A Simple KISS Model to Examine the Relationship between Atmospheric CO_2 Concentration, and Ocean & Land Surface Temperatures, taking into consideration Solar and Volcanic Activity, as well as Fossil Fuel Use.

James P. Wallace III, Anthony Finizza, Joseph D'Aleo[1]
August 6, 2010

Abstract

The paper presents a simple "KISS" (Keep It Simple Stupid) Model to examine the relationship between ocean and land surface temperatures and CO_2 atmospheric concentrations in the world's climate system. A key objective was to examine the null hypothesis that atmospheric CO_2 concentrations have a statistically significant impact on the earth's surface temperatures. Following *best practices* analysis and forecasting principles, the paper develops a KISS Model to test this null hypothesis. The paper demonstrates:

(1) The simplest model that can characterize the atmospheric CO_2 concentration-surface temperature interaction must contain at least two simultaneous equations, one for each of these two state variables, and therefore must be analyzed using simultaneous equation estimation techniques.
(2) CO_2 atmospheric concentrations do <u>not</u> have a statistically significant impact on either ocean or U.S. surface temperatures,
(3) Surface temperatures may be explained, and accurately forecast, by variables that relate to solar activity, volcanic activity, and ocean oscillations,
(4) However, the KISS temperature equations for the Atlantic/Indian Ocean, Pacific Ocean, and the U.S. are radically different; suggesting that the appropriate process for developing a Global Average Surface Temperature would involve separate temperature equation for a mutually exclusive, collectively exhaustive set of ocean and land areas encompassing all the earth's surface. The KISS Model's coverage exceeds 70% of the Earth's surface.
(5) The forecasts of surface temperature and CO_2 concentrations for the period 2001-2008, using the model estimated from 1960-2000, capture the downturns in all three temperatures, while accurately forecasting the continued rise in $CO_{2.}$ In every case, the KISS model forecasts outperform naïve model forecasts over the same period.
(6) The 30 year forecast from the KISS Model strongly suggests that the most likely outlook is for declining Ocean & U.S. land surface temperatures, again despite forecasting rising CO_2 levels.

1. Introduction

The notion that human – caused increases in atmospheric CO_2 levels are leading to serious adverse impacts on the Earth's Climate System is causing many governments to commit to CO_2 emission reduction plans. A key claim is that CO_2 generated by the

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

complete combustion of any Fossil Fuel, naturally leads to increased atmospheric CO_2 levels, which then, via the so called Greenhouse Effect, must lead to a statistically significant increase in surface temperatures. These higher surface temperatures are then tied to adverse effects involving droughts, floods, hurricanes and rising sea levels. Thus, the statistical significance of CO_2 as a predictor of ocean and land surface temperature is the key assumption underlying government policy decisions involving CO_2. Many papers in the literature have suggested a statistically significant, positive impact. To date, most of the arguments have been over *how positive*. These papers invariably used single equation regression or logically equivalent methodologies, which will be shown below to be inappropriate for the purpose intended.

This paper presents a simple set of equations[2], hereafter called the KISS (Keep It Simple Stupid) Model, which explains the CO_2 concentration-temperature interaction of the earth's climate system with surface area coverage well in excess of 70%. The analysis starts with first principles of model building and adheres to a set of generally accepted principles catalogued by forecasting professionals. The paper provides tentative conclusions and suggests areas for extension and research.

2. Modeling Principles

This paper documents the results of a model development and validation process that proceeded according to a set of widely accepted principles.[3] The key principles include:

(1) Following the (KISS) rule of parsimony, the model should be developed with as simple a structure as possible, using the smallest number of parameters that could predict the phenomenon.
(2) The model should have a theoretical underpinning, with expected coefficient signs suggested *a priori* by the theory.
(3) The data underlying the analysis should be free as practical of observational bias.
(4) The model should be estimated by sound statistical procedures.
(5) The model should perform well within sample, that is, provide forecasting value using a hold-out sample.
(6) In order to be useful for policy analysis, the model should have predictive power, particularly regarding turning points, as evidenced by its ability to outperform alternative models.
(7) The analysis results should be transparent with all data, references, and relevant material being available to the reader.

Not all global climate forecasting efforts adhere to these principles.

