C. Taylor, 2014: Individual feedback contributions to the seasonality of surface warming. *Journal of Climate,* **27,** 5653-5669. http://dx.doi.org/10.1175/JCLI-D-13-00658.1

Seppälä, R., 2009: A global assessment on adaptation of forests to climate change. *Scandinavian Journal of Forest Research,* **24,** 469-472. http://dx.doi.org/10.1080/02827580903378626

Seppälä, A., K. Matthes, C.E. Randall, and I.A. Mironova, 2014: What is the solar influence on climate? Overview of activities during CAWSES-II. *Progress in Earth and Planetary Science,* **1,** 1-12. http://dx.doi.org/10.1186/s40645-014-0024-3

Shepherd, T.G. and C. McLandress, 2011: A robust mechanism for strengthening of the Brewer–Dobson circulation in response to climate change: Critical-layer control of subtropical wave breaking. *Journal of the Atmospheric Sciences,* **68,** 784-797. http://dx.doi.org/10.1175/2010jas3608.1

Shindell, D. and G. Faluvegi, 2009: Climate response to regional radiative forcing during the twentieth century. *Nature Geoscience,* **2,** 294-300. http://dx.doi.org/10.1038/ngeo473

Shiogama, H., D.A. Stone, T. Nagashima, T. Nozawa, and S. Emori, 2013: On the linear additivity of climate forcing-response relationships at global and continental scales. *International Journal of Climatology,* **33,** 2542-2550. http://dx.doi.org/10.1002/joc.3607

Silvano, A., S.R. Rintoul, and L. Herraiz-Borreguero, 2016: Ocean-ice shelf interaction in East Antarctica. *Oceanography,* **29,** 130-143. http://dx.doi.org/10.5670/oceanog.2016.105

Skeie, R.B., T. Berntsen, G. Myhre, C.A. Pedersen, J. Ström, S. Gerland, and J.A. Ogren, 2011: Black carbon in the atmosphere and snow, from pre-industrial times until present. *Atmospheric Chemistry and Physics,* **11,** 6809-6836. http://dx.doi.org/10.5194/acp-11-6809-2011

FINAL DRAFT

Skiba, U.M. and R.M. Rees, 2014: Nitrous oxide, climate change and agriculture. *CAB Reviews,* **9,** 7. http://dx.doi.org/10.1079/PAVSNNR20149010

Smith, G.L., B.R. Barkstrom, E.F. Harrison, R.B. Lee, and B.A. Wielicki, 1994: Radiation budget measurements for the eighties and nineties. *Advances in Space Research,* **14,** 81-84. http://dx.doi.org/10.1016/0273-1177(94)90351-4

Smith, S.J. and T.C. Bond, 2014: Two hundred fifty years of aerosols and climate: The end of the age of aerosols. *Atmospheric Chemistry and Physics,* **14,** 537-549. http://dx.doi.org/10.5194/acp-14-537-2014

Smith, W.K., S.C. Reed, C.C. Cleveland, A.P. Ballantyne, W.R.L. Anderegg, W.R. Wieder, Y.Y. Liu, and S.W. Running, 2016: Large divergence of satellite and Earth system model estimates of global terrestrial CO2 fertilization. *Nature Climate Change,* **6,** 306-310. http://dx.doi.org/10.1038/nclimate2879

Soden, B.J. and I.M. Held, 2006: An assessment of climate feedbacks in coupled ocean–atmosphere models. *Journal of Climate,* **19,** 3354-3360. http://dx.doi.org/10.1175/JCLI3799.1

Sohn, B.J., T. Nakajima, M. Satoh, and H.S. Jang, 2010: Impact of different definitions of clear-sky flux on the determination of longwave cloud radiative forcing: NICAM simulation results. *Atmospheric Chemistry and Physics,* **10,** 11641-11646. http://dx.doi.org/10.5194/acp-10-11641-2010

Solomon, S., K.H. Rosenlof, R.W. Portmann, J.S. Daniel, S.M. Davis, T.J. Sanford, and G.-K. Plattner, 2010: Contributions of stratospheric water vapor to decadal changes in the rate of global warming. *Science,* **327,** 1219-1223. http://dx.doi.org/10.1126/science.1182488

Steinacher, M., F. Joos, T.L. Frölicher, L. Bopp, P. Cadule, V. Cocco, S.C. Doney, M. Gehlen, K. Lindsay, and J.K. Moore, 2010: Projected 21st century decrease in marine productivity: A multi-model analysis. *Biogeosciences,* **7,** 979-1005. http://dx.doi.org/10.5194/bg-7-979-2010

Stenchikov, G., T.L. Delworth, V. Ramaswamy, R.J. Stouffer, A. Wittenberg, and F. Zeng, 2009: Volcanic signals in oceans. *Journal of Geophysical Research,* **114,** D16104. http://dx.doi.org/10.1029/2008JD011673

Stevens, B. and G. Feingold, 2009: Untangling aerosol effects on clouds and precipitation in a buffered system. *Nature,* **461,** 607-613. http://dx.doi.org/10.1038/nature08281

Stjern, C.W. and J.E. Kristjánsson, 2015: Contrasting influences of recent aerosol changes on clouds and precipitation in Europe and East Asia. *Journal of Climate,* **28,** 8770-8790. http://dx.doi.org/10.1175/jcli-d-14-00837.1

FINAL DRAFT

Straneo, F. and P. Heimbach, 2013: North Atlantic warming and the retreat of Greenland's outlet glaciers. *Nature,* **504,** 36-43. http://dx.doi.org/10.1038/nature12854

Streets, D.G., C. Yu, Y. Wu, M. Chin, Z. Zhao, T. Hayasaka, and G. Shi, 2008: Aerosol trends over China, 1980–2000. *Atmospheric Research,* **88,** 174-182. http://dx.doi.org/10.1016/j.atmosres.2007.10.016

Swartz, W.H., R.S. Stolarski, L.D. Oman, E.L. Fleming, and C.H. Jackman, 2012: Middle atmosphere response to different descriptions of the 11-yr solar cycle in spectral irradiance in a chemistry-climate model. *Atmospheric Chemistry and Physics,* **12,** 5937-5948. http://dx.doi.org/10.5194/acp-12-5937-2012

Szopa, S., Y. Balkanski, M. Schulz, S. Bekki, D. Cugnet, A. Fortems-Cheiney, S. Turquety, A. Cozic, C. Déandreis, D. Hauglustaine, A. Idelkadi, J. Lathière, F. Lefevre, M. Marchand, R. Vuolo, N. Yan, and J.-L. Dufresne, 2013: Aerosol and ozone changes as forcing for climate evolution between 1850 and 2100. *Climate Dynamics,* **40,** 2223-2250. http://dx.doi.org/10.1007/s00382-012-1408-y

Tai, A.P.K., L.J. Mickley, C.L. Heald, and S. Wu, 2013: Effect of CO2 inhibition on biogenic isoprene emission: Implications for air quality under 2000 to 2050 changes in climate, vegetation, and land use. *Geophysical Research Letters,* **40,** 3479-3483. http://dx.doi.org/10.1002/grl.50650

Taylor, P.C., R.G. Ellingson, and M. Cai, 2011: Geographical distribution of climate feedbacks in the NCAR CCSM3.0. *Journal of Climate,* **24,** 2737-2753. http://dx.doi.org/10.1175/2010JCLI3788.1

Taylor, P.C., S. Kato, K.-M. Xu, and M. Cai, 2015: Covariance between Arctic sea ice and clouds within atmospheric state regimes at the satellite footprint level. *Journal of Geophysical Research: Atmospheres,* **120,** 12656-12678. http://dx.doi.org/10.1002/2015JD023520

Thoma, M., J. Determann, K. Grosfeld, S. Goeller, and H.H. Hellmer, 2015: Future sea-level rise due to projected ocean warming beneath the Filchner Ronne Ice Shelf: A coupled model study. *Earth and Planetary Science Letters,* **431,** 217-224. http://dx.doi.org/10.1016/j.epsl.2015.09.013

Thornton, P.E., J.-F. Lamarque, N.A. Rosenbloom, and N.M. Mahowald, 2007: Influence of carbon-nitrogen cycle coupling on land model response to CO2 fertilization and climate variability. *Global Biogeochemical Cycles,* **21,** GB4018. http://dx.doi.org/10.1029/2006GB002868

Trenberth, K.E., P.D. Jones, P. Ambenje, R. Bojariu, D. Easterling, A.K. Tank, D. Parker, F. Rahimzadeh, J.A. Renwick, M. Rusticucci, B. Soden, and P. Zhai, 2007: Observations:

FINAL DRAFT

Surface and atmospheric 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. http://www.ipcc.ch/publications_and_data/ar4/wg1/en/ch3.html

Tsigaridis, K., N. Daskalakis, M. Kanakidou, P.J. Adams, P. Artaxo, R. Bahadur, Y. Balkanski, S.E. Bauer, N. Bellouin, A. Benedetti, T. Bergman, T.K. Berntsen, J.P. Beukes, H. Bian, K.S. Carslaw, M. Chin, G. Curci, T. Diehl, R.C. Easter, S.J. Ghan, S.L. Gong, A. Hodzic, C.R. Hoyle, T. Iversen, S. Jathar, J.L. Jimenez, J.W. Kaiser, A. Kirkevåg, D. Koch, H. Kokkola, Y.H. Lee, G. Lin, X. Liu, G. Luo, X. Ma, G.W. Mann, N. Mihalopoulos, J.J. Morcrette, J.F. Müller, G. Myhre, S. Myriokefalitakis, N.L. Ng, D. O'Donnell, J.E. Penner, L. Pozzoli, K.J. Pringle, L.M. Russell, M. Schulz, J. Sciare, Ø. Seland, D.T. Shindell, S. Sillman, R.B. Skeie, D. Spracklen, T. Stavrakou, S.D. Steenrod, T. Takemura, P. Tiitta, S. Tilmes, H. Tost, T. van Noije, P.G. van Zyl, K. von Salzen, F. Yu, Z. Wang, Z. Wang, R.A. Zaveri, H. Zhang, K. Zhang, Q. Zhang, and X. Zhang, 2014: The AeroCom evaluation and intercomparison of organic aerosol in global models. *Atmospheric Chemistry and Physics,* **14,** 10845-10895. http://dx.doi.org/10.5194/acp-14-10845-2014

Turnock, S.T., D.V. Spracklen, K.S. Carslaw, G.W. Mann, M.T. Woodhouse, P.M. Forster, J. Haywood, C.E. Johnson, M. Dalvi, N. Bellouin, and A. Sanchez-Lorenzo, 2015: Modelled and observed changes in aerosols and surface solar radiation over Europe between 1960 and 2009. *Atmospheric Chemistry and Physics,* **15,** 9477-9500. http://dx.doi.org/10.5194/acp-15-9477-2015

Twohy, C.H., M.D. Petters, J.R. Snider, B. Stevens, W. Tahnk, M. Wetzel, L. Russell, and F. Burnet, 2005: Evaluation of the aerosol indirect effect in marine stratocumulus clouds: Droplet number, size, liquid water path, and radiative impact. *Journal of Geophysical Research: Atmospheres,* **110,** D08203. http://dx.doi.org/10.1029/2004JD005116

Unger, N., S. Menon, D.M. Koch, and D.T. Shindell, 2009: Impacts of aerosol-cloud interactions on past and future changes in tropospheric composition. *Atmospheric Chemistry and Physics,* **9,** 4115-4129. http://dx.doi.org/10.5194/acp-9-4115-2009

van den Broeke, M., J. Bamber, J. Ettema, E. Rignot, E. Schrama, W.J. van de Berg, E. van Meijgaard, I. Velicogna, and B. Wouters, 2009: Partitioning recent Greenland mass loss. *Science,* **326,** 984-986. http://dx.doi.org/10.1126/science.1178176

Velders, G.J.M., D.W. Fahey, J.S. Daniel, S.O. Andersen, and M. McFarland, 2015: Future atmospheric abundances and climate forcings from scenarios of global and regional hydrofluorocarbon (HFC) emissions. *Atmospheric Environment,* **123, Part A,** 200-209. http://dx.doi.org/10.1016/j.atmosenv.2015.10.071

FINAL DRAFT

Vial, J., J.-L. Dufresne, and S. Bony, 2013: On the interpretation of inter-model spread in CMIP5 climate sensitivity estimates. *Climate Dynamics,* **41,** 3339-3362. http://dx.doi.org/10.1007/s00382-013-1725-9

Voulgarakis, A., V. Naik, J.F. Lamarque, D.T. Shindell, P.J. Young, M.J. Prather, O. Wild, R.D. Field, D. Bergmann, P. Cameron-Smith, I. Cionni, W.J. Collins, S.B. Dalsøren, R.M. Doherty, V. Eyring, G. Faluvegi, G.A. Folberth, L.W. Horowitz, B. Josse, I.A. MacKenzie, T. Nagashima, D.A. Plummer, M. Righi, S.T. Rumbold, D.S. Stevenson, S.A. Strode, K. Sudo, S. Szopa, and G. Zeng, 2013: Analysis of present day and future OH and methane lifetime in the ACCMIP simulations. *Atmospheric Chemistry and Physics,* **13,** 2563-2587. http://dx.doi.org/10.5194/acp-13-2563-2013

Wang, Y., Y. Yang, S. Han, Q. Wang, and J. Zhang, 2013: Sunshine dimming and brightening in Chinese cities (1955-2011) was driven by air pollution rather than clouds. *Climate Research,* **56,** 11-20. http://dx.doi.org/10.3354/cr01139

Wang, Y., J.H. Jiang, and H. Su, 2015: Atmospheric responses to the redistribution of anthropogenic aerosols. *Journal of Geophysical Research: Atmospheres,* **120,** 9625-9641. http://dx.doi.org/10.1002/2015JD023665

Ward, D.S., N.M. Mahowald, and S. Kloster, 2014: Potential climate forcing of land use and land cover change. *Atmospheric Chemistry and Physics,* **14,** 12701-12724. http://dx.doi.org/10.5194/acp-14-12701-2014

Wenzel, S., P.M. Cox, V. Eyring, and P. Friedlingstein, 2016: Projected land photosynthesis constrained by changes in the seasonal cycle of atmospheric CO2. *Nature,* **538,** 499-501. http://dx.doi.org/10.1038/nature19772

Wieder, W.R., C.C. Cleveland, W.K. Smith, and K. Todd-Brown, 2015: Future productivity and carbon storage limited by terrestrial nutrient availability. *Nature Geoscience,* **8,** 441-444. http://dx.doi.org/10.1038/ngeo2413

Wielicki, B.A., E.F. Harrison, R.D. Cess, M.D. King, and D.A. Randall, 1995: Mission to planet Earth: Role of clouds and radiation in climate. *Bulletin of the American Meteorological Society,* **76,** 2125-2153. http://dx.doi.org/10.1175/1520-0477(1995)076<2125:mtpero>2.0.co;2

Wielicki, B.A., B.R. Barkstrom, E.F. Harrison, R.B. Lee, III, G.L. Smith, and J.E. Cooper, 1996: Clouds and the Earth's Radiant Energy System (CERES): An Earth observing system experiment. *Bulletin of the American Meteorological Society,* **77,** 853-868. http://dx.doi.org/10.1175/1520-0477(1996)077<0853:catere>2.0.co;2

Wild, M., 2009: Global dimming and brightening: A review. *Journal of Geophysical Research: Atmospheres,* **114,** D00D16. http://dx.doi.org/10.1029/2008JD011470

FINAL DRAFT

Wild, M., 2016: Decadal changes in radiative fluxes at land and ocean surfaces and their relevance for global warming. *Wiley Interdisciplinary Reviews: Climate Change,* **7,** 91-107. http://dx.doi.org/10.1002/wcc.372

Winton, M., 2006: Surface albedo feedback estimates for the AR4 climate models. *Journal of Climate,* **19,** 359-365. http://dx.doi.org/10.1175/JCLI3624.1

WMO, 2014: Scientific Asssessment of Ozone Depletion: 2014. Report No. 55. World Meteorological Organization Geneva, Switzerland. 416 pp. http://www.esrl.noaa.gov/csd/assessments/ozone/2014/

Xi, F., S.J. Davis, P. Ciais, D. Crawford-Brown, D. Guan, C. Pade, T. Shi, M. Syddall, J. Lv, L. Ji, L. Bing, J. Wang, W. Wei, K.-H. Yang, B. Lagerblad, I. Galan, C. Andrade, Y. Zhang, and Z. Liu, 2016: Substantial global carbon uptake by cement carbonation. *Nature Geoscience,* **9,** 880-883. http://dx.doi.org/10.1038/ngeo2840

Xu, J. and A.M. Powell, 2013: What happened to surface temperature with sunspot activity in the past 130 years? *Theoretical and Applied Climatology,* **111,** 609-622. http://dx.doi.org/10.1007/s00704-012-0694-y

Yang, S., B. Xu, J. Cao, C.S. Zender, and M. Wang, 2015: Climate effect of black carbon aerosol in a Tibetan Plateau glacier. *Atmospheric Environment,* **111,** 71-78. http://dx.doi.org/10.1016/j.atmosenv.2015.03.016

Yue, X., L.J. Mickley, J.A. Logan, R.C. Hudman, M.V. Martin, and R.M. Yantosca, 2015: Impact of 2050 climate change on North American wildfire: consequences for ozone air quality. *Atmospheric Chemistry and Physics,* **15,** 10033-10055. http://dx.doi.org/10.5194/acp-15-10033-2015

Zanchettin, D., C. Timmreck, H.-F. Graf, A. Rubino, S. Lorenz, K. Lohmann, K. Krüger, and J.H. Jungclaus, 2012: Bi-decadal variability excited in the coupled ocean–atmosphere system by strong tropical volcanic eruptions. *Climate Dynamics,* **39,** 419-444. http://dx.doi.org/10.1007/s00382-011-1167-1

Zhai, P.-W., Y. Hu, C.A. Hostetler, B. Cairns, R.A. Ferrare, K.D. Knobelspiesse, D.B. Josset, C.R. Trepte, P.L. Lucker, and J. Chowdhary, 2013: Uncertainty and interpretation of aerosol remote sensing due to vertical inhomogeneity. *Journal of Quantitative Spectroscopy and Radiative Transfer,* **114,** 91-100. http://dx.doi.org/10.1016/j.jqsrt.2012.08.006

Zhang, D., R. Blender, and K. Fraedrich, 2013: Volcanoes and ENSO in millennium simulations: Global impacts and regional reconstructions in East Asia. *Theoretical and Applied Climatology,* **111,** 437-454. http://dx.doi.org/10.1007/s00704-012-0670-6

FINAL DRAFT

Zhu, Z., S. Piao, R.B. Myneni, M. Huang, Z. Zeng, J.G. Canadell, P. Ciais, S. Sitch, P. Friedlingstein, A. Arneth, C. Cao, L. Cheng, E. Kato, C. Koven, Y. Li, X. Lian, Y. Liu, R. Liu, J. Mao, Y. Pan, S. Peng, J. Penuelas, B. Poulter, T.A.M. Pugh, B.D. Stocker, N. Viovy, X. Wang, Y. Wang, Z. Xiao, H. Yang, S. Zaehle, and N. Zeng, 2016: Greening of the Earth and its drivers. *Nature Climate Change,* **6,** 791-795. http://dx.doi.org/10.1038/nclimate3004

FINAL DRAFT

3. Detection and Attribution of Climate Change

Key Findings

1. The *likely* range of the human contribution to the global mean temperature increase over the period 1951–2010 is 1.1° to 1.4°F (0.6° to 0.8°C), and the central estimate of the observed warming of 1.2°F (0.65°C) lies within this range (*high confidence*). This translates to a *likely* human contribution of 93%–123% of the observed 1951–2010 change. It is *extremely likely* that more than half of the global mean temperature increase since 1951 was caused by human influence on climate (*high confidence*). The *likely* contributions of natural forcing and internal variability to global temperature change over that period are minor (*high confidence*).

2. The science of event attribution is rapidly advancing through improved understanding of the mechanisms that produce extreme events and the marked progress in development of methods that are used for event attribution (*high confidence*).

3.1 Introduction

Detection and attribution of climate change involves assessing the causes of observed changes in the climate system through systematic comparison of climate models and observations using various statistical methods. Detection and attribution studies are important for a number of reasons. For example, such studies can help determine whether a human influence on climate variables (for example, temperature) can be distinguished from natural variability. Detection and attribution studies can help evaluate whether model simulations are consistent with observed trends or other changes in the climate system. Results from detection and attribution studies can inform decision making on climate policy and adaptation.

