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Key Points:

- Our observational data-driven model shows good skill in the decadal hindcasts initialized from 1984, 1994, and 2004
- Our ensemble mean warming projection from 1986–2005 to 2016–2035 is just two-thirds of that from CMIP5 Earth system models
- Our ensemble mean temperature projections by the year 2100 are consistent with CMIP5 model results

Supporting Information:

- Supporting Information S1

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Global warming projection in the 21st century based on an observational data-driven model

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Abstract Global warming has been projected primarily by Earth system models (ESMs). Complementary to this approach, here we provide the decadal and long-term global warming projections based on an observational data-driven model. This model combines natural multidecadal variability with anthropogenic warming that depends on the history of annual emissions. It shows good skill in decadal hindcasts with the recent warming slowdown well captured. While our ensemble mean temperature projections at the end of 21st century are consistent with those from ESMs, our decadal warming projection of 0.35 (0.30–0.43) K from 1986–2005 to 2016–2035 is within their projection range and only two-thirds of the ensemble mean from ESMs. Our predicted warming rate in the next few years is slower than in the 1980s and 1990s, followed by a greater warming rate. Our projection uncertainty range is just one-third of that from ESMs, and its implication is also discussed.

1. Introduction

The increase of the global temperature in the 21st century has been projected primarily by Earth system models (ESMs) from the Coupled Model Intercomparison Project (CMIP5), as summarized in the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) [Intergovernmental Panel on Climate Change (IPCC), 2013]. However, the ensemble mean trend of the global annual mean surface temperature anomaly (TA) from ESMs of 0.21°C/decade during 1998–2012 is much greater than the observed trend [IPCC, 2013], leading to questions about the reliability of ESM's short- and long-term TA projections [Lewandowsky et al., 2015]. This discrepancy has been subsequently explained from different perspectives, including internal climate variability, missing or incorrect radiative forcing, model response error, uninitialized decadal prediction, and coverage bias in the observations [Fyfe et al., 2016, and references therein]. Furthermore, England et al. [2015] demonstrated that the 21st century warming projections are statistically unchanged when considering only ensemble members that capture the recent warming slowdown. Nevertheless, it is still desirable to corroborate the ESM decadal and long-term projections by observation-based empirical models.

Indeed, apart from the use of ESMs, the observational TA time series itself has been analyzed in an attempt to quantify the relative roles of anthropogenic warming versus natural variability in the global warming trend [Lean and Rind, 2009; Swanson et al., 2009; Foster and Rahmstorf, 2011; Wu et al., 2011; Tung and Zhou, 2013]. In his pioneering work in combining the anthropogenic global warming as a linear function of the logarithm of [CO₂] (denoting the CO₂ concentration in the atmosphere) with multidecadal natural variability based on the Greenland ice core data, Broecker [1975] correctly predicted the end of cooling in the 1970s and the subsequent rapid warming. More recently, other observation-based minimal models have been developed for TA projections [Lovejoy, 2015; Monckton of Brenchley et al., 2015; Rypdal, 2016]. Some of these models included both anthropogenic warming and natural variability in their decadal TA projections, but they did not address the long-term projection under different emission scenarios [Broecker, 1975; Lean and Rind, 2009; Lovejoy, 2015]. Others focused on the anthropogenic warming only, which is relevant to long-term projection, but not to decadal prediction [Monckton of Brenchley et al., 2015; Rypdal, 2016].

The goal of this study is to develop an observational data-driven model that is suitable for both decadal and long-term TA projections in the 21st century. Our approach of separately treating anthropogenic warming and natural variability follows previous observation-based modeling efforts [Broecker, 1975; Lovejoy, 2015]. Our key innovations are to explicitly track the impact of each year's [CO₂] change on TA changes in all subsequent years and to use an ensemble of sine functions to represent the natural multidecadal variability.

Figure 1. (a) HadCRUT4 temperature anomaly (TA) and its n -year running means (with $n = 10, 20, 40, 60$, and 80), (b) 80 year running mean of TA and TAh (from our model; due to human activities), and (c) $(TA - TA_{10})$ (i.e., natural interannual variability) and $(TA - TAh)$ (i.e., natural variability).