3. Scientific Basis for the Model

The simplest KISS Model to examine the interaction of CO_2 atmospheric concentration levels and surface temperatures contains three temperature equations and a carbon concentration equation, each representing a state variable in the system.

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

The representative temperature equation is:

[1] $T = f_1 [g_1(S), g_2(C), g_3(S*V)]$

Where:
T =Temperature
S= Solar activity
C= Atmospheric CO_2 concentrations
V = Volcanic activity
$S*V$= Interaction between solar and volcanic activity
$g_i(.)$ are distributed lag functions of the indicated variables

The expected signs are: positive for S and C, and negative for S*V, if the Volcanic activity is expressed in positive terms. Versions of this equation will be used for the Atlantic/Indian Ocean, Pacific Ocean and the U.S.

The CO_2 equation is:

[2] $(\Delta C - c_{fossil}) = f_2[g_5(T), g_6(L)]$

Where:
$C = \Delta C + C_{-1}$ and
the dependent variable, $\Delta C - c_{fossil}$, is the efflux of Net <u>non-fossil</u> fuel CO_2 emissions from the oceans and land <u>into</u> the atmosphere.
T = temperature
L = Land use
$c_{fossil} = CO_2$ emissions from fossil fuel use

The expected signs are: positive for T and uncertain for L, depending on the particular measure used.

4. Data Analysis

The first step in an applied statistics/econometric analysis is to examine the endogenous and exogenous variables of the system. The model formulated above has data for the common window 1960 to 2008. The model is estimated over the period from 1960-2000.

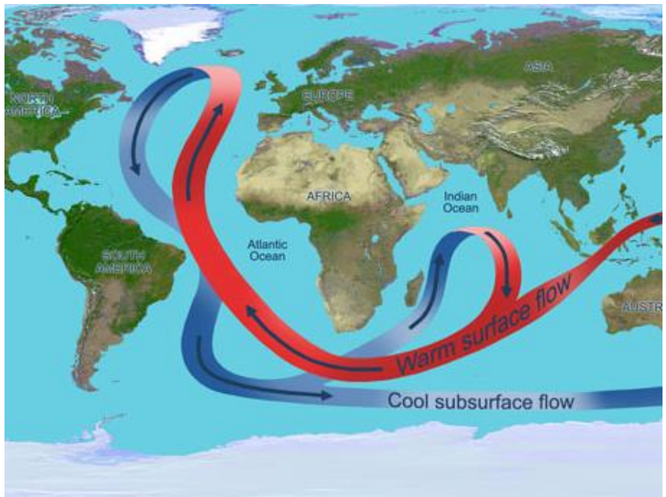
Endogenous/ Dependent Variables of the KISS System.

The endogenous variables are three temperature variables representing Atlantic/Indian and Pacific Ocean surface temperatures, US land surface temperature, and atmospheric CO_2 concentrations. Because of the well known Atlantic/Indian ocean conveyor belt, as shown in Figure 1, the AMO is best thought of as a proxy for these two oceans behaving as one in terms of their impact on atmospheric CO_2 concentrations. Figure 2 displays the temperature time series in level form. NINO3.4[4] represents the sea surface temperatures in the east central tropical Pacific, PDO[5] reflects the temperature for the North Pacific

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

Basin, AMO[6] is the temperature for the North Atlantic, and US[7] is the surface temperature of the United States.

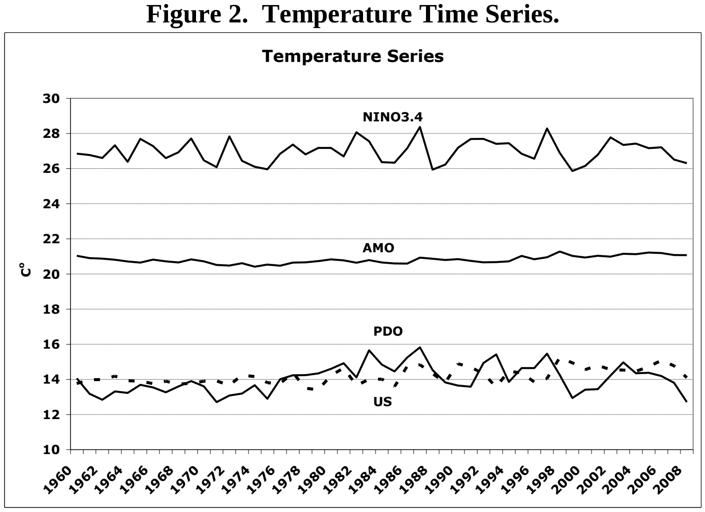
Figure 1. Thermohaline Circulation Flow



Source:Thermohaline circulation from NASA

For example, according to Feng and Hu [1], "Observations have indicated that the North Atlantic SST variations have persistent effects on the Indian summer rainfall at multidecadal and longer timescales."[8]

Figure 2. Temperature Time Series.