There are several general types of detection and attribution studies, including: attribution of trends or long-term changes in climate variables; attribution of changes in extremes; attribution of weather or climate events; attribution of climate-related impacts; and the estimation of climate sensitivity using observational constraints. Paleoclimate proxies can also be useful for detection and attribution studies, particularly to provide a longer-term perspective on climate variability as a baseline on which to compare recent climate changes of the past century or so (for example, see Figure 12.2 from Ch. 12: Sea Level Rise). Detection and attribution studies can be done at various scales, from global to regional.

Since the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) chapter on detection and attribution (Bindoff et al. 2013) and the Third National Climate Assessment (NCA3, Melillo et al. 2014), the science of detection and attribution has advanced, with a major scientific question being the issue of attribution of extreme events (Hulme 2014; Stott 2016; Easterling et al. 2016; NAS 2016). Therefore, the methods used in this developing

FINAL DRAFT

area of the science are briefly reviewed in Appendix C: Detection and Attribution Methods, along with a brief overview of the various general detection and attribution methodologies, including some recent developments in these areas. Detection and attribution of changes in extremes in general presents a number of challenges (Zwiers et al. 2013), including limitations of observations, models, statistical methods, process understanding for extremes, and uncertainties about the natural variability of extremes. Although the present report does not focus on climate impacts on ecosystems or human systems, a relatively new and developing area of detection and attribution science (reviewed in Stone et al. 2013), concerns detecting and attributing the impacts of climate change on natural or human systems. Many new developments in detection and attribution science have been fostered by the International Detection and Attribution Group (IDAG; http://www.image.ucar.edu/idag/ and http://www.clivar.org/clivar-panels/etccdi/idag/international-detection-attribution-group-idag) which is an international group of scientists who have collaborated since 1995 on "assessing and reducing uncertainties in the estimates of climate change."

In the remainder of this chapter, we review highlights of detection and attribution science, particularly key attribution findings for the rise in global mean temperature. However, as this is a U.S.-focused assessment, the report as a whole will focus more on the detection and attribution findings for particular regional phenomena (for example, regional temperature, precipitation) or at least global-scale phenomena that are directly affecting the United States (for example, sea level rise). Most of these findings are contained in the individual phenomena chapters, rather than in this general overview chapter on detection and attribution. We provide summary links to the chapters where particular detection and attribution findings are presented in more detail.

3.2 Detection and Attribution of Global Temperature Changes

The concept of detection and attribution is illustrated in Figure 3.1, which shows a very simple example of detection and attribution of global mean temperature. While more powerful pattern-based detection and attribution methods (discussed later), and even greater use of time averaging, can result in much stronger statements about detection and attribution, the example in Figure 3.1 serves to illustrate the general concept. In the figure, observed global mean temperature anomalies (relative to a 1901–1960 baseline) are compared with anomalies from historical simulations of CMIP5 models. The spread of different individual model simulations (the blue and red shading) arises both from differences between the models in their responses to the different specified climate forcing agents (natural and anthropogenic) and from internal (unforced) climate variability. Observed annual temperatures after about 1980 are shown to be inconsistent with models that include only natural forcings (blue shading) and are consistent with the model simulations that include both anthropogenic and natural forcing (red shading). This implies that the observed global warming is attributable in large part to anthropogenic forcing. A key aspect of a detection and attribution finding will be the assessment of the adequacy of the

FINAL DRAFT

models and observations used for these conclusions, as discussed and assessed in Flato et al. (2013), Bindoff et al. (2013), and IPCC (2013a).

[INSERT FIGURE 3.1 HERE]

The detection and attribution of global temperature change to human causes has been one of the most important and visible findings over the course of the past global climate change scientific assessments by the IPCC. The first IPCC report (IPCC 1990) concluded that a human influence on climate had not yet been detected, but judged that "the unequivocal detection of the enhanced greenhouse effect from observations is not likely for a decade or more." The second IPCC report (IPCC 1996) concluded that "the balance of evidence suggests a discernible human influence on climate." The third IPCC report (IPCC 2001) strengthened this conclusion to: "most of the observed warming over the last 50 years is likely to have been due to the increase of greenhouse gas concentrations." The fourth IPCC report (IPCC 2007) further strengthened the conclusion to: "Most of the observed increase in global average temperatures since the mid-20th century is very likely due to the observed increase in anthropogenic greenhouse gas concentrations." The fifth IPCC report (IPCC 2013a) further strengthened this to: "It is extremely likely that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together." These increasingly confident statements have resulted from scientific advances, including better observational datasets, improved models and detection/attribution methods, and improved estimates of climate forcings. Importantly, the continued long-term warming of the global climate system since the time of the first IPCC report and the broad-scale agreement of the spatial pattern of observed temperature changes with climate model projections of greenhouse gas-induced changes as published in the late 1980s (e.g., Stouffer and Manabe 2017) give more confidence in the attribution of observed warming since 1951 as being due primarily to human activity.

The IPCC AR5 presented an updated assessment of detection and attribution research at the global to regional scale (Bindoff et al. 2013) which is briefly summarized here. Key attribution assessment results from IPCC AR5 for global mean temperature are summarized in Figure 3.2, which shows assessed *likely* ranges and midpoint estimates for several factors contributing to increases in global mean temperature. According to Bindoff et al., the *likely* range of the anthropogenic contribution to global mean temperature increases over 1951–2010 was 0.6°C to 0.8°C (1.1°F to 1.4°F), compared with the observed warming 5th to 95th percentile range of 0.59°C to 0.71°C (1.1°F to 1.3°F). The estimated *likely* contribution ranges for natural forcing and internal variability were both much smaller (–0.1°C to 0.1°C, or –0.2°F to 0.2°F) than the observed warming. The confidence intervals that encompass the *extremely likely* range for the anthropogenic contribution are wider than the *likely* range. Using these wider confidence limits, the lower limit of attributable warming contribution range still lies above 50% of the observed warming rate, and thus Bindoff et al. concluded that it is *extremely likely* that more than half of

FINAL DRAFT

the global mean temperature increase since 1951 was caused by human influence on climate. This assessment concurs with the Bindoff et al. assessment of attributable warming and cooling influences.

[INSERT FIGURE 3.2 HERE]

Apart from formal detection attribution studies such as those underlying the results above, which use global climate model output and pattern-based regression methods, anthropogenic influences on global mean temperature can also be estimated using simpler empirical models, such as multiple linear regression/energy balance models (e.g., Canty et al. 2013; Zhou and Tung, 2013). For example, Figure 3.3 illustrates how the global mean surface temperature changes since the late 1800s can be decomposed into components linearly related to several forcing variables (anthropogenic forcing, solar variability, volcanic forcing, plus an internal variability component, here related to El Niño–Southern Oscillation). Using this approach, Canty et al. also infer a substantial contribution of anthropogenic forcing to the rise in global mean temperature since the late 1800s. Stern and Kaufmann (2014) use another method—Granger causality tests—and again infer that "human activity is partially responsible for the observed rise in global temperature and that this rise in temperature also has an effect on the global carbon cycle." They also conclude that anthropogenic sulfate aerosol effects may only be about half as large as inferred in a number of previous studies.

Multi-century to multi-millennial-scale climate model integrations with unchanging external forcing provide a means of estimating potential contributions of internal climate variability to observed trends. Bindoff et al. (2013) conclude, based on multimodel assessments, that the likely range contribution of internal variability to observed trends over 1951–2010 is about ±0.2°F, compared to the observed warming of about 1.2 °F over that period. A recent 5,200 year integration of the CMIP5 model having apparently the largest global mean temperature variability among CMIP5 models shows rare instances of multidecadal global warming approaching the observed 1951–2010 warming trend (Knutson et al. 2016). However, even that most extreme model cannot simulate century-scale warming trends from internal variability that approach the observed global mean warming over the past century. According to a multimodel analysis of observed versus CMIP5 modeled global temperature trends (Knutson et al. 2013a, Fig. 7a), the modeled natural fluctuations (forced plus internal) would need to be larger by about a factor of three for even an unusual natural variability episode (95th percentile) to approach the observed trend since 1900. Thus, using present models there is no known source of internal climate variability that can reproduce the observed warming over the past century without including strong positive forcing from anthropogenic greenhouse gas emissions (Figure 3.1). The modeled century-scale trend due to natural forcings (solar and volcanic) is also minor (Figure 3.1), so that, using present models, there is no known source of natural variability that can reproduce the observed global warming over the past century. One study (Laepple and Huybers 2014) comparing paleoclimate data with models concluded that current climate models may

FINAL DRAFT

substantially underestimate regional sea surface temperature variability on multidecadal to multi-centennial timescales, especially at low latitudes. The causes of this apparent discrepancy--whether due to data issues, external forcings/response, or simulated internal variability issues--and its implications for simulations of global temperature variability in climate models remain unresolved. In summary, we are not aware of any convincing evidence that natural variability alone could have accounted for the amount and timing of global warming that was observed over the industrial era.

[INSERT FIGURE 3.3 HERE]

While most detection and attribution studies focus on changes in temperature and other variables in the historical record since about 1860 or later, some studies relevant to detection and attribution focus on changes over much longer periods. For example, geological and tide-based reconstructions of global mean sea level (Ch. 12: Sea Level Rise, Figure 12.2b) suggest that the rate of sea level rise in the last century was faster than during any century over the past ~2,800 years. As an example for northern hemisphere annual mean temperatures, Schurer et al. (2013) use detection and attribution fingerprinting methods along with paleoclimate reconstructions and millennial-scale climate model simulations from eight models to explore causes for temperature variations from 850 AD to the present, including the Medieval Climate Anomaly (MCA, around 900 to 1200 AD) and the Little Ice Age (LIA, around 1450 to 1800 AD). They conclude that solar variability and volcanic eruptions were the main causal factors for changes in northern hemisphere temperatures from 1400 to 1900, but that greenhouse gas changes of uncertain origin apparently contributed to the cool conditions during 1600–1800. Their study provides further support for previous IPCC report conclusions (e.g., IPCC 2007) that internal variability alone was extremely unlikely to have been the cause of the recent observed 50- and 100-year warming trends. Andres and Peltier (2016) also inferred from millennial-scale climate model simulations that volcanoes, solar variability, greenhouse gases, and orbital variations all contributed significantly to the transition from the MCA to the LIA.

An active and important area of climate research that involves detection and attribution science is the estimation of global climate sensitivity, based on past observational constraints. An important measure of climate sensitivity, with particular relevance for climate projections over the coming decades, is the transient climate response (TCR), defined as the rise in global mean surface temperature at the time of CO_2 doubling for a 1% per year transient increase of atmospheric CO_2. (Equilibrium climate sensitivity is discussed in Ch. 2: Physical Drivers of Climate Change). The TCR of the climate system has an estimated range of 0.9° to 2.0°C (1.6° to 3.6°F) and 0.9° to 2.5°C (1.6° to 4.5°F), according to two recent assessments (Otto et al. 2013 and Lewis and Curry 2015, respectively). Marvel et al. (2016) suggest, based on experiments with a single climate model, that after accounting for the different efficacies of various historical climate forcing agents, the TCR could be adjusted upward from the Otto et al. and Lewis and Curry estimates. Richardson et al. (2016) report a best estimate for TCR of 1.66°C (2.99 °F), with a 5% to 95%

FINAL DRAFT

confidence range of 1.0°C to 3.3°C (1.8°F to 5.9°F). Furthermore, Richardson et al. conclude that the earlier studies noted above may underestimate TCR, because the surface temperature data set they used undersamples rapidly warming regions due to limited coverage and because surface water warms less than surface air. Gregory et al. (2015) note, within CMIP5 models, that the TCR to the second doubling of CO_2 (that is, from doubling to quadrupling) is 40% higher than that for the first doubling. They explore the various physical reasons for this finding, and conclude this may also lead to an underestimate of TCR in the empirical observation-based studies. In summary, estimation of TCR from observations continues to be an active area of research with considerable remaining uncertainties, as discussed above.

3.3 Detection and Attribution with a United States Regional Focus

Detection and attribution at regional scales is generally more challenging than at the global scale for a number of reasons. At the regional scale, the magnitude of natural variability swings are typically larger than for global means. If the climate change signal is similar in magnitude at the regional and global scales, this makes it more difficult to detect anthropogenic climate changes at the regional scale. Further, there is less spatial pattern information at the regional scale that can be used to distinguish contributions from various forcings. Other forcings that have typically received less attention than greenhouse gases, such as land-use change, could be more important at regional scales than globally (Pielke et al. 2016). Also, simulated internal variability at regional scales may be less reliable than at global scales (Bindoff et al. 2013). While detection and attribution of changes in extremes (including at the regional scale) presents a number of key challenges (Zwiers et al. 2013), previous studies (e.g., Zwiers et al. 2011) have demonstrated how detection and attribution methods, combined with generalized extreme value distributions, can be used to detect a human influence on extreme temperatures at the regional scale, including over North America.

In IPCC AR5 (Bindoff et al. 2013), which had a broader global focus than this report, attributable human contributions were reported for warming over all continents except Antarctica. Changes in daily temperature extremes throughout the world; ocean surface and subsurface temperature and salinity sea level pressure patterns; Arctic sea ice loss; northern hemispheric snow cover decrease; global mean sea level rise; and ocean acidification were all associated with human activity in AR5 (Bindoff et al. 2013). IPCC AR5 also reported medium confidence in anthropogenic contributions to increased atmospheric specific humidity, zonal mean precipitation over northern hemisphere mid to high latitudes, and intensification of heavy precipitation over land regions. IPCC AR5 had weaker attribution conclusions than IPCC AR4 on some phenomena, including tropical cyclone and drought changes.

Although the present assessment follows most of the IPCC AR5 conclusions on detection and attribution of relevance to the United States, we make some additional attribution assessment statements in the relevant chapters of this report. Among the notable detection and attribution-relevant findings in this report are the following (refer to the listed chapters for further details):

FINAL DRAFT

- Ch. 5: Circulation and Variability: Human activities have played a role in the observed expansion of the tropics (by 70 to 200 miles since 1979), although confidence is presently *low* regarding the magnitude of the human contribution relative to natural variability.

- Ch. 6: Temperature Change: Detectable anthropogenic warming since 1901 has occurred over the western and northern regions of the contiguous United States according to observations and CMIP5 models, although over the southeastern United States there has been no detectable warming trend since 1901. The combined influence of natural and anthropogenic forcings on temperature *extremes* have been detected over large subregions of North America.

- Ch. 7: Precipitation Change: For the continental United States, there is *high confidence* in the detection of extreme precipitation increases, while there is *low confidence* in attributing the extreme precipitation changes purely to anthropogenic forcing. There is stronger evidence for a human contribution (*medium confidence*) when taking into account process-based understanding (for example, increased water vapor in a warmer atmosphere).

- Ch. 8: Drought, Floods, and Wildfire: No detectable change in long-term U.S. drought statistics has emerged. Detectable changes—a mix of increases and decreases—in some classes of flood frequency have occurred in parts of the United States, although attribution studies have not established a robust connection between increased riverine flooding and human-induced climate change. There is *medium confidence* for a human-caused climate change contribution to increased forest fire activity in Alaska in recent decades and *low* to *medium confidence* in the western United States.

- Ch. 9: Extreme Storms: There is broad agreement in the literature that human factors (greenhouse gases and aerosols) have had a measurable impact on the observed oceanic and atmospheric variability in the North Atlantic, and there is *medium confidence* that this has contributed to the observed increase in hurricane activity since the 1970s. There is no consensus on the relative magnitude of human and natural influences on past changes in hurricane activity.

- Ch. 10: Land Cover: Modifications to land use and land cover due to human activities produce changes in surface albedo and in atmospheric aerosol and greenhouse gas concentrations, accounting for an estimated 40% ± 16% of the human-caused global radiative forcing from 1850 to 2010.

- Ch. 11: Arctic Changes: It is *virtually certain* that human activities have contributed to arctic surface temperature warming, sea ice loss since 1979, glacier mass loss, and northern hemisphere snow extent decline observed across the Arctic. Human activities

FINAL DRAFT

have *likely* contributed to more than half of the observed arctic surface temperature rise and September sea ice decline since 1979.

- Ch. 12: Sea Level Rise: Human-caused climate change has made a substantial contribution to global mean sea level rise since 1900, contributing to a rate of rise faster than during any comparable period over the past ~2,800 years.

- Ch. 13: Ocean Changes: The world's oceans have absorbed more than 90% of the excess heat caused by greenhouse warming since the mid-20th Century. The world's oceans are currently absorbing more than a quarter of the carbon dioxide emitted to the atmosphere annually from human activities (*very high confidence*), making them more acidic.

3.4 Extreme Event Attribution

Since the IPCC AR5 and NCA3 (Melillo et al. 2014), the attribution of extreme weather and climate events has been an emerging area in the science of detection and attribution. Attribution of extreme weather events under a changing climate is now an important and highly visible aspect of climate science. As discussed in the recent National Academy of Sciences report (NAS 2016), the science of event attribution is rapidly advancing, including the understanding of the mechanisms that produce extreme events and the rapid progress in development of methods used for event attribution.

When an extreme weather event occurs, the question is often asked: was this event caused by climate change? A generally more appropriate framing for the question is whether climate change has altered the odds of occurrence of an extreme event like the one just experienced. Extreme event attribution studies to date have generally been concerned with answering the latter question. In recent developments, Hannart et al. (2016b) discuss the application of causal theory to event attribution, including discussion of conditions under which stronger causal statements can be made, in principle, based on theory of causality and distinctions between necessary and sufficient causality.

Several recent studies, including NAS (2016), have reviewed aspects of extreme event attribution (Hulme 2014; Stott 2016; Easterling et al. 2016). Hulme (2014) and NAS (2016) discuss the motivations for scientists to be pursuing extreme event attribution, including the need to inform risk management and adaptation planning. Hulme (2014) categorizes event attribution studies/statements into general types, including those based on: physical reasoning, statistical analysis of time series, fraction of attributable risk (FAR) estimation (discussed in the Appendix), or those that rely on the philosophical argument that there are no longer any purely natural weather events. The NAS (2016) report outlines two general approaches to event attribution: 1) using observations to estimate a change in probability of magnitude of events, or 2) using model simulations to compare an event in the current climate versus that in a hypothetical "counterfactual" climate not influenced by human activities. As discussed by

FINAL DRAFT

Trenberth et al. (2015), Shepherd (2016), and Horton et al. 2016, an ingredients-based or conditional attribution approach can also be used, when one examines the impact of certain environmental changes (for example, greater atmospheric moisture) on the character of an extreme event using model experiments, all else being equal. Further discussion of methodologies is given in Appendix C.

Examples of extreme event attribution studies are numerous. Many are cited by Hulme (2014), NAS (2016), Easterling et al. (2016), and there are many further examples in an annual collection of studies of extreme events of the previous year, published in the *Bulletin of the American Meteorological Society* (Peterson et al. 2012, 2013; Herring et al. 2014, 2015, 2016).

While an extensive review of extreme event attribution is beyond the scope of this report, particularly given the recent publication of several assessments or review papers on the topic, some general findings from the more comprehensive NAS (2016) report are summarized here:

- Confidence in attribution findings of anthropogenic influence is greatest for extreme events that are related to an aspect of temperature, followed by hydrological drought and heavy precipitation, with little or no confidence for severe convective storms or extratropical storms.

- Event attribution is more reliable when based on sound physical principles, consistent evidence from observations, and numerical models that can replicate the event.

- Statements about attribution are sensitive to the way the questions are posed (that is, framing).

- Assumptions used in studies must be clearly stated and uncertainties estimated in order for a clear, unambiguous interpretation of an event attribution to be possible.

The NAS report noted that uncertainties about the roles of low-frequency natural variability and confounding factors (for example, the effects of dams on flooding) could be sources of difficulties in event attribution studies. In addition, the report noted that attribution conclusions would be more robust in cases where observed changes in the event being examined are consistent with expectations from model-based attribution studies. The report endorsed the need for more research to improve understanding of a number of important aspects of event attribution studies, including physical processes, models and their capabilities, natural variability, reliable long-term observational records, statistical methods, confounding factors, and future projections of the phenomena of interest.

