# AN ESTIMATE OF ECS BASED ON OBSERVATIONS:

# THE IMPACT OF FORCING EFFICACY

A Thesis

by

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ABSTRACT

The Equilibrium Climate Sensitivity (ECS) is the amount of surface warming that would occur in response to doubled carbon dioxide. It is a widely-used diagnostic in climate science and is also important for informing policy decisions. Estimates of ECS from 20$^{th}$ century observations predict a lower value than values obtained from climate models. However, studies based on observations typically assume that all forcing agents affect the climate equally. We apply the concept of forcing efficacy, which is the amount of warming per unit global average forcing, divided by the warming per unit forcing from carbon dioxide, to our observation-based estimate.

We find an ECS of 2.3 K (5%-95%-confidence range of 1.6-4.1 K), which is near the bottom of the IPCC's likely range of 1.5-4.5 K, but is consistent with other observational studies, under the traditional assumption that forcing efficacy is unity. We show that our calculation of ECS is sensitive to the assumed efficacy of aerosol and ozone forcing and that increasing the efficacy of these two agents to 1.33 yields an ECS of 3.0 K (1.9-6.8 K). This value agrees well with model results, demonstrating a way to reconcile different estimates of ECS.

## CONTRIBUTORS AND FUNDING SOURCES

### Contributors

This work was supervised by a thesis committee consisting of Professor Andrew Dessler (chair) and Associate Professor Robert Korty, of the Department of Atmospheric Science, and Professor Gerald North of the Department of Oceanography.

All work for the thesis was completed by the student, under the advisement of Andrew Dessler of the Department of Atmospheric Science.

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NOMENCLATURE

| | |
|---|---|
| TOA | Top Of Atmosphere |
| ECS | Equilibrium Climate Sensitivity |
| GCM | Global Circulation Model |
| CMIP5 | Coupled Model Intercomparison Project Phase 5 |
| WMGHG | Well Mixed Greenhouse Gas |

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# 1. INTRODUCTION

One of the most consequential but uncertain quantities in climate science is the Equilibrium Climate Sensitivity (ECS), which is the equilibrium surface warming in response to a doubling of carbon dioxide. While no one lives in the global average, the magnitude of changes in local temperature extremes are related to ECS (Seneviratne et al., 2016). Thus, constraining the ECS is of great interest to society.

Estimates of ECS can be obtained from observations of the warming over the 20$^{th}$ century (Gregory et al., 2002, Murphy et al., 2009, Otto et al., 2013, Kummer and Dessler, 2014), climate models (Soden and Held, 2006, Andrews et al., 2012, Dalton and Shell, 2013), paleoclimate data (Hoffert and Covey, 1992, Crucifix, 2006, Lunt et al., 2010, Schmittner et al., 2011), or from analysis of interannual variations (Forster and Gregory, 2006, Dessler, 2013).

These various estimates often do not agree. In particular, estimates of ECS from 20$^{th}$ century observations generally imply most-likely values less than 2.5 K, lower than from the other data sources (although the uncertainties in all estimates are large enough to overlap). These low ECS estimates were one of the main reasons that the most recent IPCC report extended the bottom end of the likely ECS range from 2.0 K to 1.5 K (Collins et al., 2013). Understanding the differences in these estimates of ECS should therefore be a high priority.

Changes to the global TOA energy flux[1] imbalance can be related to changes in the global mean surface temperature by:

$$\Delta N = \Delta F - \lambda \Delta T_s \qquad 1$$

Equation 1 can be derived using a Taylor series expansion about temperature, as follows:

$$N(T_s + \Delta T_s) = N_0 + \frac{\partial N}{\partial T_s} \Delta T_s + O((\Delta T_s))^2 \qquad 2$$

In the limit that $\Delta T_s$ is small, the quadratic and higher order terms can be neglected, giving:

$$N(T_s + \Delta T_s) \cong N_0 + \frac{\partial N}{\partial T_s} \Delta T_s \qquad 3$$

$N_0$, then, represents the climate forcing associated with $T_s$. An energy flux into the climate system (i.e. towards the Earth's surface) is regarded as positive. The partial derivative represents the dependence of TOA energy flux on temperature, which must be negative in a stable climate. In other words, if $\frac{\partial N}{\partial T_s} > 0$, then small fluctuations in $N$

[1] Strictly speaking, this is an energy flux density. The phrase "energy flux" is used here, consistent with the literature.

would drive temperature responses that would amplify the original perturbation, which is not observed, nor theoretically expected[2] from known feedback processes (in the aggregate). To make clear the direction in which energy flows across the TOA, we define $\lambda$ as:

$$\lambda \equiv -\frac{\partial N}{\partial T_s} \qquad (4)$$

which, after substitution, recovers Equation 1.