The various temperature time series exhibit significant differences in variability. Table 1 shows the coefficient of variation (the ratio of standard deviation to the mean of each time series). The North Pacific temperature time series has the largest variation and the Atlantic by far, the smallest.

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

Table 1. Coefficient of Variation in the Temperature Time Series (1960-2000).

	AMO	NINO3.4	PDO	US
Mean (^oC)	20.8	27.0	14.0	14.2
Coefficient of Variation (Ratio Standard deviation/mean, %)	**1.0**	**2.3**	**5.6**	**3.2**

The KISS Model choice of temperature series allows good coverage of the earth's surface. The Pacific, Atlantic, and US coverage are about 57% of the world's surface area. If we add in the surface area of the Indian Ocean, KISS model coverage, very loosely speaking, extends to 72%.[9] It should be noted that one cannot simply average the separate temperature forecasts for different geographic areas to obtain a global average temperature forecast.

As shown in Table 2, the Nino3.4 temperature series does not have a statistically significant trend, which remains true even over its entire 1950 to 2008 history. The AMO, PDO and US all have statistically significant, positive trends over the 1960-2000 period.

Table 2. Estimates of Linear Trend in the Temperature Data, 1960-2000

	AMO	NINO3.4	PDO	US
Slope Coefficient	.0047	.0031	.0333	.0184
t-statistic	2.10	.35	3.51	3.63
p-value	.042	.725	.001	.001

Table 3. Correlation among Temperature Times Series

	AMO	NINO3.4	PDO	US
AMO	**1.0**	**.059**	**.167**	**.479**
NINO3.4		**1.0**	**.454**	**.010**
PDO			**1.0**	**.119**
US				**1.0**

From the correlations shown in Table 3, and looking ahead to the modeling of temperature, it would appear that the equation structure that works for the AMO might be a starting point for the U.S., but that it is highly unlikely to work at all for the PDO. This will turn out to be correct.

Atmospheric concentrations of CO_2 have increased at an average annual rate of 0.4% from 1960 through 2000.

Exogenous/Independent Variables of the System.

The exogenous variables in the entire KISS Model system of equations are: Total Solar Irradiance[10](TSI), volcanic activity[11](DVI), the Southern Oscillation Index (SOI) "Central Tendency" (defined in Section 5 below), and fossil fuel emissions into the atmosphere.[12] The annual TSI composite record was constructed by Hoyt and Schatten [2] (and updated in 2005) utilizing all five historical proxies of solar irradiance including sunspot cycle amplitude, sunspot cycle length, solar equatorial rotation rate, fraction of penumbral

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

spots, and decay rate of the 11-year sunspot cycle. Note the regular *solar seasonal* cycle of about 11 years, which is superimposed on the much longer term Trend Cycle in the data. (See Abdussamov [3].)

Major volcanism a factor that alters global climate for up to several years, Lamb [4a,b,c] formulated the Dust Veil Index (DVI) as a numerical index that quantified the impact of a particular volcanic eruption's release of dust and aerosols over the years following the event on the Earth's energy balance of changes in atmospheric composition due to explosive volcanic eruptions. The series plotted in Figure 3 shows two of the exogenous variables, Total Solar Irradiance and a variable that is the product of TSI and DVI, used to represent the interaction of the two exogenous variables.

Figure 3. Total Solar Irradiance and the TSI - Volcanic Interaction Variables.