As discussed in Appendix C: Detection and Attribution Methodologies, confidence is typically lower for an attribution-without-detection statement than for an attribution statement accompanied by an established, detectable anthropogenic influence (for example, a detectable and attributable long-term trend or increase in variability) for the phenomenon itself. An example

FINAL DRAFT

of the former would be stating that a change in the probability or magnitude of a heat wave in the southeastern United States was attributable to rising greenhouse gases, because there has not been a detectable century-scale trend in either temperature or temperature variability in this region (e.g., Ch. 6: Temperature Change; Knutson et al. 2013a).

To our knowledge, no extreme weather event observed to date has been found to have zero probability of occurrence in a preindustrial climate, according to climate model simulations. Therefore, the causes of attributed extreme events are a combination of natural variations in the climate system compounded (or alleviated) by the anthropogenic change to the climate system. Event attribution statements quantify the relative contribution of these human and natural causal factors. In the future, as the climate change signal gets stronger compared to natural variability, humans may experience weather events which are essentially impossible to simulate in a preindustrial climate. This is already becoming the case at large time and spatial scales, where for example the record global mean surface temperature anomaly observed in 2016 (relative to a 1901–1960 baseline) is essentially impossible for global climate models to reproduce under preindustrial climate forcing conditions (for example, see Figure 3.1).

The European heat wave of 2003 (Stott et al. 2004) and Australia's extreme temperatures and heat indices of 2013 (e.g., Arblaster et al. 2014; King et al. 2014; Knutson et al. 2014; Lewis and Karoly 2014; Perkins et al. 2014) are examples of extreme weather or climate events where relatively strong evidence for a human contribution to the event has been found. Similarly, in the United States, the science of event attribution for weather and climate extreme events has been actively pursued since the NCA3. For example, for the case of the recent California drought, investigators have attempted to determine, using various methods discussed in this chapter, whether human-caused climate change contributed to the event (see discussion in Ch. 8: Droughts, Floods, and Wildfires).

As an example, illustrating different methods of attribution for an event in the United States, Hoerling et al. (2013) concluded that the 2011 Texas heat wave/meteorological drought was primarily caused by antecedent and concurrent negative rainfall anomalies due mainly to natural variability and the La Niña conditions at the time of the event, but with a relatively small (not detected) warming contribution from anthropogenic forcing. The anthropogenic contribution nonetheless doubled the chances of reaching a new temperature record in 2011 compared to the 1981–2010 reference period, according to their study. Rupp et al. (2012), meanwhile, concluded that extreme heat events in Texas were about 20 times more likely for 2008 La Niña conditions than similar conditions during the 1960s. This pair of studies illustrates how the framing of the attribution question can matter. For example, the studies used different baseline reference periods to determine the magnitude of anomalies, which can also affect quantitative conclusions, since using an earlier baseline period typically results in larger magnitude anomalies (in a generally warming climate). The Hoerling et al. analysis focused on both what caused most of the magnitude of the anomalies as well as changes in probability of the event, whereas Rupp et al.

FINAL DRAFT

focused on the changes in the probability of the event. Otto et al. (2012) showed for the case of the Russian heat wave of 2010 how a different focus of attribution (fraction of anomaly explained vs. change in probability of occurrence over a threshold) can give seemingly conflicting results, yet have no real fundamental contradiction. In the illustrative case for the 2011 Texas heat/drought, we conclude that there is *medium* confidence that anthropogenic forcing contributed to the heat wave, both in terms of a small contribution to the anomaly magnitude and a significant increase in the probability of occurrence of the event.

In this report, we do not assess or compile all individual weather or climate extreme events for which an attributable anthropogenic climate change has been claimed in a published study, as there are now many such studies that provide this information. Some event attribution-related studies that focus on the United States are discussed in more detail in Chapters 6–9, which primarily examine phenomena such as precipitation extremes, droughts, floods, severe storms, and temperature extremes. For example, as discussed in Chapter 6: Temperature Change (Table 6.3), a number of extreme temperature events (warm anomalies) in the United States have been partly attributed to anthropogenic influence on climate.

FINAL DRAFT

TRACEABLE ACCOUNTS

Key Finding 1

The *likely* range of the human contribution to the global mean temperature increase over the period 1951–2010 is 1.1°F to 1.4°F (0.6°C to 0.8°C), and the central estimate of the observed warming of 1.2°F (0.65°C) lies within this range (*high confidence*). This translates to a *likely* human contribution of 93%–123% of the observed 1951-2010 change. It is *extremely likely* that more than half of the global mean temperature increase since 1951 was caused by human influence on climate (*high confidence*). The *likely* contributions of natural forcing and internal variability to global temperature change over that period are minor (*high confidence*).

Description of evidence base

This Key Finding summarizes key detection and attribution evidence documented in the climate science literature and in the IPCC AR5 (Bindoff et al. 2013), and references therein. The Key Finding is essentially the same as the summary assessment of IPCC AR5.

According to Bindoff et al. (2013), the *likely* range of the anthropogenic contribution to global mean temperature increases over 1951–2010 was 1.1°F to 1.4°F (0.6°C to 0.8°C, compared with the observed warming 5th to 95th percentile range of 1.1°F to 1.3°F (0.59°C to 0.71°C). The estimated likely contribution ranges for natural forcing and internal variability were both much smaller (–0.2°F to 0.2°F, or –0.1°F to 0.1°F) than the observed warming. The confidence intervals that encompass the *extremely likely* range for the anthropogenic contribution are wider than the *likely* range, but nonetheless allow for the conclusion that it is *extremely likely* that more than half of the global mean temperature increase since 1951 was caused by human influence on climate (*high confidence*).

The attribution of temperature increases since 1951 is based largely on the detection and attribution analyses of Gillett et al. (2013), Jones et al. (2013), and consideration of Ribes and Terray (2013), Huber and Knutti (2011), Wigley and Santer (2013), and IPCC AR4 (Hegerl et al. 2007. The IPCC finding receives further support from alternative approaches, such as multiple linear regression/energy balance modeling (Canty et al. 2013) and a new methodological approach to detection and attribution that uses additive decomposition and hypothesis testing (Ribes et al. 2017), which infer similar attributable warming results. Individual study results used to derive the IPCC finding are summarized in Figure 10.4 of Bindoff et al. (2013), which also assesses model dependence by comparing results obtained from several individual CMIP5 models. The estimated potential influence of internal variability is based on Knutson et al. (2013a) and Huber and Knutti (2011), with consideration of the above references. Moreover, simulated global temperature multidecadal variability is assessed to be adequate (Bindoff et al. 2013), with *high confidence* that models reproduce global and northern hemisphere temperature variability across a range of timescales (Flato et al. 2013). Further support for these assessments comes from assessments of paleoclimate data (Masson-Delmotte et al. 2013) and increased

FINAL DRAFT

confidence in physical understanding and models of the climate system (IPCC 2013a; Stouffer and Manabe 2017). A more detailed traceable account is contained in Bindoff et al. (2013). Post-IPCC AR5 supporting evidence includes additional analyses showing the unusual nature of observed global warming since the late 1800s compared to simulated internal climate variability (Knutson et al. 2016), and the recent occurrence of new record high global mean temperatures are consistent with model projections of continued warming on multidecadal scales (for example, Figure 3.1).

Major uncertainties

As discussed in the main text, estimation of the transient climate response (TCR), defined as the global mean surface temperature change at the time of CO_2 doubling in a 1% per year CO_2 transient increase experiment, continues to be an active area of research with considerable remaining uncertainties. Some detection attribution methods use model-based methods together with observations to attempt to infer scaling magnitudes of the forced responses based on regression methods (that is, they do not use the models' climate sensitivities directly). However, if climate models are significantly more sensitive to CO_2 increases than the real world, as suggested by the studies of Otto et al. 2013 and Lewis and Curry (2014) (though see differing conclusions from other studies in the main text), this could lead to an overestimate of attributable warming estimates, at least as obtained using some detection and attribution methods. In any case it is important to better constrain the TCR to have higher confidence in general in attributable warming estimates obtained using various methods.

The global temperature change since 1951 attributable to anthropogenic forcings other than greenhouse gases has a wide estimated *likely* range (−1.1 to +0.2°F in Fig. 3.1). This wide range is largely due to the considerable uncertainty of estimated total radiative forcing due to aerosols (i.e., the direct effect combined with the effects of aerosols on clouds [Myhre et al. 2013]). Although more of the relevant physical processes are being included in models, confidence in these model representations remains low (Boucher et al. 2013). In detection/attribution studies there are substantial technical challenges in quantifying the separate attributable contributions to temperature change from greenhouse gases and aerosols (Bindoff et al. 2013). Finally, there is a range of estimates of the potential contributions of internal climate variability, and some sources of uncertainty around modeled estimates (e.g., Laepple and Huybers 2014). However, current CMIP5 multimodel estimates (*likely* range of ±0.2°F, or 0.1°C, over 60 years) would have to increase by a factor of about three for even half of the observed 60-year trend to lie within a revised *likely* range of potential internal variability (e.g., Knutson et al. 2013a; Huber and Knutti 2012). Recently, Knutson et al. (2016) examined a 5000-year integration of the CMIP5 model having the strongest internal multidecadal variability among 25 CMIP5 models they examined. While the internal variability within this strongly varying model can on rare occasions produce 60-year warmings approaching that observed from 1951–2010, even this most extreme model

FINAL DRAFT

did not produce any examples of centennial-scale internal variability warming that could match the observed global warming since the late 1800s, even in a 5000-year integration.

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 global temperature has been increasing and that anthropogenic forcings have played a major role in the increase observed over the past 60 years, with strong evidence from several studies using well-established detection and attribution techniques. There is *high confidence* that the role of internal variability is minor, as the CMIP5 climate models as a group simulate only a minor role for internal variability over the past 60 years, and the models have been assessed by IPCC AR5 as adequate for the purpose of estimating the potential role of internal variability.

If appropriate, estimate likelihood of impact or consequence, including short description of basis of estimate

The amount of historical warming attributable to anthropogenic forcing has a very high likelihood of consequence, as it is related to the amount of future warming to be expected under various emission scenarios, and the impacts of global warming are generally larger for higher warming rates and higher warming amounts.

Summary sentence or paragraph that integrates the above information

Detection and attribution studies, climate models, observations, paleoclimate data, and physical understanding lead to *high confidence* (*extremely likely*) that more than half of the observed global mean warming since 1951 was caused by humans, and *high confidence* that internal climate variability played only a minor role (and possibly even a negative contribution) in the observed warming since 1951. The key message and supporting text summarizes extensive evidence documented in the peer-reviewed detection and attribution literature, including in the IPCC AR5.

Key Finding 2

The science of event attribution is rapidly advancing through improved understanding of the mechanisms that produce extreme events and the marked progress in development of methods that are used for event attribution (*high confidence*).

Description of evidence base

This Key Finding paraphrases a conclusion of the National Academy of Sciences report (NAS 2016) on attribution of extreme weather events in the context of climate change. That report

FINAL DRAFT

discusses advancements in event attribution in more detail than possible here due to space limitations. Weather and climate science in general continue to seek improved physical understanding of extreme weather events. One aspect of improved understanding is the ability to more realistically simulate extreme weather events in models, as the models embody current physical understanding in a simulation framework that can be tested on sample cases. NAS (2016) provides references to studies that evaluate weather and climate models used to simulated extreme events in a climate context. Such models can include coupled climate models (e.g., Taylor et al. 2012; Flato et al. 2013), atmospheric models with specified sea surface temperatures, regional models for dynamical downscaling, weather forecasting models, or statistical downscaling models. Appendix C includes a brief description of the evolving set of methods used for event attribution, discussed in more detail in references such as NAS (2016), Hulme (2014), Trenberth et al. (2015), Shepherd (2016), Horton et al. (2016), Hannart (2016), and Hannart et al. (2016a,b). Most of this methodology as applied to extreme weather and climate event attribution, has evolved since the European heat wave study of Stott et al. (2004).

Major uncertainties

While the science of event attribution is rapidly advancing, studies of individual events will typically contain caveats. In some cases, attribution statements are made without a clear detection of an anthropogenic influence on observed occurrences of events similar to the one in question, so that there is reliance on models to assess probabilities of occurrence. In such cases there will typically be uncertainties in the model-based estimations of the anthropogenic influence, in the estimation of the influence of natural variability on the event's occurrence, and even in the observational records related to the event (e.g., long-term records of hurricane occurrence). Despite these uncertainties in individual attribution studies, the science of event attribution is advancing through increased physical understanding and development of new methods of attribution and evaluation of 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 weather and climate science are advancing in their understanding of the physical mechanisms that produce extreme events. For example, hurricane track forecasts have improved in part due to improved models. There is *high confidence* that new methods being developed will help lead to further advances in the science of event attribution.

If appropriate, estimate likelihood of impact or consequence, including short description of basis of estimate

Improving science of event attribution has a high likelihood of impact, as it is one means by which scientists can better understand the relationship between occurrence of extreme events and long-term climate change. A further impact will be the improved ability to communicate this

FINAL DRAFT

information to the public and to policymakers for various uses, including improved adaptation planning (Hulme 2014; NAS 2016).

Summary sentence or paragraph that integrates the above information

Owing to the improved physical understanding of extreme weather and climate events as the science in these fields progress, and owing to the high promise of newly developed methods for exploring the roles of different influences on occurrence of extreme events, there is *high confidence* that the science of event attribution is rapidly advancing.

FINAL DRAFT

FIGURES

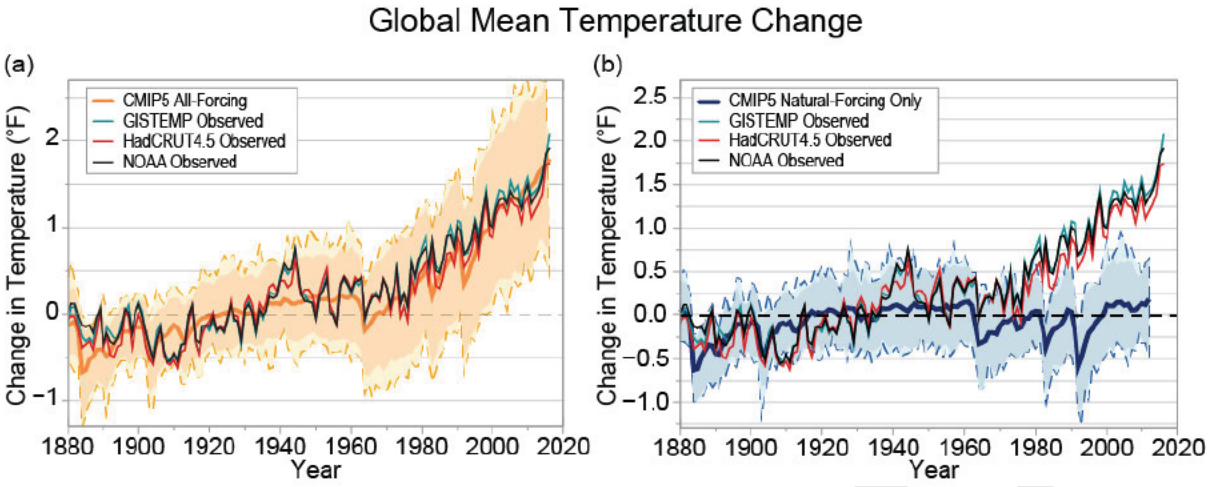


Figure 3.1: Comparison of observed global mean temperature anomalies from three observational datasets to CMIP5 climate model historical experiments using: (a) anthropogenic and natural forcings combined, or (b) natural forcings only. In (a) the thick orange curve is the CMIP5 grand ensemble mean across 36 models while the orange shading and outer dashed lines depict the ± 2 standard deviation and absolute ranges of annual anomalies across all individual simulations of the 36 models. Model data are a masked blend of surface air temperature over land regions and sea surface temperature over ice-free ocean regions to be more consistent with observations than using surface air temperature alone. All time series (°F) are referenced to a 1901–1960 baseline value. The simulations in (a) have been extended from 2006 through 2016 using the RCP8.5 scenario projections. (b) As in (a) but the blue curves and shading are based on 18 CMIP5 models using natural forcings only. See legends to identify observational datasets. Observations after about 1980 are shown to be inconsistent with the natural forcing-only models (indicating detectable warming) and also consistent with the models that include both anthropogenic and natural forcing, implying that the warming is attributable in part to anthropogenic forcing according to the models.

FINAL DRAFT

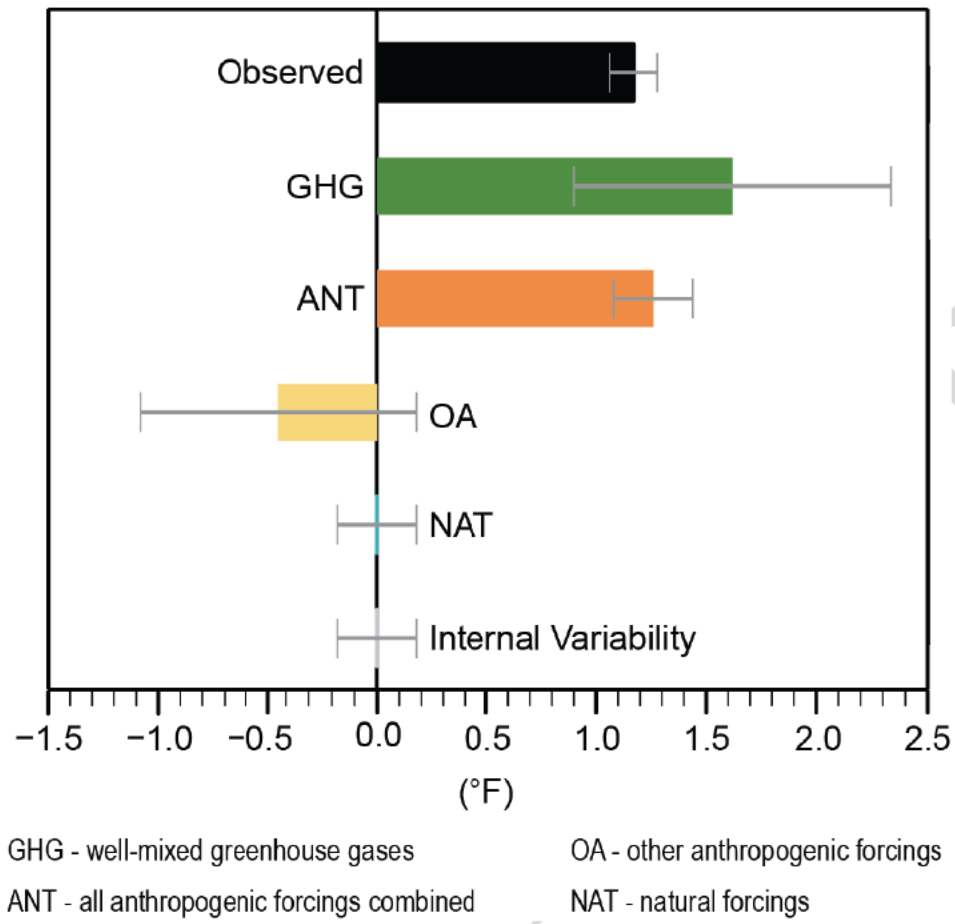


Figure 3.2: Observed global mean temperature trend (black bar) and attributable warming or cooling influences of anthropogenic and natural forcings over 1951–2010. Observations are from HadCRUT4, along with observational uncertainty (5% to 95%) error bars (Morice et al. 2012). Likely ranges (bar-whisker plots) and midpoint values (colored bars) for attributable forcings are from IPCC AR5 (Bindoff et al. 2013). GHG refers to well-mixed greenhouse gases, OA to other anthropogenic forcings, NAT to natural forcings, and ANT to all anthropogenic forcings combined. Likely ranges are broader for contributions from well-mixed greenhouse gases and for other anthropogenic forcings, assessed separately, than for the contributions from all anthropogenic forcings combined, as it is more difficult to quantitatively constrain the separate contributions of the various anthropogenic forcing agents. (Figure source: redrawn from Bindoff et al. 2013; © IPCC. Used with permission.)