N and F both have units of $\frac{W}{m^2}$, whereas the "feedback parameter" has units of $\frac{W}{m^2 K}$. All terms are understood to be global averages. The climate forcing, F, represents an imposed energy imbalance at the TOA, to which the surface temperature responds. F can arise due to human emissions of carbon dioxide, aerosols, or other radiatively active effluents, or natural processes such as volcanic eruptions or solar variability.

The feedback parameter λ specifies by how much the surface temperature must change in order to eliminate a given TOA imbalance, and thus restore equilibrium. In this formulation, λ is *defined* in terms of a non-zero forcing. For this reason, a GCM control run (where F≡0) cannot be used to calculate λ under this

[2] At least, in the "vicinity" of today's climate state.

definition. Assumptions and limitations of Equation 1 are discussed in the Conclusions section.

The radiative forcing caused by changes in atmospheric $CO_2$ concentration is of particular interest, because the lifetime of this species is especially long (See box 6.1 of Ciais et al. (2013)). Using $CO_2$ as a benchmark, the Equilibrium Climate Sensitivity (ECS) is defined as the amount of surface temperature warming that would occur in response to a doubling of $CO_2$, after the climate has returned to equilibrium. Mathematically,

$$ECS \equiv \frac{F_{2xCO_2}}{\lambda} \qquad 5$$

A value of 3.7 $\frac{W}{m^2}$ is commonly used for $F_{2xCO2}$.

GCMs can be used to simulate the climate response to a forcing agent, such as carbon dioxide. Running a model to equilibrium is costly, however, because it can take the climate thousands of years to fully respond. Gregory et al. (2004) described a new method by which both the forcing term and feedback parameter can be diagnosed from a shorter GCM run, even one that ends well before the model reaches equilibrium. To do this, they regress TOA flux against surface temperature under a forced scenario. The intersection with the ordinate axis ($\Delta T_s \equiv 0$) gives forcing. The slope of the regression line gives $-\lambda$. Andrews et al. (2012) use this method, with the more recent CMIP5 data, to characterize inter-model differences in feedback parameter (i.e. climate sensitivity).

The feedback parameter can also be estimated with 20th century observations (Gregory et al., 2002). Because over 90% of the TOA flux imbalance is sequestered in the ocean (Trenberth et al., 2014), ocean heat content (OHC) is an observable proxy for the integral of net TOA flux. Murphy et al. (2009) argue that integrating Equation 1 will reduce noise from short timescales. Along with estimates of forcing (from climate models) and surface temperature (from various observational data sets), the feedback parameter can thus be directly estimated. Otto et al. (2013) use this approach to calculate ECS (and therefore the feedback parameter). A typical feature of estimates based on 20th century observations, is that they constrain the lower bounds of ECS more so than the upper bounds, as represented by skewed PDFs (Gregory et al., 2002, Otto et al., 2013, Roe and Armour, 2011).

Because TOA flux can be measured from space, Forster and Gregory (2006) estimate the feedback parameter using a regression method. However, the net TOA flux is the residual of offsetting terms, which are two orders of magnitude greater than the residual itself. This, along with other issues, make inference of $\lambda$ from space-based instruments difficult given their limited length (about 1.5 decades) (Zhou et al., 2013).

It is possible that, in the real climate, the feedback parameter varies as a function of climate state. For example, during the Eocene, when there was no ice on the planet, the ice-albedo feedback would have a magnitude of zero. GCM simulations offered early indications that the feedback parameter could vary nontrivially with equilibrium temperature response (Senior and Mitchell, 2000). Gregory et al. (2004) confirmed this finding with a new method, but in a similar GCM. Hansen et al. (2005) use different methods, in an unrelated model, yet also show that climate sensitivity is dependent on the climate state.