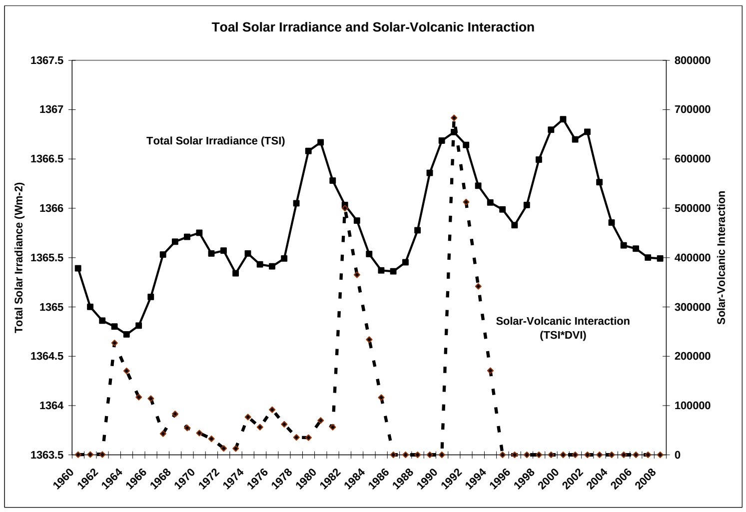
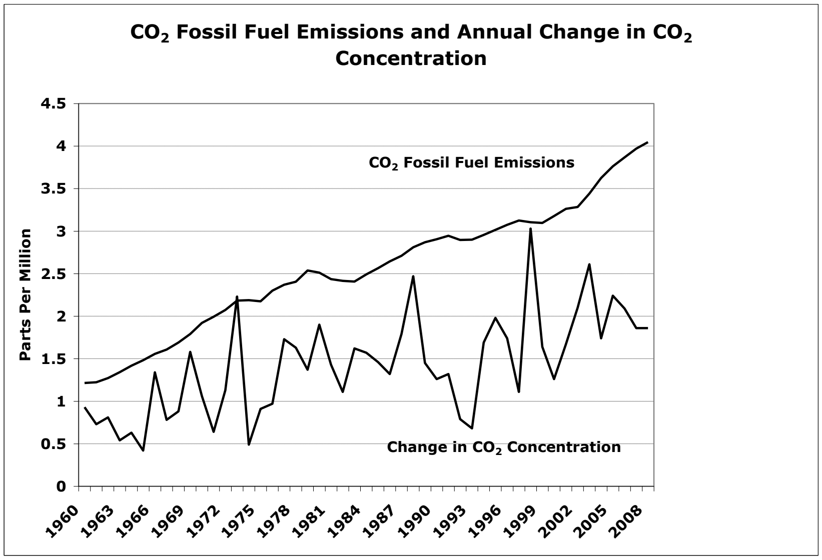


Figure 4 compares fossil fuel CO_2 emissions with changes in atmospheric CO_2 concentration. Note that annual fossil fuel emissions are larger than the changes in CO_2 emissions suggesting that oceans and land surface flora are absorbing some fossil fuel-related CO_2 emissions. Over this period, about 44% of the fossil emissions did not show up in the atmosphere.

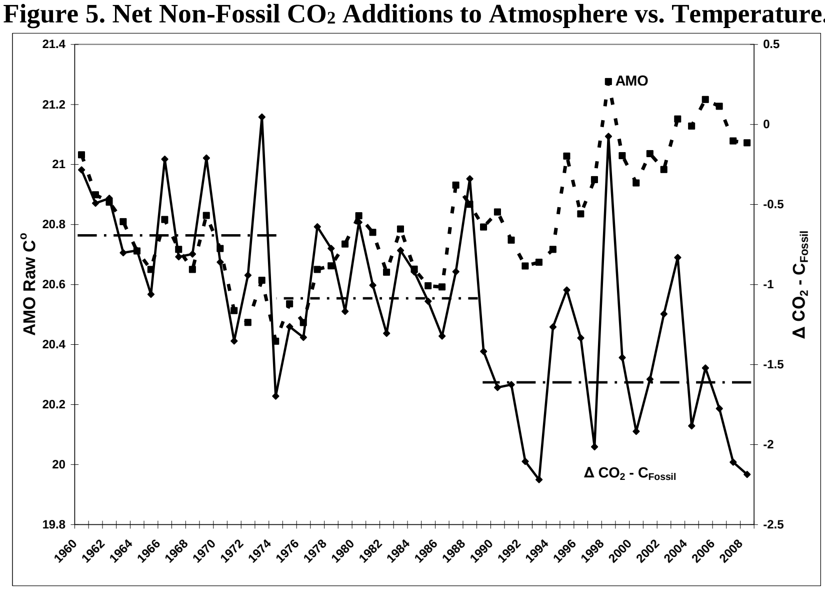
Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

Figure 4. Fossil Fuel CO_2 Emissions and Changes in Atmospheric CO_2 Concentration.