FINAL

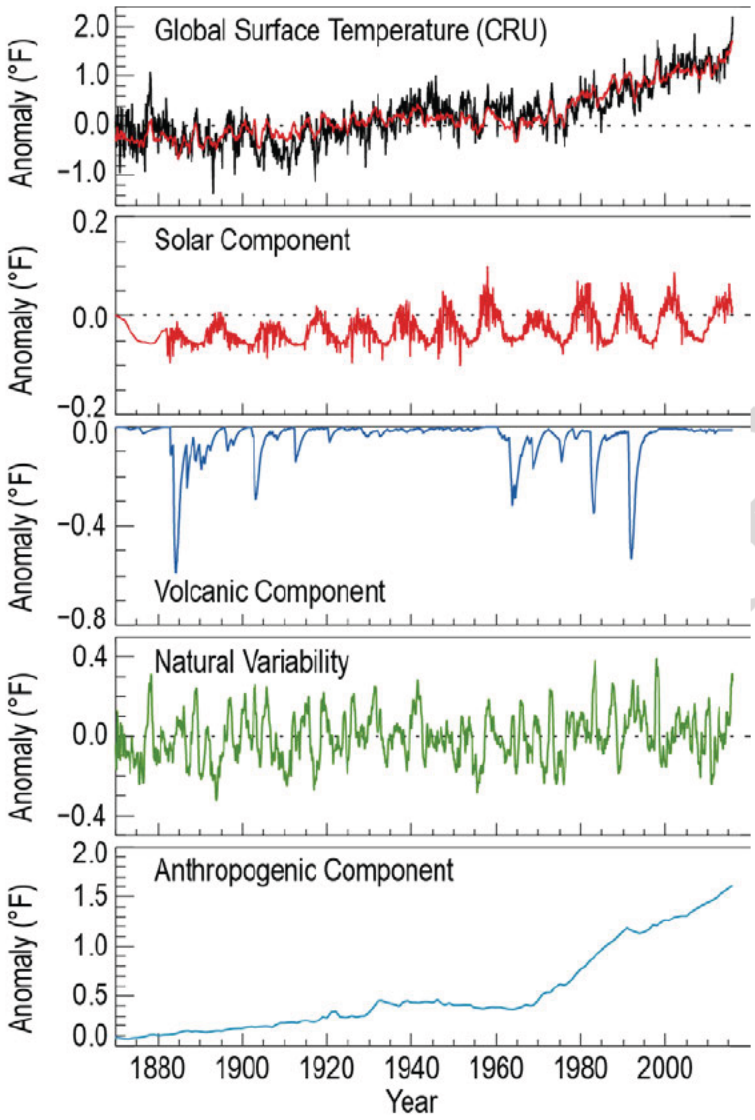


Figure 3.3: Estimates of the contributions of several forcing factors and internal variability to global mean temperature change since 1870, based on an empirical approach using multiple linear regression and energy balance models. The top panel shows global temperature anomalies (°F) from the observations (Morice et al. 2012) in black with the multiple linear regression result in red (1901–1960 base period). The lower four panels show the estimated contribution to global mean temperature anomalies from four factors: solar variability; volcanic eruptions; internal variability related to El Niño/Southern Oscillation; and anthropogenic forcing. The anthropogenic contribution includes a warming component from greenhouse gases concentrations and a cooling component from anthropogenic aerosols. (Figure source: adapted from Canty et al. 2013.)

REFERENCES

Andres, H.J. and W.R. Peltier, 2016: Regional influences of natural external forcings on the transition from the Medieval Climate Anomaly to the Little Ice Age. *Journal of Climate,* **29,** 5779-5800. http://dx.doi.org/10.1175/jcli-d-15-0599.1

Arblaster, J.M., E.-P. Lim, H.H. Hendon, B.C. Trewin, M.C. Wheeler, G. Liu, and K. Braganza, 2014: Understanding Australia's hottest September on record [in "Explaining Extreme Events of 2013 from a Climate Perspective"]. *Bulletin of the American Meteorological Society,* **95 (9),** S37-S41. http://dx.doi.org/10.1175/1520-0477-95.9.S1.1

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/

Boucher, O., D. Randall, P. Artaxo, C. Bretherton, G. Feingold, P. Forster, V.-M. Kerminen, Y. Kondo, H. Liao, U. Lohmann, P. Rasch, S.K. Satheesh, S. Sherwood, B. Stevens, and X.Y. Zhang, 2013: Clouds and aerosols. *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, 571–658. 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

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

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.

FINAL DRAFT

Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 741–866. http://www.climatechange2013.org/report/full-report/

Gillett, N.P., J.C. Fyfe, and D.E. Parker, 2013: Attribution of observed sea level pressure trends to greenhouse gas, aerosol, and ozone changes. *Geophysical Research Letters,* **40,** 2302-2306. http://dx.doi.org/10.1002/grl.50500

Gregory, J.M., T. Andrews, and P. Good, 2015: The inconstancy of the transient climate response parameter under increasing CO_2. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences,* **373,** 20140417. http://dx.doi.org/10.1098/rsta.2014.0417

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

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

Herring, S.C., M.P. Hoerling, T.C. Peterson, and P.A. Stott, 2014: Explaining Extreme Events of 2013 from a Climate Perspective. *Bulletin of the American Meteorological Society,* **95,** S1-S104. http://dx.doi.org/10.1175/1520-0477-95.9.s1.1

Herring, S.C., M.P. Hoerling, J.P. Kossin, T.C. Peterson, and P.A. Stott, 2015: Explaining Extreme Events of 2014 from a Climate Perspective. *Bulletin of the American Meteorological Society,* **96,** S1-S172. http://dx.doi.org/10.1175/BAMS-ExplainingExtremeEvents2014.1

Herring, S.C., A. Hoell, M.P. Hoerling, J.P. Kossin, C.J. Schreck III, and P.A. Stott, 2016: Explaining Extreme Events of 2015 from a Climate Perspective. *Bulletin of the American Meteorological Society,* **97,** S1-S145. http://dx.doi.org/10.1175/BAMS-ExplainingExtremeEvents2015.1

FINAL DRAFT

Hoerling, M., M. Chen, R. Dole, J. Eischeid, A. Kumar, J.W. Nielsen-Gammon, P. Pegion, J. Perlwitz, X.-W. Quan, and T. Zhang, 2013: Anatomy of an extreme event. *Journal of Climate,* **26,** 2811–2832. http://dx.doi.org/10.1175/JCLI-D-12-00270.1

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

Huber, M. and R. Knutti, 2012: Anthropogenic and natural warming inferred from changes in Earth's energy balance. *Nature Geoscience,* **5,** 31-36. http://dx.doi.org/10.1038/ngeo1327

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

IPCC, 1990: *Climate Change: The IPCC Scientific Assessment*. Houghton, J.T., G.J. Jenkins, and J.J. Ephraums, Eds. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 212 pp.

IPCC, 1996: *Climate Change 1995: The Science of Climate Change. Contribution of Working Group I to the Second Assessment Report of the Intergovernmental Panel on Climate Change*. Houghton, J.T., L.G. Meira Filho, B.A. Callander, N. Harris, A. Kattenberg, and K. Maskell, Eds. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 584 pp.

IPCC, 2001: *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change*. Houghton, J.T., Y. Ding, D.J. Griggs, M. Noquer, P.J. van der Linden, X. Dai, K. Maskell, and C.A. Johnson, Eds. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 881 pp.

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. http://www.ipcc.ch/publications_and_data/publications_ipcc_fourth_assessment_report_wg1_report_the_physical_science_basis.htm

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/

FINAL DRAFT

Jones, G.S., P.A. Stott, and N. Christidis, 2013: Attribution of observed historical near surface temperature variations to anthropogenic and natural causes using CMIP5 simulations. *Journal of Geophysical Research,* **118,** 4001-4024. http://dx.doi.org/10.1002/jgrd.50239

King, A.D., D.J. Karoly, M.G. Donat, and L.V. Alexander, 2014: Climate change turns Australia's 2013 Big Dry into a year of record-breaking heat [in "Explaining Extreme Events of 2013 from a Climate Perspective"]. *Bulletin of the American Meteorological Society,* **95 (9),** S41-S45. http://dx.doi.org/10.1175/1520-0477-95.9.S1.1

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

Knutson, T.R., F. Zeng, and A.T. Wittenberg, 2014: Multimodel assessment of extreme annual-mean warm anomalies during 2013 over regions of Australia and the western tropical Pacific [in "Explaining Extreme Events of 2013 from a Climate Perspective"]. *Bulletin of the American Meteorological Society,* **95 (9),** S26-S30. http://dx.doi.org/10.1175/1520-0477-95.9.S1.1

Knutson, T.R., R. Zhang, and L.W. Horowitz, 2016: Prospects for a prolonged slowdown in global warming in the early 21st century. *Nature Communcations,* **7,** 13676. http://dx.doi.org/10.1038/ncomms13676

Laepple, T. and P. Huybers 2014: Ocean surface temperature variability: large model-data differences at decadal and longer periods. *Proceedings of the National Academy of Sciences*, **111**, 16682-16687. http://dx.doi.org/10.1073/pnas.1412077111

Lewis, N. and J.A. Curry, 2015: The implications for climate sensitivity of AR5 forcing and heat uptake estimates. *Climate Dynamics,* **45,** 1009-1023. http://dx.doi.org/10.1007/s00382-014-2342-y

Lewis, S. and D.J. Karoly, 2014: The role of anthropogenic forcing in the record 2013 Australia-wide annual and spring temperatures [in "Explaining Extreme Events of 2013 from a Climate Perspective"]. *Bulletin of the American Meteorological Society,* **95 (9),** S31-S33. http://dx.doi.org/10.1175/1520-0477-95.9.S1.1

Marvel, K., G.A. Schmidt, R.L. Miller, and L.S. Nazarenko, 2016: Implications for climate sensitivity from the response to individual forcings. *Nature Climate Change,* **6,** 386-389. http://dx.doi.org/10.1038/nclimate2888

Masson-Delmotte, V., M. Schulz, A. Abe-Ouchi, J. Beer, A. Ganopolski, J.F. González Rouco, E. Jansen, K. Lambeck, J. Luterbacher, T. Naish, T. Osborn, B. Otto-Bliesner, T. Quinn, R. Ramesh, M. Rojas, X. Shao, and A. Timmermann, 2013: Information from paleoclimate archives. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group*

FINAL DRAFT

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, 383–464. http://www.climatechange2013.org/report/full-report/

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

Morice, C.P., J.J. Kennedy, N.A. Rayner, and P.D. Jones, 2012: Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: The HadCRUT4 dataset. *Journal of Geophysical Research,* **117,** D08101. http://dx.doi.org/10.1029/2011JD017187

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, 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

Otto, A., F.E.L. Otto, O. Boucher, J. Church, G. Hegerl, P.M. Forster, N.P. Gillett, J. Gregory, G.C. Johnson, R. Knutti, N. Lewis, U. Lohmann, J. Marotzke, G. Myhre, D. Shindell, B. Stevens, and M.R. Allen, 2013: Energy budget constraints on climate response. *Nature Geoscience,* **6,** 415-416. http://dx.doi.org/10.1038/ngeo1836

Otto, F.E.L., N. Massey, G.J. van Oldenborgh, R.G. Jones, and M.R. Allen, 2012: Reconciling two approaches to attribution of the 2010 Russian heat wave. *Geophysical Research Letters,* **39,** L04702. http://dx.doi.org/10.1029/2011GL050422

Perkins, S.E., S.C. Lewis, A.D. King, and L.V. Alexander, 2014: Increased simulated risk of the hot Australian summer of 2012/13 due to anthropogenic activity as measured by heat wave frequency and intensity [in "Explaining Extreme Events of 2013 from a Climate Perspective"]. *Bulletin of the American Meteorological Society,* **95 (9),** S34-S37. http://dx.doi.org/10.1175/1520-0477-95.9.S1.1

FINAL DRAFT

Peterson, T.C., P.A. Stott, and S. Herring, 2012: Explaining extreme events of 2011 from a climate perspective. *Bulletin of the American Meteorological Society,* **93,** 1041-1067. http://dx.doi.org/10.1175/BAMS-D-12-00021.1

Peterson, T.C., M.P. Hoerling, P.A. Stott, and S.C. Herring, 2013: Explaining Extreme Events of 2012 from a Climate Perspective. *Bulletin of the American Meteorological Society,* **94,** S1-S74. http://dx.doi.org/10.1175/bams-d-13-00085.1

Pielke Sr., R.A., R. Mahmood, and C. McAlpine, 2016: Land's complex role in climate change. *Physics Today,* **69,** 40-46. http://dx.doi.org/10.1063/PT.3.3364

Ribes, A. and L. Terray, 2013: Application of regularised optimal fingerprinting to attribution. Part II: Application to global near-surface temperature. *Climate Dynamics,* **41,** 2837-2853. http://dx.doi.org/10.1007/s00382-013-1736-6

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

Richardson, M., K. Cowtan, E. Hawkins, and M.B. Stolpe, 2016: Reconciled climate response estimates from climate models and the energy budget of Earth. *Nature Climate Change,* **6,** 931-935. http://dx.doi.org/10.1038/nclimate3066

Rupp, D.E., P.W. Mote, N. Massey, C.J. Rye, R. Jones, and M.R. Allen, 2012: Did human influence on climate make the 2011 Texas drought more probable? [in Explaining Extreme Events of 2011 from a Climate Perspective]. *Bulletin of the American Meteorological Society,* **93,** 1052-1054. http://dx.doi.org/10.1175/BAMS-D-12-00021.1

Schurer, A.P., G.C. Hegerl, M.E. Mann, S.F.B. Tett, and S.J. Phipps, 2013: Separating forced from chaotic climate variability over the past millennium. *Journal of Climate,* **26,** 6954-6973. http://dx.doi.org/10.1175/jcli-d-12-00826.1

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

Stone, D., M. Auffhammer, M. Carey, G. Hansen, C. Huggel, W. Cramer, D. Lobell, U. Molau, A. Solow, L. Tibig, and G. Yohe, 2013: The challenge to detect and attribute effects of climate change on human and natural systems. *Climatic Change,* **121,** 381-395. http://dx.doi.org/10.1007/s10584-013-0873-6

FINAL DRAFT

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

Stouffer, R.J. and S. Manabe, 2017: Assessing temperature pattern projections made in 1989. *Nature Climate Change,* **7,** 163-165. http://dx.doi.org/10.1038/nclimate3224

Taylor, K.E., R.J. Stouffer, and G.A. Meehl, 2012: An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society,* **93,** 485-498. http://dx.doi.org/10.1175/BAMS-D-11-00094.1

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

Wigley, T.M.L. and B.D. Santer, 2013: A probabilistic quantification of the anthropogenic component of twentieth century global warming. *Climate Dynamics,* **40,** 1087-1102. http://dx.doi.org/10.1007/s00382-012-1585-8

Zhou, J. and K.-K. Tung, 2013: Deducing multidecadal anthropogenic global warming trends using multiple regression analysis. *Journal of the Atmospheric Sciences,* **70,** 3-8. http://dx.doi.org/10.1175/jas-d-12-0208.1

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

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

4. Climate Models, Scenarios, and Projections

KEY FINDINGS

1. If greenhouse gas concentrations were stabilized at their current level, existing concentrations would commit the world to at least an additional 1.1°F (0.6°C) of warming over this century relative to the last few decades (*high confidence* in continued warming, *medium confidence* in amount of warming).

2. Over the next two decades, global temperature increase is projected to be between 0.5°F and 1.3°F (0.3°–0.7°C) (*medium confidence*). This range is primarily due to uncertainties in natural sources of variability that affect short-term trends. In some regions, this means that the trend may not be distinguishable from natural variability (*high confidence*).

3. Beyond the next few decades, the magnitude of climate change depends primarily on cumulative emissions of greenhouse gases and aerosols and the sensitivity of the climate system to those emissions (*high confidence*). Projected changes range from 4.7°–8.6°F (2.6°–4.8°C) under the higher RCP8.5 scenario to 0.5°–1.3°F (0.3°–1.7°C) under the lower RCP2.6 scenario, for 2081–2100 relative to 1986–2005 (*medium confidence*).

4. Global mean atmospheric carbon dioxide (CO_2) concentration has now passed 400 ppm, a level that last occurred about 3 million years ago, when global average temperature and sea level were significantly higher than today (*high confidence*). Continued growth in CO_2 emissions over this century and beyond would lead to an atmospheric concentration not experienced in tens of millions of years (*medium confidence*). The present-day emissions rate of nearly 10 GtC per year suggests that there is no climate analog for this century any time in at least the last 50 million years (*medium confidence*).

5. The observed increase in global carbon emissions over the past 15–20 years has been consistent with higher scenarios (*very high confidence*). In 2014 and 2015, emission growth rates slowed as economic growth has become less carbon-intensive (*medium confidence*). Even if this trend continues, however, it is not yet at a rate that would meet the long-term temperature goal of the Paris Agreement of holding the increase in the global average temperature to well below 3.6°F (2°C) above preindustrial levels (*high confidence*).

6. Combining output from global climate models and dynamical and statistical downscaling models using advanced averaging, weighting, and pattern scaling approaches can result in more relevant and robust future projections. For some regions, sectors, and impacts, these techniques are increasing the ability of the scientific community to provide guidance on the use of climate projections for quantifying regional-scale changes and impacts (*medium to high confidence*).

FINAL DRAFT

4.1. The Human Role in Future Climate

The Earth's climate, past and future, is not static; it changes in response to both natural and anthropogenic drivers (see Ch. 2: Physical Drivers of Climate Change). Human emissions of carbon dioxide (CO_2), methane (CH_4), and other greenhouse gases now overwhelm the influence of natural drivers on the external forcing of the Earth's climate (see Ch. 3: Detection and Attribution). Climate change (see Ch. 1: Our Globally Changing Climate) and ocean acidification (see Ch. 13: Ocean Changes) are already occurring due to the buildup of atmospheric CO_2 from human emissions in the industrial era (Hartmann et al. 2013; Rhein et al. 2013).

Even if existing concentrations could be immediately stabilized, temperature would continue to increase by an estimated 1.1°F (0.6°C) over this century, relative to 1980–1999 (Collins et al. 2013). This is because of the long timescale over which some climate feedbacks act (Ch. 2: Physical Drivers of Climate Change). Over the next few decades, concentrations are projected to increase and the resulting global temperature increase is projected to range from 0.5°F to 1.3°F (0.3°C to 0.7°C). This range depends on natural variability, on emissions of short-lived species such as CH_4 and black carbon that contribute to warming, and on emissions of sulfur dioxide (SO_2) and other aerosols that have a net cooling effect (Ch. 2: Physical Drivers of Climate Change). The role of emission reductions of non-CO_2 gases and aerosols in achieving various global temperature targets is discussed in Chapter 14: Mitigation.

Over the past 15–20 years, the growth rate in carbon emissions from human activities has increased from 1.5 to 2 parts per million (ppm) per year due to increasing carbon emissions from human activities that track the rate projected under higher scenarios, in large part to growing contributions from developing economies (Tans and Keeling 2017; Raupach et al. 2007; Le Quéré et al. 2009). One possible analog for the rapid pace of change occurring today is the relatively abrupt warming of 9°–14°F (5°–8°C) that occurred during the Paleocene-Eocene Thermal Maximum (PETM), approximately 55–56 million years ago (Bowen et al. 2015; Kirtland Turner et al. 2014; Penman et al. 2014; Crowley et al. 1990). However, emissions today are nearly 10 GtC per year. During the PETM, the rate of maximum sustained carbon release was less than 1.1 GtC per year, with significant differences in both background conditions and forcing relative to today. This suggests that there is no precise past analog any time in the last 66 million years for the conditions occurring today (Zeebe et al. 2016; Crowley et al. 1990).

Since 2014, growth rates of global carbon emissions have declined, a trend cautiously attributed to declining coal use in China, despite large uncertainties in emissions reporting (Jackson et al. 2016; Korsbakken et al. 2016). Economic growth is becoming less carbon-intensive, as both developed and emerging economies begin to phase out coal and transition to natural gas and renewable, non-carbon energy (IEA 2016; Green and Stern 2016).

FINAL DRAFT

Beyond the next few decades, the magnitude of future climate change will be primarily a function of future carbon emissions and the response of the climate system to those emissions. This chapter describes the scenarios that provide the basis for the range of future projections presented in this report: from those consistent with continued increases in greenhouse gas emissions, to others that can only be achieved by various levels of emission reductions (see Ch. 14: Mitigation). This chapter also describes the models used to quantify projected changes at the global to regional scale and how it is possible to estimate the range in potential climate change—as determined by climate sensitivity, which is the response of global temperature to a natural or anthropogenic forcing (see Ch. 2: Physical Drivers of Climate Change)—that would result from a given scenario (Collins et al. 2013).