Representing complementary and independent approaches, our projections will also be compared with those from ESMs.

2. Observational Data

We primarily use the observational TA data set for 1850–2014 from HadCRUT4 [Morice *et al.*, 2012]. Additional data sets are also used for uncertainty quantification, including the NASA Goddard Institute for Space Studies Surface Temperature Analysis (GISTEMP) product from 1880 to 2014 [Hansen *et al.*, 2010], the NOAA Merged Land–Ocean Surface Temperature (MLOST) product from 1880 to 2014 [Smith *et al.*, 2008], and two versions (Berkeley1 and Berkeley2) of the Berkeley Earth product from 1850 to 2014 [Rohde *et al.*, 2013]. Each TA data set has the same base period of 1961–1990 by subtracting the average from 1961 to 1990 from the time series. The 10 year running mean of TA, $TA_{10}(y)$, is computed from year $(y + 1 - 10/2)$ to year $(y + 10/2)$. The running mean for different periods (e.g., 80 years) can be similarly defined.

We also use the observation-based annual $[CO_2]$ from IPCC [2013] for 1850 to 2005 and from Masarie and Tans [1995] and Ballantyne *et al.* [2012] for 2006–2014. Furthermore, we use the projected $[CO_2]$ after 2014 for three Representative Concentration Pathways (RCP2.6, RCP4.5, and RCP8.5) [Meinhausen *et al.*, 2011; Van Vuuren *et al.*, 2011]. RCP8.5 is characterized by increasing $[CO_2]$ over time, reaching around 936 ppm in 2100, while RCP4.5 is a stabilization scenario, with $[CO_2]$ reaching around 538 ppm in 2100. RCP2.6 is a “peak-and-decline” scenario, with $[CO_2]$ reaching the peak of around 443 ppm in 2052 and then decreasing to around 421 ppm by 2100.

3. Our Observational Data-Driven Model for Anthropogenic Warming

The dominant interannual variability is reflected by the differences between TA and TA_{10} (Figures 1a and 1c), and it is primarily associated with the El Niño–Southern Oscillation (ENSO) events over the tropical Pacific on

time scales of 2–7 years. The multidecadal variability is reflected by the differences between TA10 and TA80 (Figure 1a), and it is primarily associated with the Interdecadal Pacific Oscillation (IPO) [Meehl *et al.*, 2013] and Atlantic Multidecadal Oscillation (AMO) [Tung and Zhou, 2013]. For the 80 year running mean (TA80), effects from natural variability are largely removed [DelSole *et al.*, 2011; Tung and Zhou, 2013]. Therefore TA80, with its smooth temporal variation, rather than TA itself, is primarily caused by human activities (greenhouse gases, aerosols, and land use).

The temporal variation of TA is not proportional to $[\text{CO}_2]$ (in ppm) itself but more likely to the logarithm of $[\text{CO}_2]$ [Broecker, 1975; Lovejoy, 2015]. Furthermore, there is a time delay in the impact of $[\text{CO}_2]$ change on TA. Qualitatively, it takes a few years for TA to adjust in response to changes in $[\text{CO}_2]$, followed by a slower response with the time scale of decades to even millennia due to the heat storage and release in the ocean [Held *et al.*, 2010; IPCC, 2013]. Here we compute the human-caused annual temperature change as (supporting information)

$$\text{TAh}(y) = c + \lambda \sum_{i=1851}^y \ln \frac{[\text{CO}_2](i)}{[\text{CO}_2](i-1)} \left(1 - \exp\left(-\frac{y-i+1}{\tau}\right) \right) \quad (1)$$

where τ is the temperature adjustment time scale (rather than time lag), λ is the climate sensitivity, and c is the (constant) temperature anomaly at the starting date of the series with respect to the anomaly reference period.

For a given τ , equation (1) allows us to compute the TA increments at year 70 when $[\text{CO}_2]$ is doubled in a scenario of $[\text{CO}_2]$ increasing at 1% per year and at equilibrium when $[\text{CO}_2]$ is doubled (supporting information). These two TA increments are essentially the transient climate response and equilibrium climate sensitivity, which are estimated as 1.0–2.5°C and 1.5–4.5°C, respectively [IPCC, 2013]. Only their ratio is needed to determine τ , and this ratio is 1.87/3.0 for $\tau = 30$ years or 1.61/3.0 for $\tau = 40$ year, both within the cited range [IPCC, 2013]. Here we choose $\tau = 30$ years.