It is straightforward to calculate the Net-non-fossil CO_2 additions placed into the atmosphere by subtracting fossil fuel emissions from the change in atmospheric CO_2 concentration. This arithmetic difference is plotted in Figure 5 along with AMO temperature. While the Net –non fossil additions exhibits step-changes as indicated by the horizontal lines, the high correlation in ***the annual data*** is obvious and seems remarkable on its face.

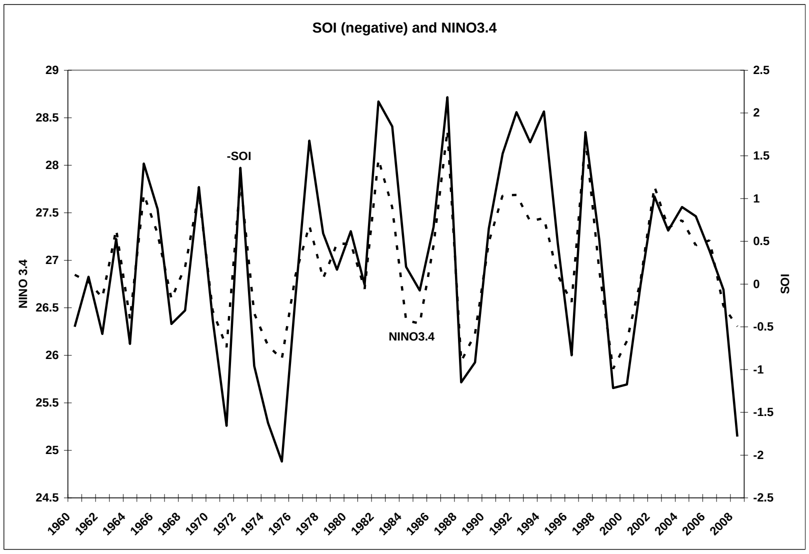
Figure 5. Net Non-Fossil CO_2 Additions to Atmosphere vs. Temperature.



Later in the paper, the Southern Oscillation Index (SOI)[13], the Tahiti minus Darwin Pressure anomalies, will be introduced as an instrumental variable to explain the impact of changes in solar/magnetic activity on Pacific temperatures. Note the high correlation (.93) in Figure 6 between SOI and NINO3.4.

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

Figure 6. Southern Oscillation Index (SOI) vs. Nino 3.4 Anomalies



5. Model Estimation and Results

AMO Temperature Equation Estimation.

The implicit KISS Model presented in Section 3 is estimated explicitly in Section 5. The explicit temperature equation for AMO is given in eqn [3].

[3] AMO = c + b*pdl (TSI,15,3,1) + d*pdl (TSI*DVI,3,3,2)) + e*C

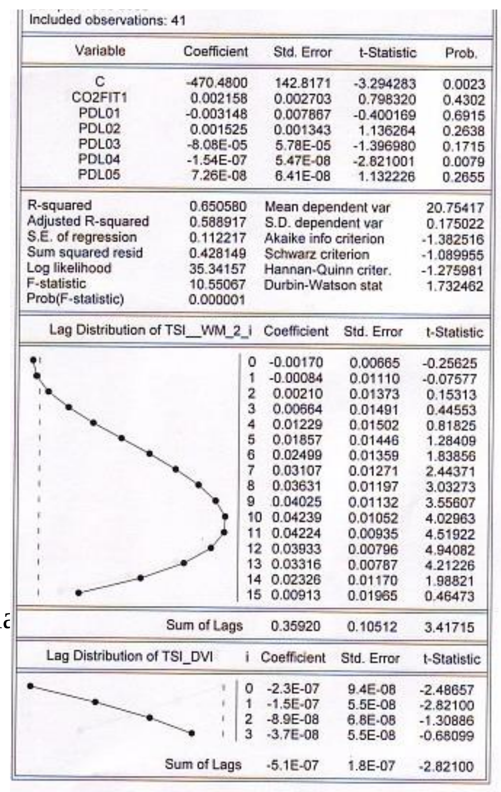
where in pdl (independent variable,x,y,z),

x is the number of lags

y is the polynomial order, and

z is the constraint (in the KISS model, TSI*DVI is constrained at the far end, but no constraints on TSI are assumed)

Figure 7. Estimation of the AMO Temperature Equation by Simultaneous Estimation Techniques.