4.2. Future Scenarios

Climate projections are typically presented for a range of plausible pathways, scenarios, or targets that capture the relationships between human choices, emissions, concentrations, and temperature change. Some scenarios are consistent with continued dependence on fossil fuels, while others can only be achieved by deliberate actions to reduce emissions. The resulting range reflects the uncertainty inherent in quantifying human activities (including technological change) and their influence on climate.

The first Intergovernmental Panel on Climate Change Assessment Report (IPCC FAR) in 1990 discussed three types of scenarios: equilibrium scenarios, in which CO_2 concentration is fixed; transient scenarios, in which CO_2 concentration increased by a fixed percentage each year over the duration of the scenario; and four brand-new Scientific Assessment (SA90) emission scenarios based on World Bank population projections (Bretherton et al. 1990). Today, that original portfolio has expanded to encompass a wide variety of time-dependent or transient scenarios that project how population, energy sources, technology, emissions, atmospheric concentrations, radiative forcing, and/or global temperature change over time.

Other scenarios are simply expressed in terms of an end-goal or target, such as capping cumulative carbon emissions at a specific level or stabilizing global temperature at or below a certain threshold. The 2015 Paris Agreement, for example, includes an aim of "holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels" (UNFCCC 2015). To stabilize climate, however, it is not enough to halt the growth in annual carbon emissions. It is projected that global net carbon emissions will eventually need to reach zero (Collins et al. 2013) and negative emissions may be needed for a greater than 50% chance of limiting warming below 3.6°F (2°C) (Smith et al. 2016; see also Ch. 14: Mitigation for a discussion of negative emissions scenarios).

And finally some scenarios, like the "commitment" scenario in Key Finding 1 and the fixed-CO_2 equilibrium scenarios described above, continue to explore hypothetical questions such as, "what

FINAL DRAFT

would the world look like, long-term, if humans were able to stabilize atmospheric CO_2 concentration at a given level?" This section describes the different types of scenarios used today, and their relevance to assessing impacts and informing policy targets.

4.2.1. Emission Scenarios, Representative Concentration Pathways, and Shared Socioeconomic Pathways

The standard sets of time-dependent scenarios used by the climate modeling community as input to global climate model simulations provide the basis for the majority of the future projections presented in IPCC assessment reports and U.S. National Climate Assessments (NCA). Developed by the integrated assessment modeling community, these sets of standard scenarios have become more comprehensive with each new generation, as the original SA90 scenarios (IPCC 1990) were replaced by the IS92 emission scenarios of the 1990s (Leggett et al. 1992), which were in turn succeeded by the Special Report on Emissions Scenarios in 2000 (SRES, Nakicenovic et al. 2000) and by the Representative Concentration Pathways in 2010 (RCPs, Moss et al. 2010).

SA90, IS92, and SRES are all emission-based scenarios. They begin with a set of storylines that were based on population projections initially. By SRES, they had become much more complex, laying out a consistent picture of demographics, international trade, flow of information and technology, and other social, technological, and economic characteristics of future worlds. These assumptions are then fed through socioeconomic and Integrated Assessment Models (IAMs) to derive emissions. For SRES, the use of various IAMs resulted in multiple emissions scenarios corresponding to each storyline; however, one scenario for each storyline was selected as the representative "marker" scenario to be used as input to global models to calculate the resulting atmospheric concentrations, radiative forcing, and climate change for the higher A1fi (fossil-intensive), mid-high A2, mid-low B2, and lower B1 storylines. IS92-based projections were used in the IPCC Second and Third Assessment Reports (SAR and TAR; Kattenberg et al. 1996; Cubasch et al. 2001) and the first NCA (NAST 2001). Projections based on SRES scenarios were used in the second and third NCAs (Karl et al. 2009; Melillo et al. 2014) as well as the IPCC TAR and Fourth Assessment Reports (AR4; Cubasch et al. 2001; Meehl et al. 2007).

The most recent set of time-dependent scenarios, RCPs, builds on these two decades of scenario development. However, RCPs differ from previous sets of standard scenarios in at least four important ways. First, RCPs are not emissions scenarios; they are radiative forcing scenarios. Each scenario is tied to one value: the change in radiative forcing at the tropopause by 2100 relative to preindustrial levels. The four RCPs are numbered according to the change in radiative forcing by 2100: +2.6, +4.5, +6.0 and +8.5 watts per square meter (W/m^2) (van Vuuren et al. 2011; Thomson et al. 2011; Masui et al. 2011; Riahi et al. 2011).

The second difference is that, starting from these radiative forcing values, IAMs are used to work backwards to derive a range of emissions trajectories and corresponding policies and

FINAL DRAFT

technological strategies for each RCP that would achieve the same ultimate impact on radiative forcing. From the multiple emissions pathways that could lead to the same 2100 radiative forcing value, an associated pathway of annual carbon dioxide and other anthropogenic emissions of greenhouse gases, aerosols, air pollutants, and other short-lived species has been selected for each RCP to use as input to future climate model simulations (e.g., Meinshausen et al. 2011; Cubasch et al. 2013). In addition, RCPs provide climate modelers with gridded trajectories of land use and land cover.

A third difference between the RCPs and previous scenarios is that while none of the SRES scenarios included a scenario with explicit policies and measures to limit climate forcing, all of the three lower RCP scenarios (2.6, 4.5, and 6.0) are climate-policy scenarios. At the higher end of the range, the RCP8.5 scenario corresponds to a future where carbon and methane emissions continue to rise as a result of fossil fuel use, albeit with significant declines in emission growth rates over the second half of the century (Figure 4.1), significant reduction in aerosols, and modest improvements in energy intensity and technology (Riahi et al. 2011). Atmospheric carbon dioxide levels for RCP8.5 are similar to those of the SRES A1fi scenario: they rise from current-day levels of 400 up to 936 parts per million (ppm). CO_2-equivalent levels (including emissions of other non-CO_2 greenhouse gases, aerosols, and other substances that affect climate) reach more than 1200 ppm by 2100, and global temperature is projected to increase by 5.4°–9.9°F (3°–5.5°C) by 2100 relative to the 1986–2005 average. RCP8.5 reflects the upper range of the open literature on emissions, but is not intended to serve as an upper limit on possible emissions nor as a business-as-usual or reference scenario for the other three scenarios.

Under the lower RCP4.5 and RCP2.6 scenarios (van Vuuren et al. 2011; Thomson et al. 2011), atmospheric CO_2 levels remain below 550 and 450 ppm by 2100, respectively. Emissions of other substances are also lower; by 2100, CO_2-equivalent concentrations that include all emissions from human activities reach 580 ppm under RCP4.5 and 425 ppm under RCP2.6. RCP4.5 is similar to SRES B1, but the RCP2.6 scenario is much lower than any SRES scenario because it includes the option of using policies to achieve net negative carbon dioxide emissions before the end of the century, while SRES scenarios do not. RCP-based projections were used in the most recent IPCC Fifth Assessment Report (AR5; Collins et al. 2013) and the third NCA (Melillo et al. 2014) and will be used in the upcoming fourth NCA as well.

Within the RCP family, individual scenarios have not been assigned a formal likelihood. Higher-numbered scenarios correspond to higher emissions and a larger and more rapid global temperature change (Figure 4.1); the range of values covered by the scenarios was chosen to reflect the then-current range in the open literature. Since the choice of scenario constrains the magnitudes of future changes, most assessments (including this one; see Ch. 6: Temperature Change) quantify future change and corresponding impacts under a range of future scenarios that reflect the uncertainty in the consequences of human choices over the coming century.

FINAL DRAFT

Fourth, a broad range of socioeconomic scenarios were developed independently from the RCPs and a subset of these constrained, using emissions limitations policies consistent with their underlying storylines, to create five Shared Socioeconomic Pathways (SSPs) with climate forcing that matches the RCP values. This pairing of SSPs and RCPs is designed to meet the needs of the impacts, adaptation, and vulnerability (IAV) communities, enabling them to couple alternative socioeconomic scenarios with the climate scenarios developed using RCPs to explore the socioeconomic challenges to climate mitigation and adaptation (O'Neill et al. 2014). The five SSPs consist of SSP1 ("Sustainability"; low challenges to mitigation and adaptation), SSP2 ("Middle of the Road"; middle challenges to mitigation and adaptation), SSP3 ("Regional Rivalry"; high challenges to mitigation and adaptation), SSP4 ("Inequality"; low challenges to mitigation, high challenges to adaptation), and SSP5 ("Fossil-fueled Development"; high challenges to mitigation, low challenges to adaptation). Each scenario has an underlying SSP narrative, as well as consistent assumptions regarding demographics, urbanization, economic growth, and technology development. Only SSP5 produces a reference scenario that is consistent with RCP8.5; climate forcing in the other SSPs' reference scenarios that don't include climate policy remains below 8.5 W/m^2. In addition, the nature of SSP3 makes it impossible for that scenario to produce a climate forcing as low as 2.6 W/m^2. While new research is under way to explore scenarios that limit climate forcing to 2.0 W/m^2, neither the RCPs nor the SSPs have produced scenarios in that range.

[INSERT FIGURE 4.1 HERE]

4.2.2. Alternative Scenarios

The emissions and radiative forcing scenarios described above include a component of time: how much will climate change, and by when? Ultimately, however, the magnitude of human-induced climate change depends less on the year-to-year emissions than it does on the net amount of carbon, or cumulative carbon, emitted into the atmosphere. The lower the atmospheric concentrations of CO_2, the greater the chance that eventual global temperature change will not reach the high-end temperature projections, or possibly remain below 3.6°F (2°C) relative to preindustrial levels, consistent with the long-term temperature goal included in the Paris Agreement.

Cumulative carbon targets offer an alternative approach to expressing a goal designed to limit global temperature to a certain level. As discussed in Chapter 14: Mitigation, it is possible to quantify the expected amount of carbon that can be emitted globally in order to meet a specific global warming target such as 3.6°F (2°C) or even 2.7°F (1.5°C)—although if current carbon emission rates of just under 10 GtC per year were to continue, the lower target would be reached in a matter of years. The higher target would be reached in a matter of decades (see Ch. 14: Mitigation).

FINAL DRAFT

Under RCP4.5, global temperature change is more likely than not to exceed 3.6°F (2°C) (IIASA 2016; Collins et al. 2013), whereas under RCP2.6 it is likely to remain below 3.6°F (2°C) (Sanderson et al. 2016a; Collins et al. 2013). While new research is under way to explore scenarios consistent with limiting climate forcing to 2.0 W/m^2, a level consistent with limiting global mean surface temperature change to 2.7°F (1.5°C), neither the RCPs nor the SSPs have produced scenarios that allow for such a small amount of temperature change (Sanderson et al. 2016a; see also Ch. 14: Mitigation).

[INSERT FIGURE 4.2 HERE]

Future projections are most commonly summarized for a given future scenario (for example, RCP8.5 or 4.5) over a range of future climatological time periods (for example, temperature change in 2040–2079 or 2070–2099 relative to 1980–2009). While this approach has the advantage of developing projections for a specific time horizon, uncertainty in future projections is relatively high, incorporating both the uncertainty due to multiple scenarios as well as uncertainty regarding the response of the climate system to human emissions. These uncertainties increase the further out in time the projections go. Using these same transient, scenario-based simulations, however, it is possible to analyze the projected changes for a given global mean temperature (GMT) threshold by extracting a time slice (typically 20 years) centered around the point in time at which that change is reached (Fig. 4.2).

Derived GMT scenarios offer a way for the public and policymakers to understand the impacts for any given temperature threshold, as many physical changes and impacts have been shown to scale with global mean surface temperature (GMT), including shifts in average precipitation, extreme heat, runoff, drought risk, wildfire, temperature-related crop yield changes, and even risk of coral bleaching (e.g., NRC 2011; Collins et al. 2013; Frieler et al. 2013; Swain and Hayhoe 2015). They also allow scientists to highlight the effect of global mean temperature on projected regional change by de-emphasizing the uncertainty due to both climate sensitivity and future scenarios (Herger et al. 2015; Swain and Hayhoe 2015). This approach is less useful for those impacts that vary based on rate of change, such as species migrations, or where equilibrium changes are very different from transient effects, such as sea level rise.

Pattern scaling techniques (Mitchell 2003) are based on a similar assumption to GMT scenarios, namely that large-scale patterns of regional change will scale with global temperature change. These techniques can be used to quantify regional projections for scenarios that are not readily available in preexisting databases of global climate model simulations, including changes in both mean and extremes (e.g., Fix et al. 2016). A comprehensive assessment both confirms and constrains the validity of applying pattern scaling to quantify climate response to a range of projected future changes (Tebaldi and Arblaster 2014). For temperature-based climate targets, these pattern scaling frames or GMT scenarios offer the basis for more consistent comparisons across studies examining regional change or potential risks and impacts.

FINAL DRAFT

4.2.3. Analogs from the Paleoclimate Record

Most CMIP5 simulations project transient changes in climate through 2100; a few simulations extend to 2200, 2300, or beyond. However, as discussed in Chapter 2: Physical Drivers of Climate Change, the long-term impact of human activities on the carbon cycle and Earth's climate over the next few decades and for the remainder of this century can only be assessed by considering changes that occur over multiple centuries and even millennia (NRC 2011).

In the past, there have been several examples of "hothouse" climates where carbon dioxide concentrations and/or global mean temperatures were similar to preindustrial, current, or plausible future levels. These periods are sometimes referenced as analogs, albeit imperfect and incomplete, of future climate (e.g., Crowley 1990).

The last interglacial period, approximately 125,000 years ago, is known as the Eemian. During that time, CO_2 concentration was similar to preindustrial, around 280 ppm (Schneider et al. 2013). Global mean temperature was approximately 1.8°–3.6°F (1°–2°C) higher than preindustrial levels (Lunt et al. 2012; Otto-Bleisner et al. 2013), although the poles were significantly warmer (NEEM 2013; Jouzel et al. 2007) and sea level was 6 to 9 meters (20 to 30 feet) higher than today (Fig. 4.3; Kopp et al. 2009). During the Pliocene, approximately 3 million years ago, long-term CO_2 concentration was similar to today's, around 400 ppm (Seki et al. 2010)—although this level was sustained over long periods of time, whereas today CO_2 concentration is increasing rapidly. At that time, global mean temperature was approximately 3.6°–6.3°F (2°–3.5°C) above preindustrial, and sea level was somewhere between 66 ± 33 feet (20 ± 10 meters) higher than today (Haywood et al. 2013; Dutton et al. 2015; Miller et al. 2012).

Under the RCP8.5 scenario, CO_2 concentrations are projected to reach 936 ppm by 2100. During the Eocene, 35 to 55 million years ago, CO_2 levels were between 680 and 1260 ppm, or somewhere between two and a half to four and a half times above preindustrial levels (Jagniecki et al. 2015). If Eocene conditions are used as an analog, this suggests that if the CO_2 concentrations projected to occur under the RCP8.5 scenario by 2100 were sustained over long periods of time, global temperatures would be approximately 9°–14°F (5°–8°C) above preindustrial levels (Royer 2014). During the Eocene, there were no permanent land-based ice sheets; Antarctic glaciation did not begin until approximately 34 million years ago (Pagani et al. 2011). Calibrating sea level rise models against past climate suggests that, under the RCP8.5 scenario, Antarctica could contribute 3 feet (1 meter) of sea level rise by 2100 and 50 feet (15 meters) by 2500 (DeConto and Pollard 2016). If atmospheric CO_2 were sustained at levels approximately two to three times above preindustrial for tens of thousands of years, it is estimated that Greenland and Antarctic ice sheets could melt entirely (Gasson et al. 2014), resulting in approximately 215 feet (65 meters) of sea level rise (Vaughn et al. 2013).

FINAL DRAFT

4.3. Modeling Tools

Using transient scenarios such as SRES and RCP as input, global climate models (GCMs) produce trajectories of future climate change, including global and regional changes in temperature, precipitation, and other physical characteristics of the climate system (Collins et al. 2013; Kirtman et al. 2013; see also Ch. 6: Temperature Change and Ch. 7: Precipitation Change). The resolution of global models has increased significantly since IPCC FAR (IPCC 1990). However, even the latest experimental high-resolution simulations at 25–50 km (15–30 miles) per gridbox, are unable to simulate all of the important fine-scale processes occurring at regional to local scales. Instead, downscaling methods are often used to correct systematic biases, or offsets relative to observations, in global projections and translate them into the higher-resolution information typically required for impact assessments.

Dynamical downscaling with regional climate models (RCMs) directly simulates the response of regional climate processes to global change, while empirical statistical downscaling models (ESDMs) tend to be more flexible and computationally efficient. Comparing the ability of dynamical and statistical methods to reproduce observed climate shows that the relative performance of the two approaches depends on the assessment criteria (Vattinada Ayar et al. 2016). Although dynamical and statistical methods can be combined into a hybrid framework, many assessments still tend to rely on one or the other type of downscaling, where the choice is based on the needs of the assessment. The projections shown in this report, for example, are either based on the original GCM simulations or on simulations that have been statistically downscaled using the LOcalized Constructed Analogs method (LOCA; Pierce et al. 2014). This section describes the global climate models used today, briefly summarizes their development over the past few decades, and explains the general characteristics and relative strengths and weaknesses of the dynamical and statistical downscaling.

4.3.1. Global Climate Models

Global climate models (GCMs) are mathematical frameworks that were originally built on fundamental equations of physics. They account for the conservation of energy, mass, and momentum and how these are exchanged among different components of the climate system. Using these fundamental relationships, GCMs are able to simulate many important aspects of Earth's climate: large-scale patterns of temperature and precipitation, general characteristics of storm tracks and extratropical cyclones, and observed changes in global mean temperature and ocean heat content as a result of human emissions (Flato et al. 2013).

The complexity of climate models has grown over time, as they incorporate additional components of the Earth's climate system (Figure 4.3). For example, GCMs were previously referred to as "general circulation models" when they included only the physics needed to simulate the general circulation of the atmosphere. Today, global climate models simulate many more aspects of the climate system: atmospheric chemistry and aerosols, land surface

FINAL DRAFT

interactions including soil and vegetation, land and sea ice, and increasingly even an interactive carbon cycle and/or biogeochemistry. Models that include this last component are also referred to as Earth system models (ESMs).

[INSERT FIGURE 4.3 HERE]

In addition to expanding the number of processes in the models and improving the treatment of existing processes, the total number of GCMs and the average horizontal spatial resolution of the models has increased over time, as computers become more powerful, and with each successive version of the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project (CMIP). CMIP5 provides output from over 50 GCMs with spatial resolutions ranging from about 50 to 300 km (30 to 200 miles) per horizontal size and variable vertical resolution on the order of hundreds of meters in the troposphere or lower atmosphere.

It is often assumed that higher-resolution, more complex, and more up-to-date models will perform better and/or produce more robust projections than previous-generation models. However, a large body of research comparing CMIP3 and CMIP5 simulations concludes that, although the spatial resolution of CMIP5 has improved relative to CMIP3, the overall improvement in performance is relatively minor. For certain variables, regions, and seasons, there is some improvement; for others, there is little difference or even sometimes degradation in performance, as greater complexity does not necessarily imply improved performance (Knutti and Sedlacek 2012; Kumar et al. 2014; Sheffield et al. 2013, 2014). CMIP5 simulations do show modest improvement in model ability to simulate ENSO (Bellenger et al. 2014), some aspects of cloud characteristics (Lauer and Hamilton 2012), and the rate of Arctic sea ice loss (Wang and Overland 2012), as well as greater consensus regarding projected drying in the southwestern United States and Mexico (Sheffield et al. 2014),

Projected changes in hurricane rainfall rates and the reduction in tropical storm frequency are similar, but CMIP5-based projections of increases in the frequency of the strongest hurricanes are generally smaller than CMIP3-based projections (Knutson et al. 2013). On the other hand, many studies find little to no significant difference in large-scale patterns of changes in both mean and extreme temperature and precipitation from CMIP3 to CMIP5 (Kharin et al. 2013; Knutti and Sedlacek 2013; Sheffield et al. 2014; Sun et al. 2015). Also, CMIP3 simulations are driven by SRES scenarios, while CMIP5 simulations are driven by RCP scenarios. Although some scenarios have comparable CO_2 concentration pathways (Figure 4.1), differences in non-CO_2 species and aerosols could be responsible for some of the differences between the simulations (Sheffield et al. 2014). In NCA3, projections were based on simulations from both CMIP3 and CMIP5. In this report, future projections are based on CMIP5 alone.