By taking the 80 year running mean of equation (1) and assuming $\text{TAh80} = \text{TA80}$, we obtain $c = -0.405^\circ\text{C}$ and $\lambda = 4.603^\circ\text{C}$ via linear regression based on the HadCRUT4 data from 1850 to 2014. The computed TAh80 and observed TA80 in Figure 1b agree with each other extremely well, with a correlation of 0.996 and root-mean-square error (RMSE) of 0.011°C . The correlation and RMSE between annual TAh and TA are 0.90 and 0.12°C , respectively. As our regression is based on observational data, the total anthropogenic effect of greenhouse gases, land use change, and aerosols is included in equation (1). Furthermore, the good fit in equation (1) indicates that it is reasonable to use $[\text{CO}_2]$ to represent the overall anthropogenic effect.

We can compare our model for anthropogenic warming with other observation-based models. Our key innovation is the continuous impact of each year's $[\text{CO}_2]$ change on TA in subsequent years. In other words, TA at a given year is affected by the history of annual $[\text{CO}_2]$ changes from all previous years in equation (1) (rather than just the accumulated $[\text{CO}_2]$). In contrast, Broecker [1975] and Lovejoy [2015] assumed zero lag (or $\tau = 0$ in equation (1)), Lean and Rind [2009] assumed a 10 year lag, and Lovejoy [2014] used zero to 20 year lags between the total $[\text{CO}_2]$ and TA (i.e., TA at year y depends on $[\text{CO}_2]$ at y minus the lag year). While the use of zero or 10 year lag may be appropriate for decadal predictions [Broecker, 1975; Lean and Rind, 2009; Lovejoy, 2015], it is not suitable for our purpose of both decadal and long-term projections. For instance, for the hypothetical scenario of constant $[\text{CO}_2]$ for the next 50 years, TA would remain constant after the assumed 0, 10, or 20 lag years in previous approaches (rather than continue to increase due to the warming memory in the ocean). This is why we use equation (1).

We can also compare the parameter sensitivity in our model versus in Lovejoy [2014]. Our model is insensitive to the use of 60 versus 80 year running mean in removing the natural variability and to the use of $\tau = 30$ versus 40 years, as they all yield the same correlation and RMSE between TAh and HadCRUT4 TA for the whole data period. Additionally, the relative change in climate sensitivity λ of 11% (from using $\tau = 40$ versus 30 years) is also much smaller than the relative change of 64% (from 20 year to zero lag) or 24% (from 20 to 10 year lag) in Lovejoy [2014]. Furthermore, only the 80 year running mean of observed TA, rather than the annual TA itself as in Lovejoy [2014], is used for our regression.

Finally, we can compare our model's equilibrium climate sensitivity ($=\lambda \ln 2$) and transient climate response ($=0.62 \lambda \ln 2$) for $\tau = 30$ years (supporting information) to those from IPCC [2013]. First, we need to recognize

Figure 2. (a) TAh from 1850 to 2100 for the RCP8.5 scenario based on our model with different training periods of the HadCRUT4 data (whole period; minus 10 years at beginning and end; minus 20 years at beginning and end; with a total of five possibilities). The HadCRUT4 data for the historical period are also shown. (b) TAh from 1850 to 2100 based on our model with coefficients determined using the whole data period of HadCRUT4, GISTEMP, MLOST, Berkeley1, and Berkeley2 data, respectively. These observational data for their historical periods are also shown.

that our climate sensitivity parameter λ is based on observational data and hence includes the total anthropogenic effect of greenhouse gases, land use change, and aerosols. The fractional contribution of $[\text{CO}_2]$ to the total anthropogenic forcing can be roughly estimated as $1.68/2.29 = 0.73$ based on the radiative forcing estimates in 2011 relative to 1750 [IPCC, 2013]. Therefore, we need to multiply λ by 0.73 to indicate the effect due to $[\text{CO}_2]$ alone. Then our equilibrium climate sensitivity of 2.34°C is within the IPCC [2013] range of $1.5\text{--}4.5^\circ\text{C}$, and our transient climate response of 1.46°C is also within the IPCC [2013] range of $1.0\text{--}2.5^\circ\text{C}$. Note that if $\tau = 0$ is assumed, the transient climate response would be incorrectly equal to the equilibrium climate sensitivity, further demonstrating the importance of using equation (1) in our model.