Included observations: 41

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-470.4800	142.8171	-3.294283	0.0023
CO2FIT1	0.002158	0.002703	0.798320	0.4302
PDL01	-0.003148	0.007867	-0.400169	0.6915
PDL02	0.001525	0.001343	1.136264	0.2638
PDL03	-8.08E-05	5.78E-05	-1.396980	0.1715
PDL04	-1.54E-07	5.47E-08	-2.821001	0.0079
PDL05	7.26E-08	6.41E-08	1.132226	0.2655

R-squared	0.650580	Mean dependent var	20.75417
Adjusted R-squared	0.588917	S.D. dependent var	0.175022
S.E. of regression	0.112217	Akaike info criterion	-1.382516
Sum squared resid	0.428149	Schwarz criterion	-1.089955
Log likelihood	35.34157	Hannan-Quinn criter.	-1.275981
F-statistic	10.55067	Durbin-Watson stat	1.732462
Prob(F-statistic)	0.000001		

Lag Distribution of TSI__WM_2_	i	Coefficient	Std. Error	t-Statistic
	0	-0.00170	0.00665	-0.25625
	1	-0.00084	0.01110	-0.07577
	2	0.00210	0.01373	0.15313
	3	0.00664	0.01491	0.44553
	4	0.01229	0.01502	0.81825
	5	0.01857	0.01446	1.28409
	6	0.02499	0.01359	1.83856
	7	0.03107	0.01271	2.44371
	8	0.03631	0.01197	3.03273
	9	0.04025	0.01132	3.55607
	10	0.04239	0.01052	4.02963
	11	0.04224	0.00935	4.51922
	12	0.03933	0.00796	4.94082
	13	0.03316	0.00787	4.21226
	14	0.02326	0.01170	1.98821
	15	0.00913	0.01965	0.46473
Sum of Lags		0.35920	0.10512	3.41715

Lag Distribution of TSI_DVI	i	Coefficient	Std. Error	t-Statistic
	0	-2.3E-07	9.4E-08	-2.48657
	1	-1.5E-07	5.5E-08	-2.82100
	2	-8.9E-08	6.8E-08	-1.30886
	3	-3.7E-08	5.5E-08	-0.68099
Sum of Lags		-5.1E-07	1.8E-07	-2.82100

Since the KISS Model is a system of simultaneous equations, it is possible to start with any equation. This analysis started with the temperature equation [3], using the Atlantic sea surface temperature series AMO as the dependent variable. Since the system is simultaneous, using ordinary least squares, or direct LS, on this equation would result in **biased and inconsistent** (i.e. worthless for policy

Per Don Easterbrook, "The paper will be in a specia

Climate Science" published by Elsevier."

decision making) estimates of its coefficients. To obtain unbiased and consistent parameter estimates, it is necessary to estimate the coefficients by a simultaneous equation estimation technique. There are a number of such techniques, but one of the easiest to understand and apply is called Two Stage Least Squares (TSLS).[14] TSLS is carried out by first regressing CO_2 that appears on the right-hand side of eqn [3] on all the exogenous variables of the entire system: TSI, TSI*DVI, SOI-CT and c_{fossil}. The fitted values of this variable, CO_2Fit, are then substituted for the actual CO_2 values in the estimation of this equation by direct least squares. The results of this estimation process are shown in Figure 7. Note that the coefficient of the CO_2Fit variable is statistically insignificant; while the other exogenous variables are highly significant (the t-statistic of the sum of each lag distribution is greater than 2 in absolute value).

This result is very important and allows us to conclude that the set of equations given in Section 3 is recursive and that each equation can be estimated by ordinary least squares.[15] Strictly speaking, to show that the model is recursive, it is necessary to carryout the same TSLS process for the other two regions (i.e. Pacific and US) regarding their temperature history, which was done with the same result. CO_2 was not a statistically significant variable using TSLS for any of the three temperature equations.