Furthermore, they demonstrate that different forcing agents can differentially impact surface temperature, despite similar perturbations to global TOA flux. The differential effect of forcing agent on surface temperature could result from an intrinsic property of the agent (Hansen et al., 2005), a property of the ocean that manifests as a difference between agents (Winton et al., 2010), or from differences in the spatial distribution of forcing (Shindell and Faluvegi, 2009). Alternatively, Armour et al. (2013) show that regional variations in local feedback magnitude, combined with a non-uniform temperature response, is theoretically sufficient to explain time dependence in the feedback parameter, and therefore forcing efficacy as well.

These different viewpoints overlap with one another. For example, the Northern Hemisphere extratropics contain a greater fraction of land than the Southern Hemisphere. It is therefore not surprising, given the lower heat capacity of land, that this region would warm more quickly in response to a given forcing. This differential warming would, in turn, enhance the contribution of the regional feedbacks within the global average. While this reasoning is broadly consistent with Armour et al. (2013), the approach of Shindell and Faluvegi (2009), and more recently, Shindell (2014), seems better suited for calculations involving transient 20th century observations.

Like ECS, Transient Climate Response (TCR) is another way to quantify the climate response to a forcing. It is defined as the change in global mean surface temperature that results from a 1%/year increase in carbon dioxide, at the moment of doubling of carbon dioxide. Shindell (2014) partitions forcing agents into a well-mixed greenhouse gases (WMGHG) component and an inhomogenous component. The inhomogenous component contains forcing from aerosols, ozone, and land use. He finds a TCR similar to Otto et al. (2013) using his temperature and forcing data.

The most important conclusion of Shindell (2014), though, is that he calculates a forcing efficacy of 1.5 for the inhomogenous forcers. In other words, $1\,\frac{W}{m^2}$ of aerosol forcing produces 1.5 times as much warming as $1\,\frac{W}{m^2}$ of well-mixed greenhouse gases (WMGHG). As discussed in the rest of this thesis, we have investigated the possibility that estimates of ECS, inferred from 20th century observations, could also be biased by inhomogenous forcing agents that disproportionately influence the surface temperature response (this was published in Kummer and Dessler (2014)). We start by verifying that our estimate is consistent with other observation based estimates before including a correction for forcing efficacy.  Next, we show that by including a nonunitary forcing efficacy, we achieve better agreement with the IPCC estimates of ECS.

## 2. METHODS AND DATASETS

Because most of the heat capacity of the climate system is in the ocean, there is a relation between TOA flux and changes in OHC:

$$\iint_{t1}^{t2} N dt dA \; \cong \; \Delta OHC \; \leftrightarrow \frac{d(C_{eff}T)}{dt} \cong \; \bar{N} \qquad 6$$

which gives Equation 1 rewritten in terms of OHC:

$$\Delta OHC + \; \varepsilon = \; \int_{t1}^{t2} F dt - \lambda \; \int_{t1}^{t2} T_s dt \qquad 7$$

where ε represents additional heat not stored in the ocean (e.g. ice melting). Re-arranging Equation 4 gives the feedback parameter:

$$\lambda = -\frac{\int_{t1}^{t2} F dt - \Delta OHC - \; \varepsilon}{\int_{t1}^{t2} T_s dt} \qquad 8$$

Equation 5 treats all forcing agents as equivalent. To include forcing efficacy, we can write the forcing term as:

$$F = F_1 + EF_2 \qquad 9$$

where we represent forcing from tropospheric and stratospheric ozone and aerosols with the term $F_2$. E, then, quantifies the disproportionate effect that these forcers have on surface temperature, relative to the $F_1$ agents.

The forcing time series contains the most uncertainty. For a comprehensive review of this uncertainty and how it influences estimates of λ, see Forster (2016).

We use historical forcing from Forster et al. (2013), as diagnosed from CMIP5 historical model runs. We assume the uncertainty in integrated forcing is described by a normal distribution, with one standard deviation given by 20% of the integrated value, consistent the IPCC's uncertainty estimate (Myhre et al., 2013).

OHC comes from an ocean reanalysis system, which uses measurements combined with an ocean model to constrain the state of the ocean (Balmaseda et al., 2013b). Two advantages to this approach are that the ocean model is physically consistent with the atmospheric state, and that the ocean state is internally consistent, even in sparsely observed areas. One such system, the European Centre for Medium-Range Weather Forecasts Ocean Reanalysis System 4 (ORAS4), uses state-of-the-art numerical models to assimilate a variety of observations. Argo floats, mooring systems (e.g. TAO), and AVISO retrieved sea height anomalies are examples of the observational diversity used by ORAS4.