4. Decadal and Long-Term Projections

4.1. Long-Term Projection in the 21st Century

Our TA projection (denoted as TAp) is the sum of the temperature increase primarily due to human activities (TAh) and the natural variability ($\text{TA} - \text{TAh}$). For the RCP8.5 scenario, our projected anthropogenic warming by the year 2100 (Figure 2) is greater by more than an order of magnitude than natural variability, as represented by the standard deviation of ($\text{TA} - \text{TAh}$) in Figure 1c (0.12°C). Furthermore, we can quantify projection uncertainties in two different ways. First, we compute the coefficients in our model with five different training periods of the HadCRUT data (1850–2014, 1860–2014, 1870–2014, 1850–2004, and 1850–1994). This results in a TAh uncertainty of 0.56°C (from 3.3°C to 3.8°C) in 2100 (Figure 2a). Second, we use five different data sets discussed in section 2. This leads to a TAh uncertainty of 0.61°C (from 3.7°C to 4.3°C) in 2100 (Figure 2b).

Figure 3a shows that our multidata ensemble mean of TAh for 2081–2100 relative to 1986–2005 is 3.3°C (for RCP8.5 in Figure 2b), which corroborates the CMIP5 ensemble mean of 3.7°C . Furthermore, we can compute the upper (lower) end of our projection range as the maximum (minimum) among five projections in Figure 2b plus (minus) one standard deviation of 0.12°C due to natural variability. For RCP8.5, our uncertainty range of 0.75°C is only about one-third of that from CMIP5 (2.2°C ; Figure 3a). The implication of our smaller range will be discussed in section 5.

Our conclusion remains the same if we compare our results in 2100 relative to 1880–1900 for RCP8.5 with CMIP5 results [England et al., 2015]: our multidata ensemble mean of warming (4.5°C ; Figure 2b) is consistent with the CMIP5 multimodel ensemble mean of 5.0°C , while our uncertainties in 2100 (Figures 2a and 2b) plus two standard deviations of 0.24°C due to natural variability are only about one-third of the CMIP5 uncertainty range of 3.0°C . These conclusions also remain the same for RCP4.5 and RCP2.6 (Figure 3a).

Figure 3. (a) The mean and likely range of the warming for 2081–2100 relative to 1986–2005 from this study and IPCC [2013]. (b) The mean and likely range of the warming for 2016–2035 relative to 1986–2005 from this study (with two approaches to estimate likely ranges) and IPCC.

4.2. Decadal Prediction

For decadal prediction, the natural variability is crucial. For instance, the standard deviation of $(TA - TA_{10})$ is 0.091°C (Figure 1c). Recognizing that this natural interannual variability is large and noisy, and largely unpredictable for decadal prediction, here we focus on the prediction of the 10 year running mean:

$$TA_{p10}(y) = TA_{h80}(y) + (TA_{80}(y) - TA_{h80}(y)) + (TA_{10}(y) - TA_{80}(y)) \quad (2)$$

where TA_{h80} is obtained from equation (1), the $(TA_{80} - TA_{h80})$ term represents the very small deviations of our model from observations ($\sim 0.01^{\circ}\text{C}$; Figure 1b), and a single sine function is sufficient for the fit and for future prediction (Figure 4a). The $(TA_{10} - TA_{80})$ term represents the natural multidecadal variability with a standard deviation of 0.096°C (Figure 4a). It includes both the atmospheric response to external forcings