GCMs are constantly being expanded to include more physics, chemistry, and, increasingly, even the biology and biogeochemistry at work in the climate system (Figure 4.3). Interactions within and between the various components of the climate system result in positive and negative

FINAL DRAFT

feedbacks that can act to enhance or dampen the effect of human emissions on the climate system. The extent to which models explicitly resolve or incorporate these processes determines their climate sensitivity, or response to external forcing (see Ch. 2: Physical Drivers of Climate Change, Section 2.5 on climate sensitivity, and Ch. 15: Potential Surprises on the importance of processes not included in present-day GCMs). These models build on previous generations and therefore many models are not independent from each other. Many share both ideas and model components or code, complicating the interpretation of multimodel ensembles that often are assumed to be independent (Knutti et al. 2013; Sanderson et al. 2015). Consideration of the independence of different models is one of the key pieces of information going into the weighting approach used in this report (see Appendix B: Weighting Strategy).

4.3.2. Regional Climate Models

Dynamical downscaling models are often referred to as regional climate models (RCMs), since they include many of the same physical processes that make up a global climate model, but simulate these processes at higher spatial resolution over smaller regions, such as the western or eastern United States (Figure 4.4; Kotamarthi et al. 2016). Most RCM simulations use GCM fields from pre-computed global simulations as boundary conditions. This approach allows RCMs to draw from a broad set of GCM simulations, such as CMIP5, but does not allow for possible two-way feedbacks and interactions between the regional to global scales. Dynamical downscaling can also be conducted interactively through nesting a higher-resolution regional grid or model into a global model during a simulation. Both approaches directly simulate the dynamics of the regional climate system, but only the second allows for two-way interactions between regional and global change.

RCMs are computationally intensive, providing a broad range of output variables that resolve regional climate features important for assessing climate impacts. The size of individual grid cells can be as fine as 1 to 2 km (0.6 to 1.2 miles) per gridbox in some studies, but more commonly range from about 10 to 50 km (6 to 30 miles). At smaller spatial scales, and for specific variables and areas with complex terrain, such as coastlines or mountains, regional climate models have been shown to add value (Feser et al. 2011). As model resolution increases, RCMs are also able to explicitly resolve some processes that are parameterized in global models. For example, some models with spatial scales below 4 km (2.5 miles) are able to dispense with the parameterization of convective precipitation, a significant source of error and uncertainty in coarser models (Prein et al. 2015). RCMs can also incorporate changes in land use, land cover, or hydrology into local climate at spatial scales relevant to planning and decision-making at the regional level.

Despite the differences in resolution, RCMs are still subject to many of the same types of uncertainty as GCMs. Even the highest-resolution RCM cannot explicitly model physical processes that occur at even smaller scales than the model is able to resolve; instead, parameterizations are required. Similarly, RCMs might not include a process or an interaction

FINAL DRAFT

that is not yet well understood, even if it is able to be resolved at the spatial scale of the model. One additional source of uncertainty unique to RCMs arises from the fact that at their boundaries RCMs require output from GCMs to provide large-scale circulation such as winds, temperature, and moisture; the degree to which the driving GCM correctly captures large-scale circulation and climate will affect the performance of the RCM (Wang et al. 2004). RCMs can be evaluated by directly comparing their output to observations; although this process can be challenging and time-consuming, it is often necessary to quantify the appropriate level of confidence that can be placed in their output (Kotamarthi et al. 2016).

Studies have also highlighted the importance of large ensemble simulations when quantifying regional change (Xie et al. 2015). However, due to their computational demand, extensive ensembles of RCM-based projections are rare. The largest ensemble of RCM simulations for North America is hosted by the North American Regional Climate Change Assessment Program (NARCCAP). NARCCAP simulations are useful for examining patterns of change over North America and providing a broad suite of surface and upper-air variables to characterize future impacts. Since this ensemble is based on four simulations from four CMIP3 GCMs for a single mid-high SRES scenario, these runs do not encompass the full range of uncertainty in future projections due to human activities, natural variability, and climate sensitivity.

[INSERT FIGURE 4.4 HERE]

4.3.3. Empirical Statistical Downscaling Models

Empirical statistical downscaling models (ESDMs) combine GCM output with historical observations to translate large-scale predictors or patterns into high-resolution projections at the scale of observations. The observations used in an ESDM can range from individual weather stations to gridded datasets. As output, they can generate a range of products, from large grids to analyses optimized for a specific location, variable, or decision-context.

Statistical techniques are varied, from the simple difference or delta approaches used in the first NCA (subtracting historical simulated values from future values, and adding the resulting delta to historical observations; NAST 2001) to the parametric quantile mapping approach used in NCA2 and 3 (Stoner et al. 2012; Karl et al. 2009; Melillo et al. 2014). Even more complex clustering and advanced mathematical modeling techniques can rival dynamical downscaling in their demand for computational resources (e.g. Vrac et al. 2007).

Statistical models are generally flexible and less computationally demanding than RCMs. A number of databases using a variety of methods, including LOCA, provide statistically downscaled projections for a continuous period from 1960 to 2100 using a large ensemble of global models and a range of higher and lower future scenarios to capture uncertainty due to human activities. ESDMs are also effective at removing biases in historical simulated values, leading to a good match between the average (multidecadal) statistics of observed and

FINAL DRAFT

statistically downscaled climate at the spatial scale and over the historical period of the observational data used to train the statistical model. Unless methods can simultaneously downscale multiple variables, however, statistical downscaling carries the risk of altering some of the physical interdependences between variables. ESDMs are also limited in that they require observational data as input; the longer and more complete the record, the greater the confidence that the ESDM is being trained on a representative sample of climatic conditions for that location. Application of ESDMs to remote locations with sparse temporal and/or spatial records is challenging, though in many cases reanalysis (Brands et al. 2012) or even monthly satellite data (Thrasher et al. 2013) can be used in lieu of in situ observations. Lack of data availability can also limit the use of ESDMs in applications that require more variables than temperature and precipitation. Finally, statistical models are based on the key assumption that the relationship between large-scale weather systems and local climate or the spatial pattern of surface climate will remain stationary over the time horizon of the projections. This assumption may not hold if climate change alters local feedback processes that affect these relationships.

ESDMs can be evaluated in three different ways, each of which provides useful insight into model performance (Kotamarthi et al. 2016). First, the model's goodness-of-fit can be quantified by comparing downscaled simulations for the historical period with the identical observations used to train the model. Second, the generalizability of the model can be determined by comparing downscaled historical simulations with observations from a different time period than was used to train the model; this is often accomplished via cross-validation. Third and most importantly, the stationarity of the model can be evaluated through a "perfect model" experiment using coarse-resolution GCM simulations to generate future projections, then comparing these with high-resolution GCM simulations for the same future time period. Initial analyses using the perfect model approach have demonstrated that the assumption of stationarity can vary significantly by ESDM method, by quantile, and by the time scale (daily or monthly) of the GCM input (Dixon et al. 2016).

ESDMs are best suited for analyses that require a broad range of future projections of standard, near-surface variables such as temperature and precipitation, at the scale of observations that may already be used for planning purposes. If the study needs to evaluate the full range of projected changes provided by multiple models and scenarios, then statistical downscaling may be more appropriate than dynamical downscaling. However, even within statistical downscaling, selecting an appropriate method for any given study depends on the questions being asked (see Kotamarthi et al. 2016 for further discussion on selection of appropriate downscaling methods). This report uses projections generated by the LOcalized Constructed Analogs approach (LOCA; Pierce et al. 2014) that spatially matches model-simulated days, past and future, to analogs from observations.

FINAL DRAFT

4.3.4. Averaging, Weighting, and Selection of Global Models

The results of individual climate model simulations using the same inputs can differ from each other over shorter time scales ranging from several years to several decades (Deser et al. 2012a,b). These differences are the result of normal, natural variability, as well as the various ways models characterize various small-scale processes. Although decadal predictability is an active research area (Deser et al. 2014), the timing of specific natural variations is largely unpredictable beyond several seasons. For this reason, multimodel simulations are generally averaged to remove the effects of randomly occurring natural variations from long-term trends and make it easier to discern the impact of external drivers, both human and natural, on the Earth's climate. Multimodel averaging is typically the last stage in any analysis, used to prepare figures showing projected changes in quantities such as annual or seasonal temperature or precipitation (see Ch. 6: Temperature Change and Ch. 7: Precipitation Change). While the effect of averaging on the systematic errors depends on the extent to which models have similar errors or offsetting errors, there is growing recognition of the value of large ensembles of climate model simulations in addressing uncertainty in both natural variability and scientific modeling (e.g., Deser et al. 2012a).

Previous assessments have used a simple average to calculate the multimodel ensemble. This approach implicitly assumes each climate model is independent from the others and of equal ability. Neither of these assumptions, however, are completely valid. Some models share many components with other models in the CMIP5 archive, whereas others have been developed largely in isolation (Knutti et al. 2013; Sanderson et al. 2015). Also, some models are more successful than others at replicating observed climate and trends over the past century, at simulating the large-scale dynamical features responsible for creating or affecting the average climate conditions over a certain region, such as the Arctic or the Caribbean (e.g., M. Wang et al. 2007; C. Wang et al. 2014; Ryu and Hayhoe 2014), or at simulating past climates with very different states than present day (Braconnot et al. 2012). Evaluation of the success of a specific model often depends on the variable or metric being considered in the analysis, with some models performing better than others for certain regions or variables. However, all future simulations agree that both global and regional temperatures will increase over this century in response to increasing emissions of greenhouse gases from human activities.

Can more sophisticated weighting or model selection schemes improve the quality of future projections? In the past, model weights were often based on historical performance; yet performance varies by region and variable, and may not equate to improved future projections (Knutti and Sedlacek 2013). For example, ranking GCMs based on their average biases in temperature gives a very different result than when the same models are ranked based on their ability to simulate observed temperature trends (Jun et al. 2008; Giorgi and Coppola 2010). If GCMs are weighted in a way that does not accurately capture the true uncertainty in regional change, the result can be less robust than an equally-weighted mean (Weigel et al. 2010).

FINAL DRAFT

Although the intent of weighting models is to increase the robustness of the projections, by giving lesser weight to outliers a weighting scheme may increase the risk of underestimating the range of uncertainty, a tendency that has already been noted in multi-model ensembles (see Ch. 15: Potential Surprises).

Despite these challenges, for the first time in an official U.S. Global Change Research Program report, this assessment uses model weighting to refine future climate change projections (Knutti et al. 2017; see also Appendix B: Weighting Strategy). The weighting approach is unique: it takes into account the interdependence of individual climate models as well as their relative abilities in simulating North American climate. Understanding of model history, together with the fingerprints of particular model biases, has been used to identify model pairs that are not independent. In this report, model independence and selected global and North American model quality metrics are considered in order to determine the weighting parameters (Knutti et al. 2017). Evaluation of this approach shows improved performance of the weighted ensemble over the Arctic, a region where model-based trends often differ from observations, but little change in global-scale temperature response and in other regions where modeled and observed trends are similar, although there are small regional differences in the statistical significance of projected changes. The choice of metric used to evaluate models has very little effect on the independence weighting, and some moderate influence on the skill weighting if only a small number of variables are used to assess model quality. Because a large number of variables are combined to produce a comprehensive "skill metric," the metric is not highly sensitive to any single variable. All multimodel figures in this report use the approach described in Appendix B: Weighting Strategy.

4.4. Uncertainty in Future Projections

The timing and magnitude of projected future climate change is uncertain due to the ambiguity introduced by human choices (as discussed in Section 4.2), natural variability, and scientific uncertainty (Hawkins and Sutton 2009, 2011; Deser et al. 2012a), which includes uncertainty in both scientific modeling and climate sensitivity (see Ch. 2: Physical Drivers of Climate Change). Confidence in projections of specific aspects of future climate change increases if formal detection and attribution analyses (Ch. 3: Detection and Attribution) indicate that an observed change has been influenced by human activities, and the projection is consistent with attribution. However, in many cases, especially at the regional scales considered in this assessment, a human-forced response may not yet have emerged from the noise of natural climate variability but may be expected to in the future (e.g., Hawkins and Sutton 2009, 2010). In such cases, confidence in such "projections without attribution" may still be significant under higher scenarios, if the relevant physical mechanisms of change are well understood.

Scientific uncertainty encompasses multiple factors. The first is parametric uncertainty—the ability of GCMs to simulate processes that occur on spatial or temporal scales smaller than they can resolve. The second is structural uncertainty—whether GCMs include and accurately

FINAL DRAFT

represent all the important physical processes occurring on scales they can resolve. Structural uncertainty can arise because a process is not yet recognized—such as "tipping points" or mechanisms of abrupt change—or because it is known but is not yet understood well enough to be modeled accurately—such as dynamical mechanisms that are important to melting ice sheets (see Ch. 15: Potential Surprises). The third is climate sensitivity—a measure of the response of the planet to increasing levels of CO_2, which is formally defined in Chapter 2: Physical Drivers of Climate Change as the equilibrium temperature change resulting from a doubling of CO_2 levels in the atmosphere relative to preindustrial levels. Various lines of evidence constrain the likely value of climate sensitivity to between 2.7°F and 8.1°F (1.5°C and 4.5°C; IPCC 2013b; see Ch. 2: Physical Drivers of Climate Change for further discussion).

Which of these sources of uncertainty—human, natural, and scientific—is most important depends on the time frame and the variable considered. As future scenarios diverge (Figure 4.1), so too do projected changes in global and regional temperature (Hawkins and Sutton 2009). Uncertainty in the magnitude and sign of projected changes in precipitation and other aspects of climate is even greater. The processes that lead to precipitation happen at scales smaller than what can be resolved by even high-resolution models, requiring significant parameterization. Precipitation also depends on many large-scale aspects of climate, including atmospheric circulation, storm tracks, and moisture convergence. Due to the greater level of complexity associated with modeling precipitation, scientific uncertainty tends to dominate in precipitation projections throughout the entire century, affecting both the magnitude and sometimes (depending on location) the sign of the projected change in precipitation (Hawkins and Sutton 2011).

Over the next few decades, the greater part of the range or uncertainty in projected global and regional change will be the result of a combination of natural variability (mostly related to uncertainty in specifying the initial conditions of the state of the ocean; Deser et al. 2012b) and scientific limitations in our ability to model and understand the Earth's climate system (Figure 4.5). Differences in future scenarios, shown in orange in Figure 4.5, represent the difference between scenarios, or human activity. Over the short term, this uncertainty is relatively small. As time progresses, however, differences in various possible future pathways become larger and the delayed ocean response to these differences begins to be realized. By about 2030, the human source of uncertainty becomes increasingly important in determining the magnitude and patterns of future global warming. Even though natural variability will continue to occur, most of the difference between present and future climates will be determined by choices that society makes today and over the next few decades. The further out in time we look, the greater the influence of these human choices are on the magnitude of future warming.

[INSERT FIGURE 4.5 HERE]

FINAL DRAFT

TRACEABLE ACCOUNTS

Key Finding 1

If greenhouse gas concentrations were stabilized at their current level, existing concentrations would commit the world to at least an additional 1.1°F (0.6°C) of warming over this century relative to the last few decades (*high confidence* in continued warming, *medium confidence* in amount of warming).

Description of evidence base

The basic physics underlying the impact of human emissions on global climate, and the role of climate sensitivity in moderating the impact of those emissions on global temperature, has been documented since the 1800s in a series of peer-reviewed journal articles that is summarized in a collection titled, "The Warming Papers: The Scientific Foundation for the Climate Change Forecast" (Archer and Pierrehumbert 2011).

The estimate of committed warming at constant atmospheric concentrations is based on IPCC AR5 WG1, Chapter 12, section 12.5.2, page 1103 (Collins et al. 2013) which is in turn derived from AR4 WG1, Chapter 10, section 10.7.1, page 822 (Meehl et al. 2007).

Major uncertainties

The uncertainty in projected change under a commitment scenario is low and primarily the result of uncertainty in climate sensitivity. This key finding describes a hypothetical scenario that assumes all human-caused emissions cease and the Earth system responds only to what is already in the atmosphere.

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

The statement has *high confidence* in the sign of future change and *medium confidence* in the amount of warming, based on the estimate of committed warming at constant atmospheric concentrations from Collins et al. (2013) based on Meehl et al. (2007) for a hypothetical scenario where concentrations in the atmosphere were fixed at a known level.

Summary sentence or paragraph that integrates the above information

The key finding is based on the basic physical principles of radiative transfer that have been well established for decades to centuries; the amount of estimated warming for this hypothetical scenario is derived from Collins et al. (2013) which is in turn based on Meehl et al. (2007) using CMIP3 models.

FINAL DRAFT

Key Finding 2

Over the next two decades, global temperature increase is projected to be between 0.5°F and 1.3°F (0.3°–0.7°C) (*medium confidence*). This range is primarily due to uncertainties in natural sources of variability that affect short-term trends. In some regions, this means that the trend may not be distinguishable from natural variability (*high confidence*).

Description of evidence base

The estimate of projected near-term warming under continued emissions of carbon dioxide and other greenhouse gases and aerosols was obtained directly from IPCC AR5 WG1(Kirtman et al. 2013).

The statement regarding the sources of uncertainty in near-term projections and regional uncertainty is based on Hawkins and Sutton (2009, 2011) and Deser et al. (2012a,b).

Major uncertainties

As stated in the key finding, natural variability is the primary uncertainty in quantifying the amount of global temperature change over the next two decades.

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

The first statement regarding projected warming over the next two decades has *medium confidence* in the amount of warming due to the uncertainties described in the key finding. The second statement has *high confidence*, as the literature strongly supports the statement that natural variability is the primary source of uncertainty over time scales of years to decades (Deser et al. 2012a,b, 2014).

Summary sentence or paragraph that integrates the above information

The estimated warming presented in this KF is based on calculations reported by Kirtman et al. (2013). The key finding that natural variability is the most important uncertainty over the near-term is based on multiple peer reviewed publications.

Key Finding 3

Beyond the next few decades, the magnitude of climate change depends primarily on cumulative emissions of greenhouse gases and aerosols and the sensitivity of the climate system to those emissions (*high confidence*). Projected changes range from 4.7°–8.6°F (2.6°–4.8°C) under the higher RCP8.5 scenario to 0.5°–1.3°F (0.3°–1.7°C) under the lower RCP2.6 scenario, for 2081–2100 relative to 1986–2005 (*medium confidence*).

FINAL DRAFT

Description of evidence base

The estimate of projected long-term warming under continued emissions of carbon dioxide and other greenhouse gases and aerosols under the RCP scenarios was obtained directly from IPCC AR5 WG1 (Collins et al. 2013).

All credible climate models assessed in Chapter 9 of the IPCC WG1 AR5 (IPCC 2013a) from the simplest to the most complex respond with elevated global mean temperature, the simplest indicator of climate change, when atmospheric concentrations of greenhouse gases increase. It follows then that an emissions pathway that tracks or exceeds RCP8.5 would lead to larger amounts of climate change.

The statement regarding the sources of uncertainty in long-term projections is based on Hawkins and Sutton (2009, 2011).

Major uncertainties

As stated in the key finding, the magnitude of climate change over the long term is uncertain due to human emissions of greenhouse gases and climate sensitivity.

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

The first statement regarding additional warming and its dependence on human emissions and climate sensitivity has *high confidence*, as understanding of the radiative properties of greenhouse gases and the existence of both positive and negative feedbacks in the climate system is basic physics, dating to the 19th century. The second has *medium confidence* in the specific magnitude of warming, due to the uncertainties described in the key finding.

Summary sentence or paragraph that integrates the above information

The estimated warming presented in this key finding is based on calculations reported by Collins et al. (2013). The key finding that human emissions and climate sensitivity are the most important sources of uncertainty over the long-term is based on both basic physics regarding the radiative properties of greenhouse gases, as well as a large body of peer reviewed publications.

Key Finding 4

Global mean atmospheric carbon dioxide (CO_2) concentration has now passed 400 ppm, a level that last occurred about 3 million years ago, when global average temperature and sea level were significantly higher than today (*high confidence*). Continued growth in CO_2 emissions over this century and beyond would lead to an atmospheric concentration not experienced in tens of millions of years (*medium confidence*). The present-day emissions rate of nearly 10 GtC per year

FINAL DRAFT

suggests that there is no climate analog for this century any time in at least the last 50 million years (*medium confidence*).