ORAS4 consists of five ensemble members. Four of the five members are generated by symmetrically perturbing the wind-stress field (Balmaseda et al., 2013a). The remaining member serves as an unperturbed control member. While it is common to obtain initial conditions by spinning these models up with climatological data, this does not provide an initial state representative of the ocean at a particular time. Although assimilation methods would be expected to quickly bring the model into a more consistent state, ORAS4 must begin integrations during a relatively observation-poor time period. ORAS4 is therefore carefully initialized through multiple iterations, which use strong relaxation techniques (Balmaseda et al., 2013a). This allows the model to sample uncertainty within observation coverage.

Global mean surface temperature anomalies are available from Goddard Institute for Space Studies (GISS) Global Land-Ocean Index (Hansen et al., 2010), Hadley Climate Research Unit HadCRUT4 (Morice et al., 2012), and National Climatic Data Center (NCDC) Global Index (Smith et al., 2008). Global surface temperature records have been extensively validated, and are continually updated. Although the temperature record represents, arguably, our most certain data, there are notable differences in how the three centers tackle ongoing difficulties.

One difference comes from how a given methodology extrapolates temperature into regions without observations, particularly the arctic. HadCRUT4 does not include temperature data over large, sparsely sampled portions of the arctic (Cowtan and Way, 2014). Therefore, using HadCRUT4 as a global time-series implicitly assumes that the arctic anomalies are equivalent to the hemispheric average. Both reanalysis (Simmons and Poli, 2015) and high-resolution satellite measurements (Comiso and Hall, 2014), however, indicate that the arctic is warming more quickly than the rest of the hemisphere. Because the average correlation coefficient between stations separated by 1200 km is 50% (outside of the tropics) (Hansen and Lebedeff, 1987), the GISS dataset calculates anomalies for grid boxes that are within 1200 km of a station, giving that data set better sampling in the arctic.

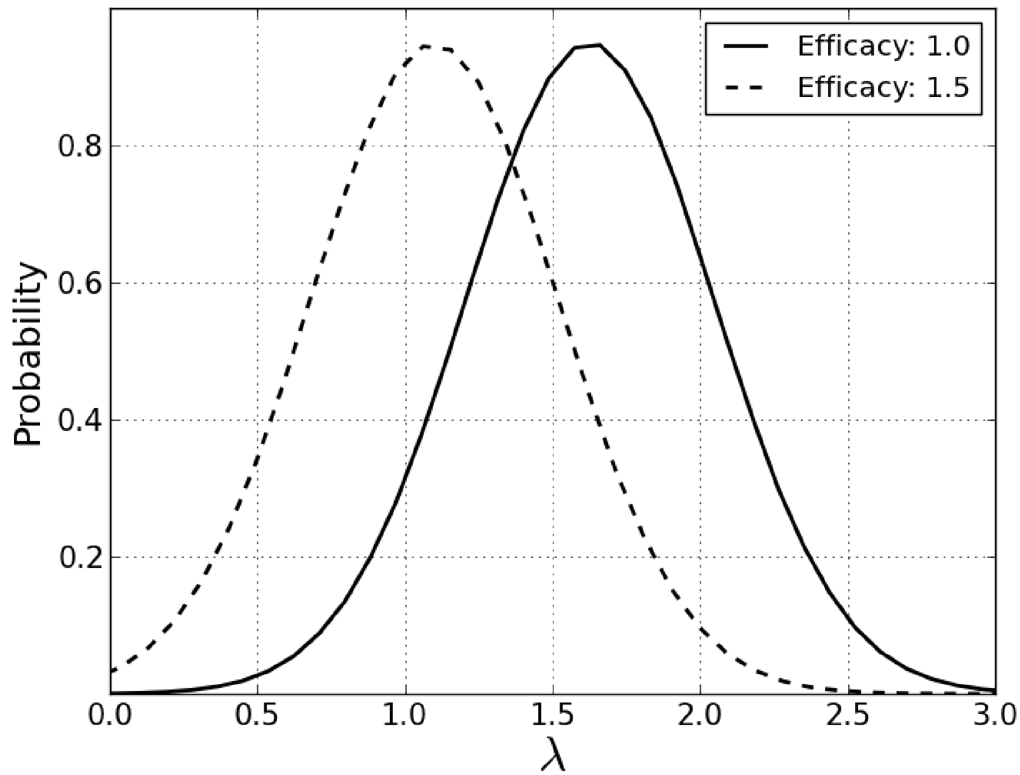
Since ORAS4 data begins in 1958 and the historical AR5 forcing ends in 2010, we integrate over this time interval. The forcing data, however, is referenced to 1750, whereas our temperature data begins in the late 19th century. We assume that there is little temperature change between 1750 and 1900, and offset the respective temperature anomalies with their 1880-1900 average. We use a constant value of 0.06 $\frac{W}{m^2}$ (Hansen et al., 2011) to account for energy storage in non-ocean reservoirs, which gives $\varepsilon$ after integration.