Figure 4. (a) $[TA_{10} - TA_{80}]$ (black lines) and $[TA_{80} - TA_{h80}]$ (green lines) and their sine function fits using the HadCRUT4 data from 1850 to 2014. (b) Decadal hindcasts of 10 year running mean (TA_{p10}) initialized from 1984, 1994, and 2004 using the HadCRUT4 data (black solid line). The colored solid and dashed lines represent the ensemble mean and the maximum/minimum values of the ensemble range in each hindcast. (c) Three-decade predictions of 10 year running mean (TA_{p10}) initialized from 2014 using the five data sets (HadCRUT4, GISTEMP, MLOST, Berkeley1, and Berkeley2) (black solid lines for historical period) for the RCP4.5 scenario. The colored solid and dashed lines (for $TA_{p10}(y)$ from $y = 2009 - 2039$) represent the ensemble mean and the maximum/minimum values of the ensemble range in each prediction.

(e.g., solar radiation variability and volcanos) and internal variability of the Earth system (e.g., IPO and AMO). To cover this natural variability (Figure 4a) and yield reasonable decadal hindcasts (Figure 4b), we use an ensemble of 125 sine functions, generated by five different amplitudes (0.14, 0.15, 0.16, 0.17, and 0.18°C), five different periods (56, 58, 60, 62, and 64 years), and five different years for the minimum value (years 1969, 1970, 1971, 1972, and 1973) of this term.

The above treatment of natural variability differs from previous observation-based models. *Lovejoy* [2015] used a scaling macroweather model based on fractional Gaussian noise to represent interannual and multi-decadal natural variability. In contrast, *Lean and Rind* [2009] separately computed the different components of the natural variability (interannual variability, solar radiation variability, and volcanos), but they did not include the multidecadal variability for their prediction of the next two decades.

Among the three scenarios, we choose RCP4.5 as the most probable scenario for the next few decades, because the projected $[\text{CO}_2]$ for the year 2014 (397.8 ppm) is closer to the observed value (397.2 ppm) than that from RCP2.6 (398.4 ppm) or RCP8.5 (399.0 ppm). Using equation (2) for initialized decadal prediction, we also need to adjust TAp10 slightly by subtracting the difference between TAp10 and TA10 at the initialization year (so that TAp10 and TA10 are equal at the beginning).

First, we evaluate our decadal hindcasts using equation (2). For each hindcast, coefficients in our model and the sine function fit for the (TA80 – TA_h80) term in Figure 4a are determined based on observations available up to the initialization year only. The ensemble of sine functions for the (TA10 – TA80) term in Figure 4a is based on observational data, but its generation is not an exact process. Here we take the same ensemble for both hindcast and projection to reduce the arbitrariness to a certain degree.

Initialized from 2004, the predicted 10 year average from 2005 to 2014 of 0.50°C agrees very well with the HadCRUT4 value of 0.49°C (Figure 4b). For the two-decade hindcast from 1994, TAp10(y) (with $y = 1999\text{--}2009$, representing the hindcast period of 1995–2014) also agrees with TA10(y) very well with an RMSE of 0.011°C and with the global warming slowdown captured very well. The three-decade hindcast of TAp10(y) (with $y = 1989\text{--}2009$, representing the hindcast period of 1985–2014) also captures the warming slowdown with an RMSE of 0.099°C. The predicted warming between 2005–2014 and 1975–1984 of 0.55°C is only slightly greater than the observed warming of 0.49°C, and this bias of 0.06°C is less than one-third of the ensemble mean bias using CMIP5 models [*IPCC*, 2013].

The natural multidecadal variability (Figure 4a) is the reason for the warming slowdown in our hindcast (Figure 4b), as the anthropogenic warming itself is accelerating (Figure 2). This is consistent with the finding of previous data analysis [*Wu et al.*, 2011; *Tung and Zhou*, 2013] and observation-based model [*Lovejoy* 2015]. In contrast, *Lean and Rind* [2009] and *Foster and Rahmstorf* [2011] reproduced the warming slowdown without considering the multidecadal variability (i.e., by considering the natural variability due to ENSO, solar, and volcano activities only). This discrepancy has been explained by *Tung and Zhou* [2013] in their Figure 5 that multidecadal oscillation just coincidentally appeared as a positive trend from 1979 to 2010 in *Foster and Rahmstorf* [2011].