Description of evidence base

The key finding is based on a large body of research including Crowley (1990), Schneider et al. (2013), Lunt et al. (2012), Otto-Bleisner et al. (2013), NEEM (2013), Jouzel et al. (2007), Dutton et al. (2015), Seki et al. (2010), Haywood et al. (2013), Miller et al. (2012), Royer (2014), Bowen et al. (2015), Kirtland Turner et al. (2014), Penman et al. (2014), Zeebe et al. (2016), and summarized in NRC (2011) and Masson-Delmotte et al. (2013).

Major uncertainties

The largest uncertainty is the measurement of past sea level, given the contributions of not only changes in land ice mass, but also in solid earth, mantle, isostatic adjustments, etc. that occur on timescales of millions of years. This uncertainty increases the further back in time we go; however, the signal (and forcing) size is also much greater. There are also associated uncertainties in precise quantification of past global mean temperature and carbon dioxide levels. There is uncertainty in the age models used to determine rates of change and coincidence of response at shorter, sub-millennial timescales.

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

High confidence in the likelihood statement that past global mean temperature and sea level rise were higher with similar or higher CO_2 concentrations is based on Masson-Delmotte et al. (2013) in IPCC AR5. *Medium confidence* that no precise analog exists in 66 million years is based on Zeebe et al. (2016) as well as the larger body of literature summarized in Masson-Delmotte et al. (2013).

Summary sentence or paragraph that integrates the above information

The key finding is based on a vast body of literature that summarizes the results of observations, paleoclimate analyses, and paleoclimate modeling over the past 50 years and more.

Key Finding 5

The observed increase in global carbon emissions over the past 15–20 years has been consistent with higher scenarios (*very high confidence*). In 2014 and 2015, emission growth rates slowed as economic growth has become less carbon-intensive (*medium confidence*). Even if this trend continues, however, it is not yet at a rate that would meet the long-term temperature goal of the

FINAL DRAFT

Paris Agreement of holding the increase in the global average temperature to well below 3.6°F (2°C) above preindustrial levels (*high confidence*).

Description of Evidence Base

Observed emissions for 2014 and 2015 and estimated emissions for 2016 suggest a decrease in the growth rate and possibly even emissions of carbon; this shift is attributed primarily to decreased coal use in China although with significant uncertainty as noted in the references in the text. This statement is based on Tans and Keeling 2017; Raupach et al. 2007; Le Quéré et al. 2009; Jackson et al. 2016; Korsbakken et al. 2016 and personal communication with Le Quéré (2017).

The statement that the growth rate of carbon dioxide increased over the past 15–20 years is based on the data available here: https://www.esrl.noaa.gov/gmd/ccgg/trends/gr.html

The evidence that actual emission rates track or exceed the RCP8.5 scenario are as follows. The actual emission of CO_2 from fossil fuel consumption and concrete manufacture over the period 2005–2014 is 90.11 Pg (Le Quéré et al. 2015). The RCP8.5 emissions over the same period assuming linear trends between years 2000, 2005, 2010, and 2020 in the specification is 99.24 Pg.

Actual emissions:
http://www.globalcarbonproject.org/ and Le Quéré et al. (2015)

RCP8.5 emissions
http://tntcat.iiasa.ac.at:8787/RcpDb/dsd?Action=htmlpage&page=compare

The numbers for fossil fuel and industrial emissions (RCP) compared to fossil fuel and cement emissions (observed) in units of GtC are

	RCP8.5	Actual	difference
2005	7.97	8.23	0.26
2006	8.16	8.53	0.36
2007	8.35	8.78	0.42
2008	8.54	8.96	0.42
2009	8.74	8.87	0.14
2010	8.93	9.21	0.28
2011	9.19	9.54	0.36
2012	9.45	9.69	0.24

FINAL DRAFT

	2013	9.71	9.82	0.11
	2014	9.97	9.89	-0.08
	2015	10.23	9.90	-0.34
total		99.24	101.41	2.18

Major Uncertainties

None

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

Very high confidence in increasing emissions over the last 20 years and *high confidence* in the fact that recent emission trends will not be sufficient to avoid 2°C. *Medium confidence* in recent findings that the growth rate is slowing. Climate change scales with the amount of anthropogenic greenhouse gas in the atmosphere. If emissions exceed RCP8.5, the likely range of changes temperatures and climate variables will be larger than projected.

Summary sentence or paragraph that integrates the above information

The key finding is based on basic physics relating emissions to concentrations, radiative forcing, and resulting change in global mean temperature, as well as on IEA data on national emissions as reported in the peer-reviewed literature.

Key Finding 6

Combining output from global climate models and dynamical and statistical downscaling models using advanced averaging, weighting, and pattern scaling approaches can result in more relevant and robust future projections. For some regions, sectors, and impacts, these techniques are increasing the ability of the scientific community to provide guidance on the use of climate projections for quantifying regional-scale changes and impacts (*medium to high confidence*).

Description of evidence base

The contribution of weighting and pattern scaling to improving the robustness of multimodel ensemble projections is described and quantified by a large body of literature as summarized in the text, including Sanderson et al. (2015) and Knutti et al. (2017). The state of the art of dynamical and statistical downscaling and the scientific community's ability to provide guidance

FINAL DRAFT

regarding the application of climate projections to regional impact assessments is summarized in Kotamarthi et al. (2016) and supported by Feser et al. (2011) and Prein et al. (2015).

Major uncertainties

Regional climate models are subject to the same structural and parametric uncertainties as global models, as well as the uncertainty due to incorporating boundary conditions. The primary source of error in application of empirical statistical downscaling methods is inappropriate application, followed by stationarity.

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

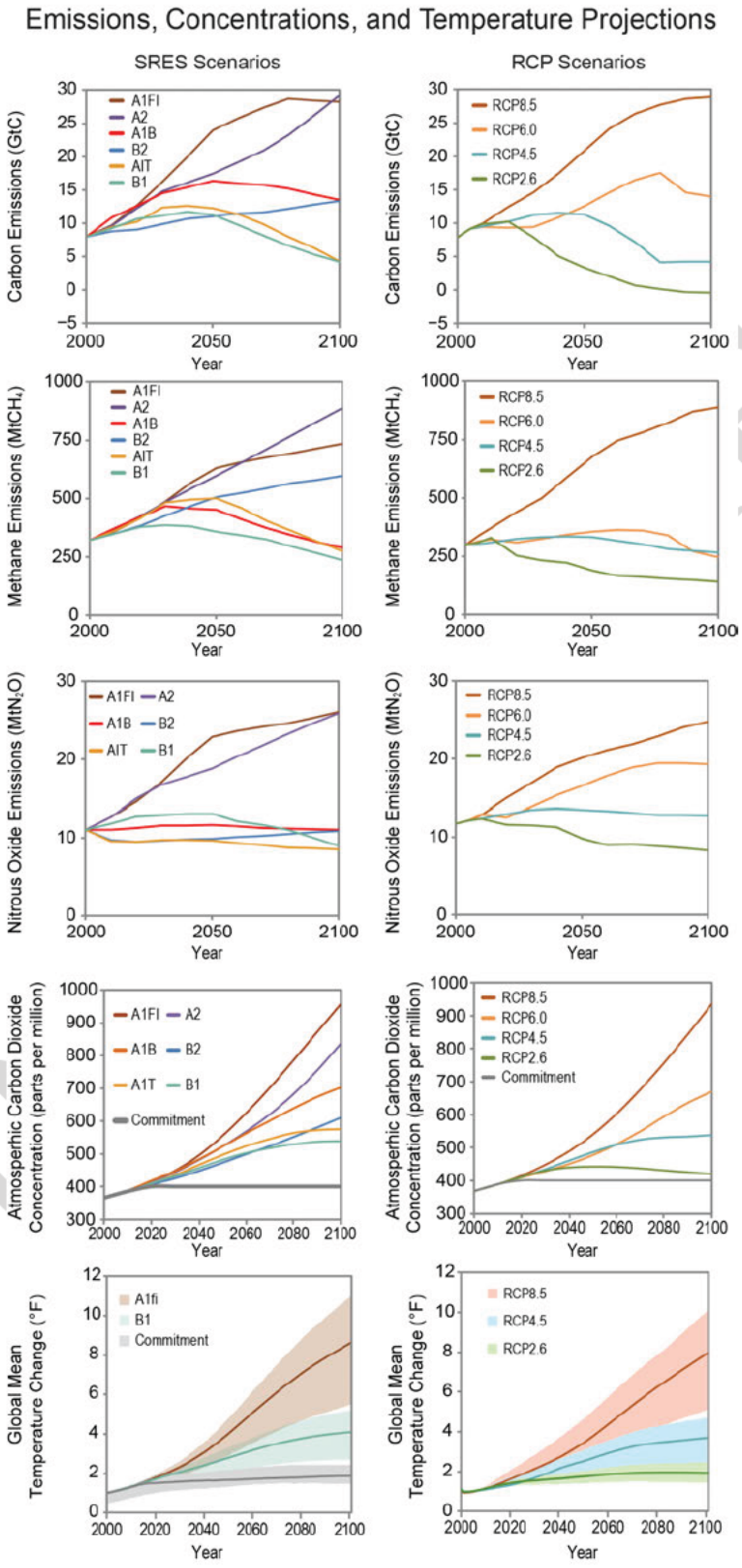
Advanced weighting techniques have significantly improved over previous Bayesian approaches; confidence in their ability to improve the robustness of multimodel ensembles, while currently rated as *medium*, is likely to grow in coming years. Downscaling has evolved significantly over the last decade and is now broadly viewed as a robust source for high-resolution climate projections that can be used as input to regional impact assessments.

Summary sentence or paragraph that integrates the above information

Scientific understanding of climate projections, downscaling, multimodel ensembles, and weighting has evolved significantly over the last decades to the extent that appropriate methods are now broadly viewed as robust sources for climate projections that can be used as input to regional impact assessments.

FINAL DRAFT

FIGURES



FINAL

Figure 4.1: The climate projections used in this report are based on the 2010 Representative Concentration Pathways (RCP, right). They are largely consistent with scenarios used in previous assessments, the 2000 Special Report on Emission Scenarios (SRES, left). This figure compares SRES and RCP annual carbon emissions (GtC, first row), annual methane emissions ($MtCH_4$, second row), nitrous oxide emissions (MtN_2O, third row), carbon dioxide concentration in the atmosphere (ppm, fourth row), global mean temperature change relative to 1900–1960 that would result from the central estimate (lines) and the likely range (shaded areas) of climate sensitivity as calculated by an energy balance model (°F, fifth row), and global mean temperature change relative to 1900–1960 as simulated by CMIP3 models for the SRES scenarios and CMIP5 models for the RCP scenarios (°F, sixth row). Note that global mean temperature from SRES A1fi simulations are only available from four global climate models, hence the much smaller range. (Data from IIASA, CMIP3, and CMIP5).

FINAL DRAFT

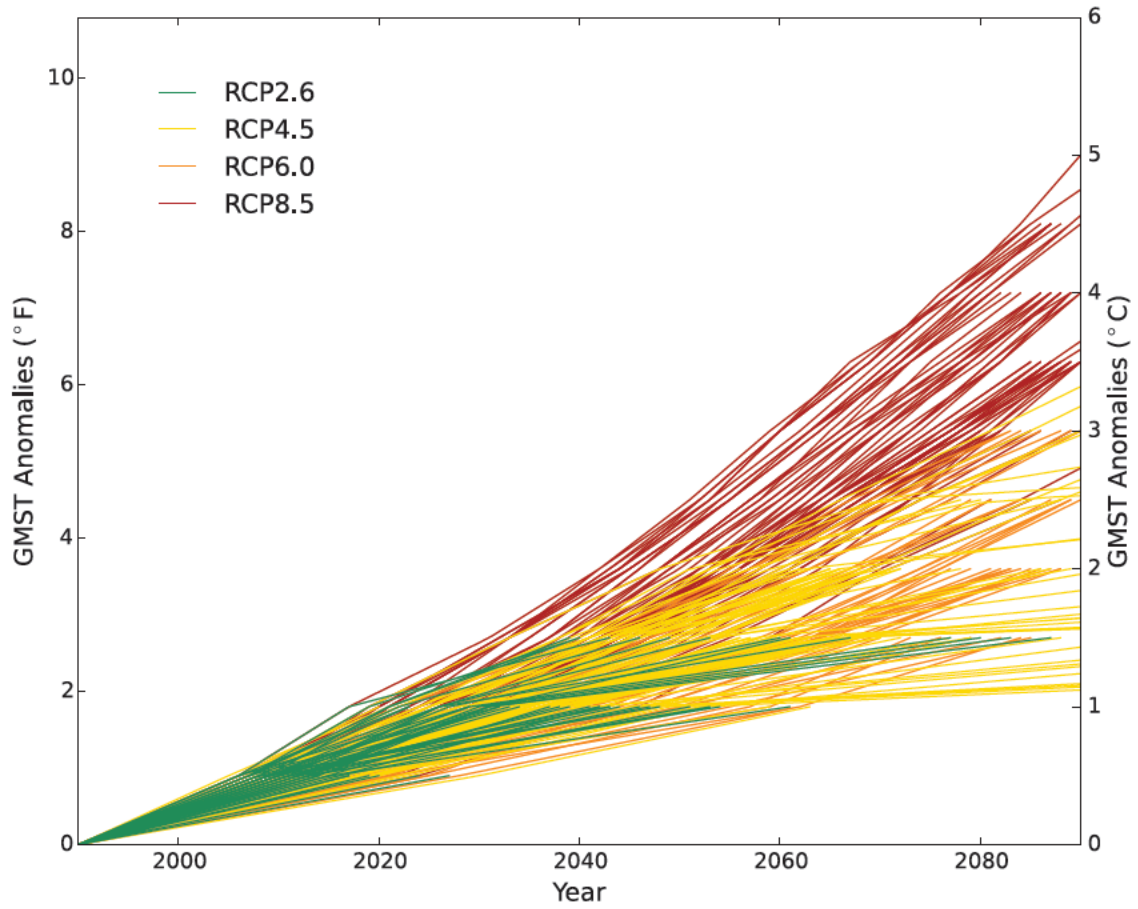


Figure 4.2: Global mean surface temperature anomalies (°F) relative to 1976–2005 for four RCP scenarios, 2.6 (green), 4.5 (yellow), 6.0 (orange), and 8.5 (red). Each line represents an individual simulation from the CMIP5 archive. Every RCP-based simulation with annual or monthly temperature outputs available was used here. The values shown here were calculated in 0.5°C increments; since not every simulation reaches the next 0.5°C increment before end of century, many lines terminate before 2100. (Figure source: adapted from Swain and Hayhoe 2015).

FINAL

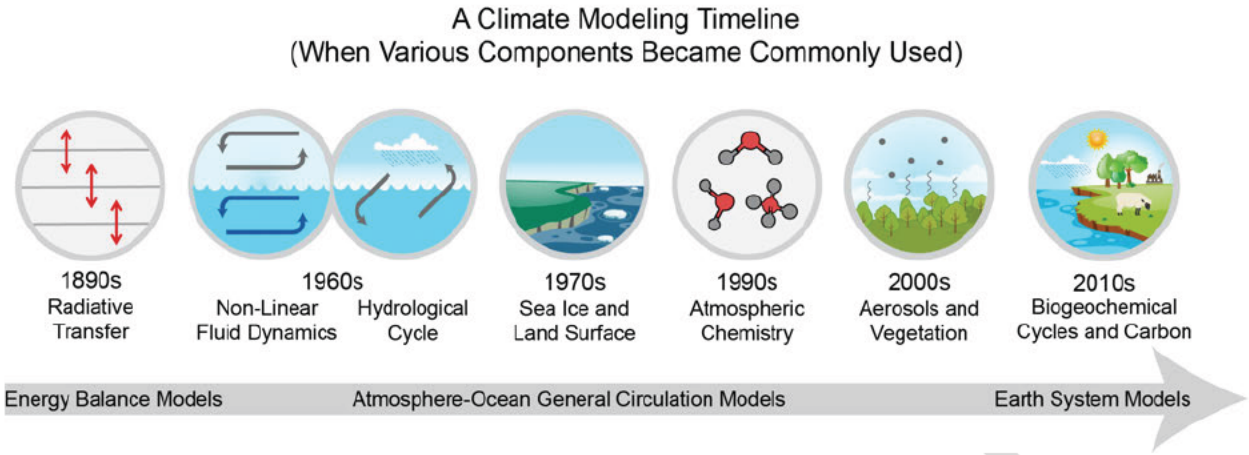


Figure 4.3: As climate modeling has evolved over the last 120 years, increasing amounts of physical science have been incorporated into the models. This figure shows when various components of the climate system became regularly included in global climate model simulations.

FINAL DRAFT

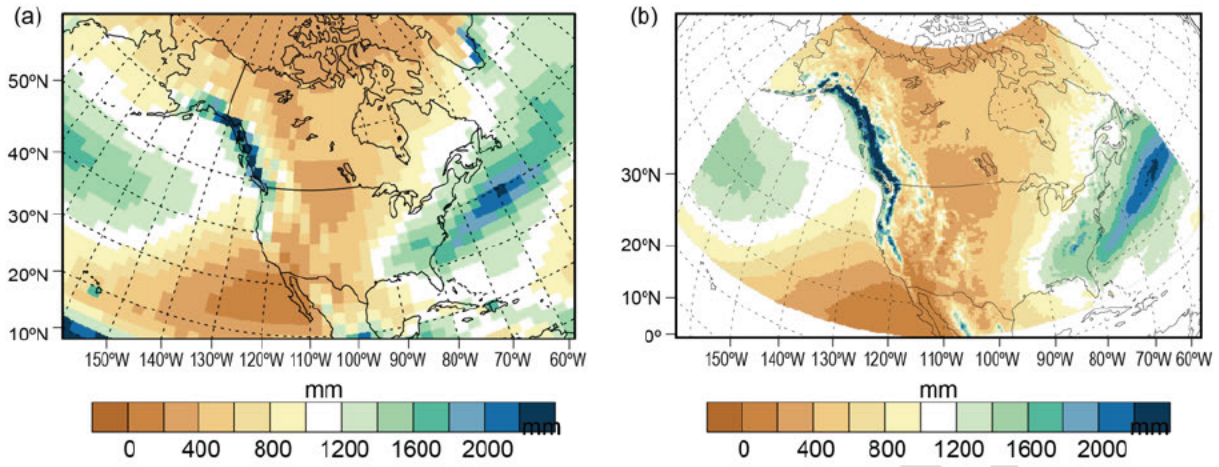


Figure 4.4: CMIP5 global climate models typically operate at coarser horizontal spatial scales on the order of 50 to 300 km (30 to 200 miles), while regional climate models have much finer resolutions, on the order of 10 to 50 km (6 to 30 miles). This figure compares annual average precipitation (in millimeters) for the historical period 1979–2008 using (a) a resolution of 250 km or 150 miles with (b) a resolution of 25 km or 15 miles to illustrate the importance of spatial scale in resolving key topographical features, particularly along the coasts and in mountainous areas. In this case, both simulations are by the GFDL HIRAM model, an experimental high-resolution model. (Figure source: adapted from Dixon et al. 2016).