For both the surface temperature and the OHC data, we generate normal distributions centered on the ensemble mean with standard deviation equal to the ensemble standard deviation.

## 3. RESULTS AND DISCUSSION

Using the data described above, we obtain an estimate for λ of 1.6 $\frac{W}{m^2K}$, with a 5-95% confidence interval of 0.9-2.3 $\frac{W}{m^2K}$; the PDF of λ is plotted in Figure 1. This corresponds to an ECS of 2.3 K, with a 5-95% confidence interval of 1.6-4.1 K. In agreement with other recent calculations (summarized in Table 1), this estimate lies towards the bottom of the IPCC's sensitivity range. Setting the forcing efficacy to 1.5, following Shindell (2014) for inhomogenous forcers, decreases λ to 1.1 $\frac{W}{m^2K}$ (0.4-1.7 $\frac{W}{m^2K}$), corresponding to an ECS of 3.5 K (2.1-10.2 K). We can reasonably simulate the IPCC's climate sensitivity range using an efficacy of 1.33, which gives an ECS of 3.0 K (1.9-6.8 K).

*Figure 1. PDF of Feedback Parameter (Kummer and Dessler, 2014)*




Probability distributions for  (W/m2/K) given two different efficacies, with units of fraction per W/m2/K.

*Table 1. Estimates of feedback and ECS based on 20th century observations (Kummer and Dessler, 2014)*

| Analysis | Central value of □ ($W/m^2/K$) | 5-95% confidence interval of □□ ($W/m^2/K$) | Central value of ECS (K) | 5-95% confidence interval of ECS (K) |
|---|---|---|---|---|
| This analysis, efficacy = 1.0 | 1.6 | 0.9-2.3 | 2.3 | 1.6-4.1 |
| This analysis, efficacy = 1.33 | 1.2 | 0.5-1.9 | 3.0 | 1.9-6.8 |
| This analysis, efficacy = 1.5 | 1.1 | 0.4-1.8 | 3.5 | 2.1-10.2 |
| Otto et al. (2013) | 1.8 | N/A | 1.9 | 0.9-5.0 |
| Annan and Hargreaves (2006) | 1.3 | N/A | 2.9 | 1.7-4.9 |
| Aldrin et al. (2012) | 1.9 | N/A | 2.0 | 1.2-3.5 |
| Masters (2014) | 2.05 | 2.05±0.66[3] | 1.98 | 1.2-5.1[4] |
| Skeie et al. (2014) | N/A | N/A | 1.8 | 0.9-3.2 |
| J. Ring et al. (2012) | N/A | N/A | ~1.8 | N/A |

[3] Represents 1 standard deviation.

[4] At 90% Confidence

Thus, we are able to reconcile our estimate of ECS, which is calculated using 20th century observations, with estimates from other sources (e.g. GCMs), by parameterizing forcing efficacy. In this sense, we extend the Shindell (2014) approach of calculating TCR to a calculation of ECS. We find an efficacy value of 1.33 as sufficient to reconcile our ECS estimate with the IPCC estimate. The lower efficacy value (1.33 vs. 1.5) is consistent with inhomogenous forcing being more important for TCR (shorter time scale) calculations, as opposed to ECS calculations.

When interpreting our results, it is important to remember the assumptions behind "classical" linearized EBMs are as follows:

1) The TOA flux is related (approximately linearly) to the surface temperature, globally, over appropriate time periods.
2) Doubling the $CO_2$ concentration will cause the same response in surface temperature independent of the initial (or final) concentration.
3) Radiative forcing is equivalent: $1\frac{W}{m^2}$ of a particular forcing agent (e.g., $CO_2$) is equal to $1\frac{W}{m^2}$ of any other forcing (e.g., aerosols).