Our three-decade prediction from 2015 to 2044 using all five observational data sets is summarized in Figure 4c. First, the warming rate in the next few years is expected to be slower than in the 1980s and 1990s, as indicated by the ensemble mean of each data set (colored solid lines). Second, the global warming slowdown could remain for a few more years, as indicated by the lower bound of the ensemble of each data set (colored dashed lines). Finally, no matter what will happen in the next decade (with or without the slowdown), the global warming will accelerate, with the projected mean rate of 0.23°C/decade for TAp10 from 2020 to 2039 even greater than the observed rate of 0.17°C/decade from 1980 to 1999.

Figure 3b compares our results with those from *IPCC* [2013]. Our projected mean warming of 0.35°C from 1986–2005 to 2016–2035 is only two-thirds of that from the *IPCC* [2013] (but still within its likely range), which is based on multiple lines of evidence and assumes that there will be no major volcanic eruptions or secular changes in total solar irradiance. Furthermore, the range of our predicted warming can be computed in two ways: as the maximum difference among the five ensemble means (0.10°C) or as the multidata mean of the ensemble range using each data set (0.13°C). Figure 3b shows that our range using both methods is much smaller than the *IPCC* [2013] range of 0.4°C. The implication of our smaller range will be discussed in section 5.

5. Conclusions

We have developed an observational data-driven model for both decadal and long-term global annual mean surface temperature anomaly (TA) projection in the 21st century. Key innovations include (a) separate consideration of the continuous impact of each year's $[CO_2]$ change on TA in subsequent years, (b) the use of an ensemble of sine functions to represent the multidecadal natural variability, and (c) the assumption that only the 80 year running mean (rather than the annual temperature) is caused by anthropogenic forcing.

The coefficients in our model are determined by using the observed annual TA and $[CO_2]$. Our model shows good hindcast skill of 10 year running means initialized from the years 1984 (three-decade hindcast), 1994, and 2004 with the global warming slowdown well captured. The warming slowdown is caused by the natural multidecadal variability, and the anthropogenic warming itself is accelerating.

Our data-driven model's equilibrium climate sensitivity, transient climate response, and the temperature projection at the end of 21st century for the RCP2.6, RCP4.5, and RCP8.5 scenarios are all consistent with IPCC AR5 results. This provides an independent and new line of support for these IPCC results, which are primarily based on ESMs. Our warming projection of $0.35^\circ C$ for 2016–2035 relative to 1986–2005 is only two-thirds of that from CMIP5 models but is still within their projection range. Furthermore, our predicted warming rate in the next few years is slower than in the 1980s and 1990s, followed by accelerated warming when the positive phase of the natural multidecadal variability aligns with continued anthropogenic warming.

Predicting the future always involves numerous assumptions. First, our model and other observation-based models [e.g., Lovejoy, 2015] assume that the fractional contribution of $[CO_2]$ to the total anthropogenic forcing in the 21st century remains the same as in the historical period. ESMs do not need to make this assumption, but they have to predict future anthropogenic emission of aerosols and greenhouse gases, and land use change, which would introduce their own uncertainties. Second, our ensemble of sine functions is assumed to be able to cover the natural multidecadal variability (including those due to solar and volcano activities) for decadal prediction. In contrast, ESMs have to predict or neglect future solar and volcanic forcings. Third, we assume that (TA10–TA80) primarily reflects the natural variability, but it may also include effects of anthropogenic aerosols over the last few decades.

Note that our uncertainty range of decadal and long-term projection in the 21st century is just one-third of that from IPCC [2013]. This does not imply that the former is “more accurate” than the latter, as our uncertainty range does not include the uncertainties due to the first and third assumptions above and, to a lesser degree, the second assumption above. Alternatively, it suggests that CMIP5 projection uncertainty can potentially be reduced by further improvements to the simulation of natural multidecadal variability and anthropogenic warming from 1850 to the present in ESMs.

The simplicity and transparency of our conceptual model, i.e., equations (1) and (2) and the generation of ensemble members to account for the natural multidecadal variability in Figure 4a, ensure the reproducibility of our results. They also make our observational data-based model a useful tool for effective climate communications (e.g., on the anthropogenic warming versus natural variability).

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