FINAL DRAFT

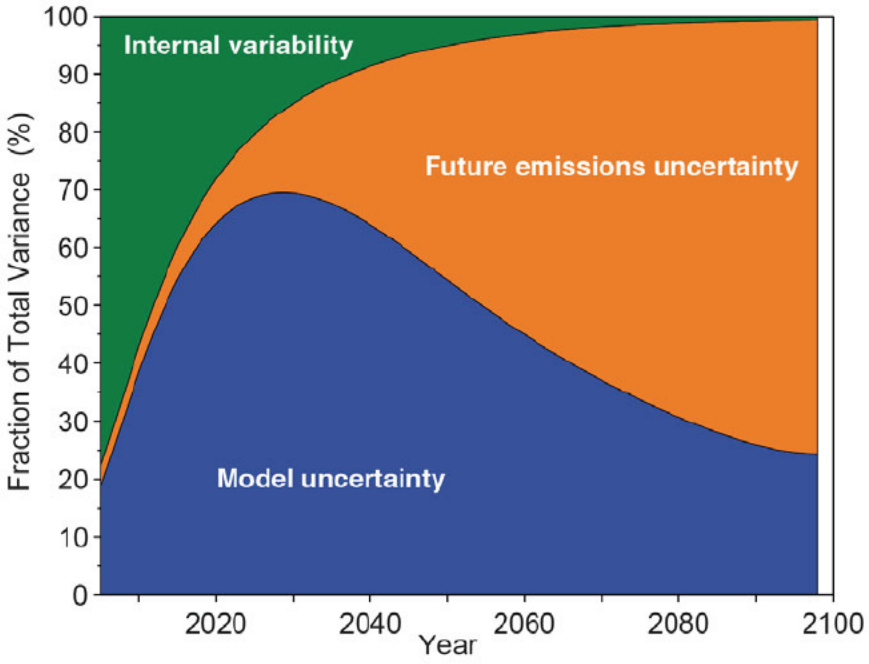


Figure 4.5: The fraction of total variance in decadal mean surface air temperature predictions explained by the three components of total uncertainty is shown for the lower 48 states (similar results are seen for Hawai'i and Alaska, not shown). Orange regions represent human or scenario uncertainty, blue regions represent model uncertainty, and green regions represent the internal variability component. As the size of the region is reduced, the relative importance of internal variability increases. In interpreting this figure, it is important to remember that it shows the fractional sources of uncertainty. Total uncertainty increases as time progresses. (Figure source: adapted from Hawkins and Sutton 2009).

FINAL DRAFT

REFERENCES

Archer, D. and R. Pierrehumbert, eds., 2011: *The Warming Papers: The Scientific Foundation for the Climate Change Forecast*. Wiley-Blackwell: Oxford, UK, 432 pp.

Bellenger, H., E. Guilyardi, J. Leloup, M. Lengaigne, and J. Vialard, 2014: ENSO representation in climate models: From CMIP3 to CMIP5. *Climate Dynamics,* **42,** 1999-2018. http://dx.doi.org/10.1007/s00382-013-1783-z

Bowen, G.J., B.J. Maibauer, M.J. Kraus, U. Rohl, T. Westerhold, A. Steimke, P.D. Gingerich, S.L. Wing, and W.C. Clyde, 2015: Two massive, rapid releases of carbon during the onset of the Palaeocene-Eocene thermal maximum. *Nature Geoscience,* **8,** 44-47. http://dx.doi.org/10.1038/ngeo2316

Braconnot, P., S.P. Harrison, M. Kageyama, P.J. Bartlein, V. Masson-Delmotte, A. Abe-Ouchi, B. Otto-Bliesner, and Y. Zhao, 2012: Evaluation of climate models using palaeoclimatic data. *Nature Climate Change,* **2,** 417-424. http://dx.doi.org/10.1038/nclimate1456

Brands, S., J.M. Gutiérrez, S. Herrera, and A.S. Cofiño, 2012: On the use of reanalysis data for downscaling. *Journal of Climate,* **25,** 2517-2526. http://dx.doi.org/10.1175/jcli-d-11-00251.1

Bretherton, F., K. Bryan, J. Woods, J. Hansen, M. Hoffert, X. Jiang, S. Manabe, G. Meehl, S. Raper, D. Rind, M. Schlesinger, R. Stouffer, T. Volk, and T. Wigley, 1990: Time-dependent greenhouse-gas-induced climate change. *Climate Change: The IPCC Scientific Assessment Report prepared for Intergovernmental Panel on Climate Change by Working Group I* Houghton, J.T., G.J. Jenkins, and J.J. Ephraums, Eds. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 173-193.

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/

Crowley, T.J., 1990: Are there any satisfactory geologic analogs for a future greenhouse warming? *Journal of Climate,* **3,** 1282-1292. http://dx.doi.org/10.1175/1520-0442(1990)003<1282:atasga>2.0.co;2

Cubasch, U., G. Meehl, G. Boer, R. Stouffer, M. Dix, A. Noda, C. Senior, S. Raper, and K. Yap, 2001: Projections of future climate change. *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental*

FINAL DRAFT

Panel on Climate Change. Houghton, J.T., Y. Ding, D.J. Griggs, M. Noquer, P.J. van der Linden, X. Dai, K. Maskell, and C.A. Johnson, Eds. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 525-582. https://www.ipcc.ch/ipccreports/tar/wg1/pdf/TAR-09.PDF

Cubasch, U., D. Wuebbles, D. Chen, M.C. Facchini, D. Frame, N. Mahowald, and J.-G. Winther, 2013: Introduction. *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, 119–158. http://www.climatechange2013.org/report/full-report/

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

Deser, C., R. Knutti, S. Solomon, and A.S. Phillips, 2012b: 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., A. Phillips, V. Bourdette, and H. Teng, 2012a: Uncertainty in climate change projections: The role of internal variability. *Climate Dynamics,* **38,** 527-546. http://dx.doi.org/10.1007/s00382-010-0977-x

Deser, C., A.S. Phillips, M.A. Alexander, and B.V. Smoliak, 2014: Projecting North American climate over the next 50 years: Uncertainty due to internal variability. *Journal of Climate,* **27,** 2271-2296. http://dx.doi.org/10.1175/JCLI-D-13-00451.1

Dixon, K.W., J.R. Lanzante, M.J. Nath, K. Hayhoe, A. Stoner, A. Radhakrishnan, V. Balaji, and C.F. Gaitán, 2016: Evaluating the stationarity assumption in statistically downscaled climate projections: Is past performance an indicator of future results? *Climatic Change,* **135,** 395-408. http://dx.doi.org/10.1007/s10584-016-1598-0

Dutton, A., A.E. Carlson, A.J. Long, G.A. Milne, P.U. Clark, R. DeConto, B.P. Horton, S. Rahmstorf, and M.E. Raymo, 2015: Sea-level rise due to polar ice-sheet mass loss during past warm periods. *Science,* **349**. http://dx.doi.org/10.1126/science.aaa4019

Feser, F., B. Rockel, H.v. Storch, J. Winterfeldt, and M. Zahn, 2011: Regional climate models add value to global model data: A review and selected examples. *Bulletin of the American Meteorological Society,* **92,** 1181-1192. http://dx.doi.org/10.1175/2011BAMS3061.1

Fix, M.J., D. Cooley, S.R. Sain, and C. Tebaldi, 2016: A comparison of U.S. precipitation extremes under RCP8.5 and RCP4.5 with an application of pattern scaling. *Climatic Change,* **First online,** 1-13. http://dx.doi.org/10.1007/s10584-016-1656-7

FINAL DRAFT

Frieler, K., M. Meinshausen, A. Golly, M. Mengel, K. Lebek, S.D. Donner, and O. Hoegh-Guldberg, 2013: Limiting global warming to 2°C is unlikely to save most coral reefs. *Nature Climate Change,* **3,** 165-170. http://dx.doi.org/10.1038/nclimate1674

Gasson, E., D.J. Lunt, R. DeConto, A. Goldner, M. Heinemann, M. Huber, A.N. LeGrande, D. Pollard, N. Sagoo, M. Siddall, A. Winguth, and P.J. Valdes, 2014: Uncertainties in the modelled CO_2 threshold for Antarctic glaciation. *Climate of the Past,* **10,** 451-466. http://dx.doi.org/10.5194/cp-10-451-2014

Giorgi, F. and E. Coppola, 2010: Does the model regional bias affect the projected regional climate change? An analysis of global model projections. *Climatic Change,* **100,** 787-795. http://dx.doi.org/10.1007/s10584-010-9864-z

Green, F. and N. Stern, 2016: China's changing economy: Implications for its carbon dioxide emissions. *Climate Policy,* **17,** 423-442. http://dx.doi.org/10.1080/14693062.2016.1156515

Hartmann, D.L., A.M.G. Klein Tank, M. Rusticucci, L.V. Alexander, S. Brönnimann, Y. Charabi, F.J. Dentener, E.J. Dlugokencky, D.R. Easterling, A. Kaplan, B.J. Soden, P.W. Thorne, M. Wild, and P.M. Zhai, 2013: Observations: Atmosphere and surface. *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, 159–254. http://www.climatechange2013.org/report/full-report/

Hawkins, E. and R. Sutton, 2009: The potential to narrow uncertainty in regional climate predictions. *Bulletin of the American Meteorological Society,* **90,** 1095-1107. http://dx.doi.org/10.1175/2009BAMS2607.1

Hawkins, E. and R. Sutton, 2011: The potential to narrow uncertainty in projections of regional precipitation change. *Climate Dynamics,* **37,** 407-418. http://dx.doi.org/10.1007/s00382-010-0810-6

Haywood, A.M., D.J. Hill, A.M. Dolan, B.L. Otto-Bliesner, F. Bragg, W.L. Chan, M.A. Chandler, C. Contoux, H.J. Dowsett, A. Jost, Y. Kamae, G. Lohmann, D.J. Lunt, A. Abe-Ouchi, S.J. Pickering, G. Ramstein, N.A. Rosenbloom, U. Salzmann, L. Sohl, C. Stepanek, H. Ueda, Q. Yan, and Z. Zhang, 2013: Large-scale features of Pliocene climate: Results from the Pliocene Model Intercomparison Project. *Climate of the Past,* **9,** 191-209. http://dx.doi.org/10.5194/cp-9-191-2013

Herger, N., B.M. Sanderson, and R. Knutti, 2015: Improved pattern scaling approaches for the use in climate impact studies. *Geophysical Research Letters,* **42,** 3486-3494. http://dx.doi.org/10.1002/2015GL063569

FINAL DRAFT

IEA, 2016: Decoupling of global emissions and economic growth confirmed. International Energy Agency, March 16. https://www.iea.org/newsroomandevents/pressreleases/2016/march/decoupling-of-global-emissions-and-economic-growth-confirmed.html

IIASA, 2016: RCP Database. Version 2.0.5. International Institute for Applied Systems Analysis. https://tntcat.iiasa.ac.at/RcpDb/dsd?Action=htmlpage&page=compare

IPCC, 1990: *Climate Change: The IPCC Scientific Assessment*. Houghton, J.T., G.J. Jenkins, and J.J. Ephraums, Eds. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 212 pp.

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/

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, United Kingdom and New York, NY, USA, 1–30. http://www.climatechange2013.org/report/

Jackson, R.B., J.G. Canadell, C. Le Quere, R.M. Andrew, J.I. Korsbakken, G.P. Peters, and N. Nakicenovic, 2016: Reaching peak emissions. *Nature Climate Change,* **6,** 7-10. http://dx.doi.org/10.1038/nclimate2892

Jagniecki, E.A., T.K. Lowenstein, D.M. Jenkins, and R.V. Demicco, 2015: Eocene atmospheric CO2 from the nahcolite proxy. *Geology,* **43,** 1075-1078. http://dx.doi.org/10.1130/g36886.1

Jouzel, J., V. Masson-Delmotte, O. Cattani, G. Dreyfus, S. Falourd, G. Hoffmann, B. Minster, J. Nouet, J.M. Barnola, J. Chappellaz, H. Fischer, J.C. Gallet, S. Johnsen, M. Leuenberger, L. Loulergue, D. Luethi, H. Oerter, F. Parrenin, G. Raisbeck, D. Raynaud, A. Schilt, J. Schwander, E. Selmo, R. Souchez, R. Spahni, B. Stauffer, J.P. Steffensen, B. Stenni, T.F. Stocker, J.L. Tison, M. Werner, and E.W. Wolff, 2007: Orbital and millennial Antarctic climate variability over the past 800,000 years. *Science,* **317,** 793-796. http://dx.doi.org/10.1126/science.1141038

Jun, M., R. Knutti, and D.W. Nychka, 2008: Local eigenvalue analysis of CMIP3 climate model errors. *Tellus A,* **60,** 992-1000. http://dx.doi.org/10.1111/j.1600-0870.2008.00356.x

FINAL DRAFT

Karl, T.R., J.T. Melillo, and T.C. Peterson, eds., 2009: *Global Climate Change Impacts in the United States*. Cambridge University Press: New York, NY, 189 pp. http://downloads.globalchange.gov/usimpacts/pdfs/climate-impacts-report.pdf

Kattenberg, A., F. Giorgi, H. Grassl, G. Meehl, J. Mitchell, R. Stouffer, T. Tokioka, A. Weaver, and T. Wigley, 1996: Climate models - projections of future climate. *Climate Change 1995: The Science of Climate Change. Contribution of Working Group I to the Second Assessment Report of the Intergovernmental Panel on Climate Change*. Houghton, J.T., L.G. Meira Filho, B.A. Callander, N. Harris, A. Kattenberg, and K. Maskell, Eds. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 285-358. https://www.ipcc.ch/ipccreports/sar/wg_I/ipcc_sar_wg_I_full_report.pdf

Kharin, V.V., F.W. Zwiers, X. Zhang, and M. Wehner, 2013: Changes in temperature and precipitation extremes in the CMIP5 ensemble. *Climatic Change,* **119,** 345-357. http://dx.doi.org/10.1007/s10584-013-0705-8

Kirtland Turner, S., P.F. Sexton, C.D. Charles, and R.D. Norris, 2014: Persistence of carbon release events through the peak of early Eocene global warmth. *Nature Geoscience,* **7,** 748-751. http://dx.doi.org/10.1038/ngeo2240

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/

Knutson, T.R., J.J. Sirutis, G.A. Vecchi, S. Garner, M. Zhao, H.-S. Kim, M. Bender, R.E. Tuleya, I.M. Held, and G. Villarini, 2013: Dynamical downscaling projections of twenty-first-century Atlantic hurricane activity: CMIP3 and CMIP5 model-based scenarios. *Journal of Climate,* **27**, 6591-6617. http://dx.doi.org/10.1175/jcli-d-12-00539.1

Knutti, R., D. Masson, and A. Gettelman, 2013: Climate model genealogy: Generation CMIP5 and how we got there. *Geophysical Research Letters,* **40,** 1194-1199. http://dx.doi.org/10.1002/grl.50256

Knutti, R. and J. Sedlacek, 2013: Robustness and uncertainties in the new CMIP5 climate model projections. *Nature Climate Change,* **3,** 369-373. http://dx.doi.org/10.1038/nclimate1716

FINAL DRAFT

Knutti, R., J. Sedláček, B.M. Sanderson, R. Lorenz, E.M. Fischer, and V. Eyring, 2017: A climate model projection weighting scheme accounting for performance and interdependence. *Geophysical Research Letters,* **44,** 1909-1918. http://dx.doi.org/10.1002/2016GL072012

Kopp, R.E., F.J. Simons, J.X. Mitrovica, A.C. Maloof, and M. Oppenheimer, 2009: Probabilistic assessment of sea level during the last interglacial stage. *Nature,* **462,** 863-867. http://dx.doi.org/10.1038/nature08686

Korsbakken, J.I., G.P. Peters, and R.M. Andrew, 2016: Uncertainties around reductions in China's coal use and CO2 emissions. *Nature Climate Change,* **6,** 687-690. http://dx.doi.org/10.1038/nclimate2963

Kotamarthi, R., L. Mearns, K. Hayhoe, C. Castro, and D. Wuebbles, 2016: Use of Climate Information for Decision-Making and Impact Research. U.S. Department of Defense, Strategic Environment Research and Development Program Report, 55 pp. http://dx.doi.org/10.13140/RG.2.1.1986.0085

Kumar, D., E. Kodra, and A.R. Ganguly, 2014: Regional and seasonal intercomparison of CMIP3 and CMIP5 climate model ensembles for temperature and precipitation. *Climate Dynamics,* **43,** 2491-2518. http://dx.doi.org/10.1007/s00382-014-2070-3

Lauer, A. and K. Hamilton, 2013: Simulating clouds with global climate models: A comparison of CMIP5 results with CMIP3 and satellite data. *Journal of Climate,* **26,** 3823-3845. http://dx.doi.org/10.1175/jcli-d-12-00451.1

Le Quéré, C., R. Moriarty, R.M. Andrew, J.G. Canadell, S. Sitch, J.I. Korsbakken, P. Friedlingstein, G.P. Peters, R.J. Andres, T.A. Boden, R.A. Houghton, J.I. House, R.F. Keeling, P. Tans, A. Arneth, D.C.E. Bakker, L. Barbero, L. Bopp, J. Chang, F. Chevallier, L.P. Chini, P. Ciais, M. Fader, R.A. Feely, T. Gkritzalis, I. Harris, J. Hauck, T. Ilyina, A.K. Jain, E. Kato, V. Kitidis, K. Klein Goldewijk, C. Koven, P. Landschützer, S.K. Lauvset, N. Lefèvre, A. Lenton, I.D. Lima, N. Metzl, F. Millero, D.R. Munro, A. Murata, J.E.M.S. Nabel, S. Nakaoka, Y. Nojiri, K. O'Brien, A. Olsen, T. Ono, F.F. Pérez, B. Pfeil, D. Pierrot, B. Poulter, G. Rehder, C. Rödenbeck, S. Saito, U. Schuster, J. Schwinger, R. Séférian, T. Steinhoff, B.D. Stocker, A.J. Sutton, T. Takahashi, B. Tilbrook, I.T. van der Laan-Luijkx, G.R. van der Werf, S. van Heuven, D. Vandemark, N. Viovy, A. Wiltshire, S. Zaehle, and N. Zeng, 2015: Global carbon budget 2015. *Earth System Science Data,* **7,** 349-396. http://dx.doi.org/10.5194/essd-7-349-2015

Le Quéré, C., M.R. Raupach, J.G. Canadell, G. Marland, L. Bopp, P. Ciais, T.J. Conway, S.C. Doney, R.A. Feely, P. Foster, P. Friedlingstein, K. Gurney, R.A. Houghton, J.I. House, C. Huntingford, P.E. Levy, M.R. Lomas, J. Majkut, N. Metzl, J.P. Ometto, G.P. Peters, I.C. Prentice, J.T. Randerson, S.W. Running, J.L. Sarmiento, U. Schuster, S. Sitch, T. Takahashi,

FINAL DRAFT

N. Viovy, G.R. van der Werf, and F.I. Woodward, 2009: Trends in the sources and sinks of carbon dioxide. *Nature Geoscience,* **2,** 831-836. http://dx.doi.org/10.1038/ngeo689

Leggett, J., W.J. Pepper, R.J. Swart, J. Edmonds, L.G.M. Filho, I. Mintzer, M.X. Wang, and J. Watson, 1992: Emissions scenarios for the IPCC: An update. *Climate Change 1992: The Supplementary Report to the IPCC Scientific Assessment*. Houghton, J.T., B.A. Callander, and S.K. Varney, Eds. Cambridge University Press, Cambridge, United Kingdom, New York, NY, USA, and Victoria, Australia, 73-95. https://www.ipcc.ch/ipccreports/1992%20IPCC%20Supplement/IPCC_Suppl_Report_1992_wg_I/ipcc_wg_I_1992_suppl_report_section_a3.pdf

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

Masson-Delmotte, V., M. Schulz, A. Abe-Ouchi, J. Beer, A. Ganopolski, J.F. González Rouco, E. Jansen, K. Lambeck, J. Luterbacher, T. Naish, T. Osborn, B. Otto-Bliesner, T. Quinn, R. Ramesh, M. Rojas, X. Shao, and A. Timmermann, 2013: Information from paleoclimate archives. *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, 383–464. http://www.climatechange2013.org/report/full-report/

Masui, T., K. Matsumoto, Y. Hijioka, T. Kinoshita, T. Nozawa, S. Ishiwatari, E. Kato, P.R. Shukla, Y. Yamagata, and M. Kainuma, 2011: An emission pathway for stabilization at 6 Wm^{-2} radiative forcing. *Climatic Change,* **109,** 59. http://dx.doi.org/10.1007/s10584-011-0150-5

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: Ch. 10: 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, UK and New York, NY, 747-845. http://www.ipcc.ch/pdf/assessment-report/ar4/wg1/ar4-wg1-chapter10.pdf

Meinshausen, M., S.J. Smith, K. Calvin, J.S. Daniel, M.L.T. Kainuma, J.-F. Lamarque, K. Matsumoto, S.A. Montzka, S.C.B. Raper, K. Riahi, A. Thomson, G.J.M. Velders, and D.P.P. van Vuuren, 2011: The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. *Climatic Change,* **109,** 213-241. http://dx.doi.org/10.1007/s10584-011-0156-z

FINAL DRAFT