We explicitly relax the third assumption. However, the historical CMIP5 forcing data that we use was calculated by first estimating the feedback parameter in a given model (using a doubled $CO_2$ experiment), and then using that parameter to derive the historical model forcing. Future work should investigate the significance of the possible circularity of this argument, and use other methods to estimate forcing in the models.

Because the climate change signal over the 20th century is comparable to noise (such as internal variability), we integrate over the longest period possible. However, as longer time series are used, the accuracy of the data becomes more questionable. Thus, in calculations involving 20th century observations, there is always a tradeoff between data quality and the climate signal-to-noise ratio. The uncertainty in the ORAS4 OHC ensemble is disproportionately located towards the start of the series. Future work could seek an optimal (and objective) way to balance these opposing constraints in the data. However, all improvements to observations are hampered by uncertainty in the historical forcing, which could be addressed in future model experiments (Forster, 2016).

## 4. SUMMARY

ECS is a widely-used metric to quantify the sensitivity of Earth's climate to an external forcing. We find that using ECS, as classically defined, could underestimate the Earth's response when calculated using 20$^{th}$-century observations. We address this discrepancy by including a forcing efficacy term in the ECS calculation. Forcing efficacy is presumably explained, at least in part, by regional feedbacks at high latitudes (Shindell, 2014). Because the observational temperature record is sparse in the arctic, quantifying this feedback directly with observations would be particularly difficult. Should future work validate the forcing efficacy as sufficient to explain discrepancies between estimates of ECS, then tying this parameter to the underlying physical processes will be crucial. Furthermore, our results suggest that policy makers *should not* interpret lower estimates of ECS as indicative of a more stable climate at this time.

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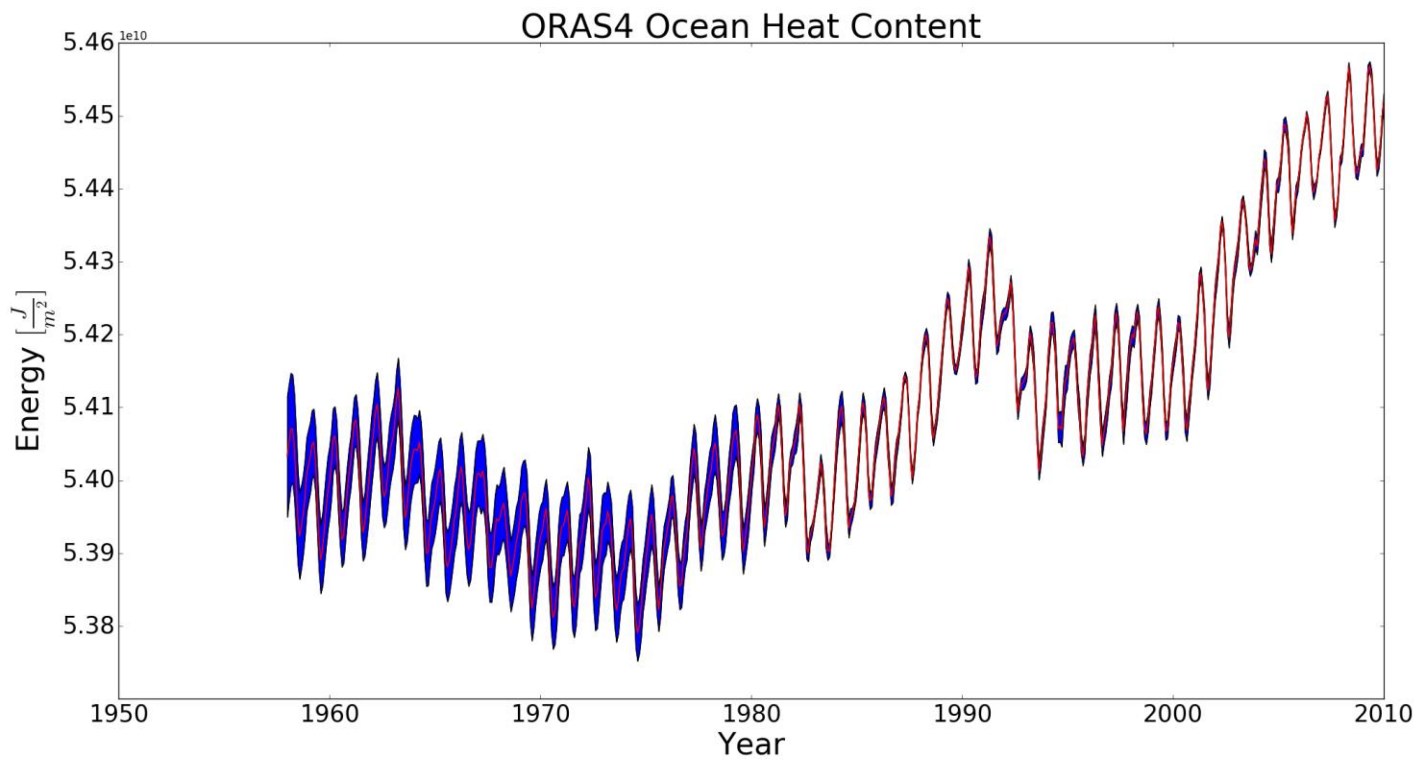
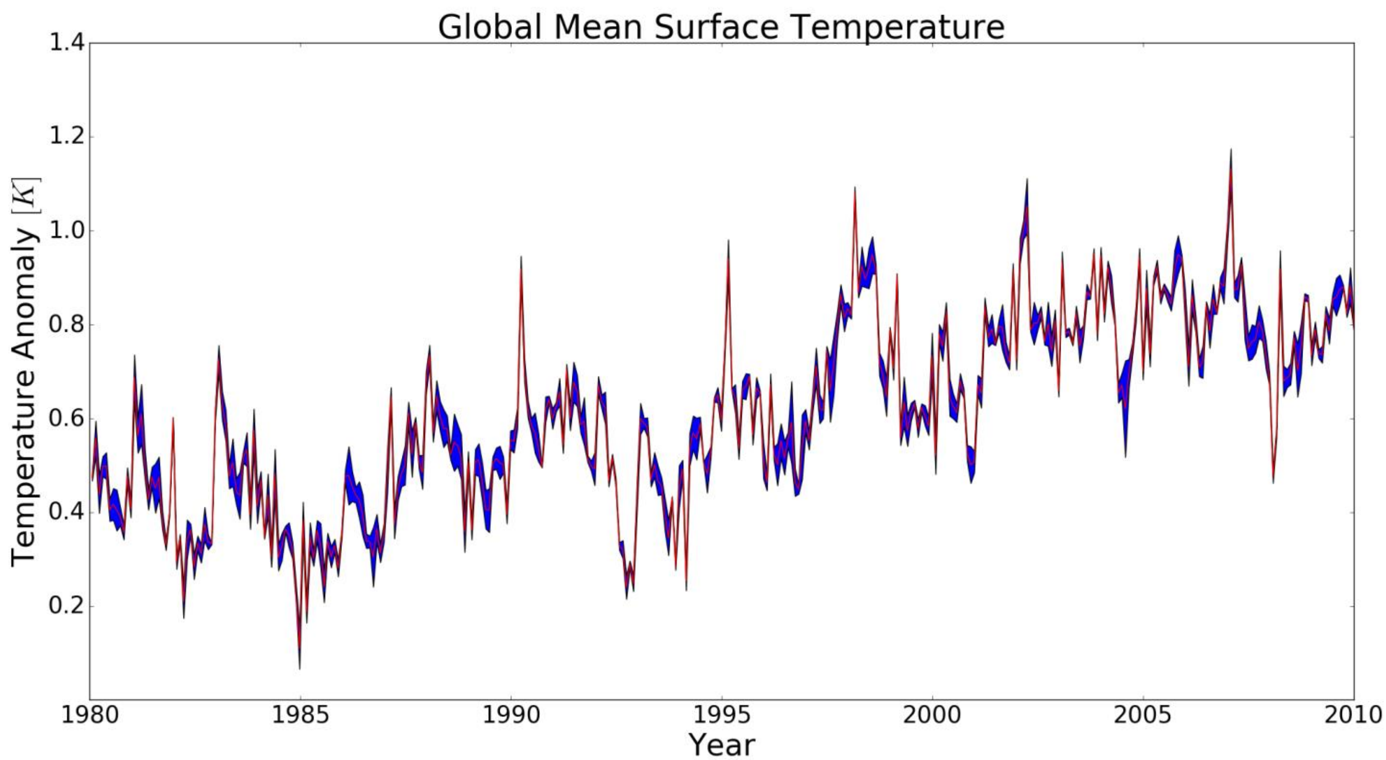
# APPENDIX A

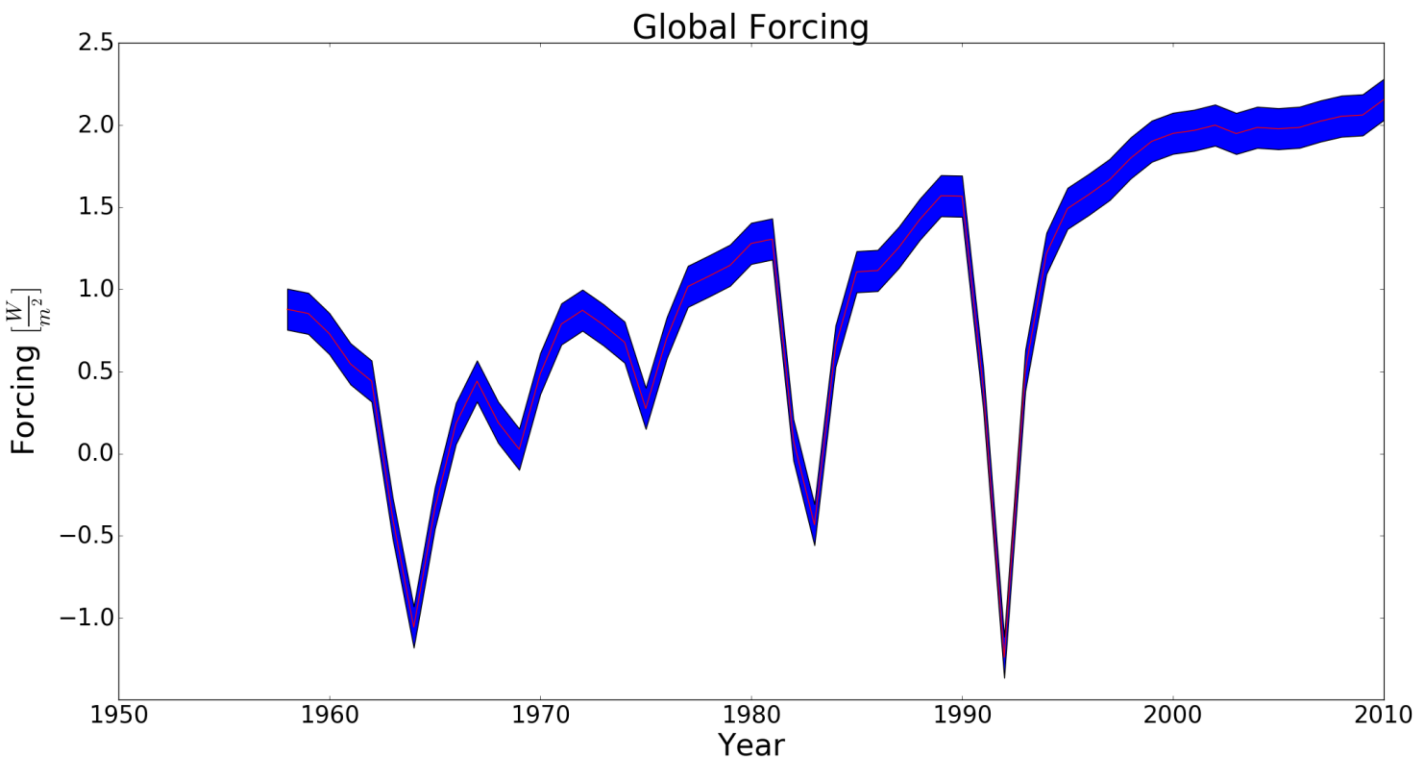
# SUPPLEMENTAL FIGURES




*Ocean Heat Content from ORAS4. Blue shading indicates 1σ Ensemble Uncertainty.*




*Temperature time series. Blue shading indicates 1σ Ensemble Uncertainty.*




*CMIP5 Historical Forcing. Blue shading indicates 1σ Ensemble Uncertainty.*