The choice of the order of the polynomial and the number of lags in the Polynomial Distributed Lag Structure (PDL) formulation was determined by considering alternative formulations and choosing the one with the largest adjusted-R squared.[16]

CO_2 Equation Estimation.

With CO_2 determined to be not statistically significant in the temperature equations, the recursive nature of the equation system allows estimation of the CO_2 equation in the system by ordinary or direct least squares.

The explicit form of the CO_2 equation is:

[4] $(\Delta C - c_{fossil})_t = a + b*AMO_t + c* CO_{2,t-1}$

Where
$(\Delta C - c_{fossil})_t$, is the efflux of Net non-fossil fuel CO_2 emissions from the oceans and land into the atmosphere
AMO_t is Atlantic sea surface temperature. The expected sign is positive.
$CO_{2,t-1}$on the right-hand side is a proxy for Land use. The expected sign is negative, because as CO_2 levels rise, other things equal, the CO_2 absorption of the flora increase.[17] [18]

Applying ordinary least squares to this equation, yields a high adjusted R-square (.53), considering that the equation is estimated on an annual basis. The coefficients have the correct signs and are statistically significant at the 95% confidence level.

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

There is a useful validation test for all of the estimated parameters of this equation. In equilibrium, if there were no fossil fuel emissions and sea surface temperature, then there would be no change in the concentration of atmospheric CO_2, so that:

Figure 8. Estimation of the Recursive CO_2 Equation.

Dependent Variable: DELTA_C___CMAN
Method: Least Squares
Date: 06/22/09 Time: 09:09
Sample: 1960 2000
Included observations: 41

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-27.88501	7.223857	-3.860127	0.0004
AMO_RAW__C_	1.720964	0.367663	4.680819	0.0000
CO2_LAG	-0.026181	0.004027	-6.500690	0.0000

R-squared	0.558018	Mean dependent var	-1.033377
Adjusted R-squared	0.534756	S.D. dependent var	0.551963
S.E. of regression	0.376487	Akaike info criterion	0.954491
Sum squared resid	5.386222	Schwarz criterion	1.079874
Log likelihood	-16.56706	Hannan-Quinn criter.	1.000148
F-statistic	23.98820	Durbin-Watson stat	1.923067
Prob(F-statistic)	0.000000		

[5] $C_t = C_{t-1} = C_{equilibrium}$

Using eqn [4], we find that:

[6] $0 = a+b*T_0 + c*C_{equilibrium}$
Or, rearranging,

[7] $C_{equilibrium} = (a + b*T_0)/(-c)$

Substituting the estimated coefficients from Figure 8 and substituting the average temperature observed over 1960-2000 for AMO (20.75) into the eqn [7], yields:

$C_{equilibrium} = (-27.88501 + 1.720964*20.75)/(.026181) = 298.88.$

Thus, in equilibrium, without any Fossil Fuel consumption, and assuming a 20.75^o C AMO, atmospheric CO_2 concentrations would average around 300 ppm.

As an additional validation of the CO_2 equation, it can be shown that the equation suggests that the fraction of CO_2 not absorbed by the land and ocean, that is, the fraction of CO_2 from fossil fuel emissions that remains in the atmosphere, is about 53%, which roughly speaking, agrees with historical observation of about 56%. It must be noted, however, that this ratio over a forecast horizon is a function of the assumed growth of fossil fuel consumption and is not a constant.

The AMO Equation

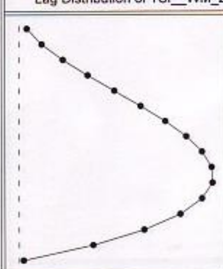
Figure 9 shows the AMO equation estimated by ordinary least squares. The coefficients have the expected signs, the adjusted R-square is high, and the variables are statistically significant at the 95-percent confidence level. The lagged terms for the TSI variable indicate a maximum impact at about 10 years, and the TSI-DVI interaction variable, as expected, has a statistically significant negative impact, fading out over 3 or 4 years.

Figure 9. Estimation
AMO

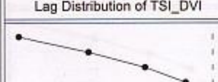
Dependent Variable: AMO_RAW__C_
Method: Least Squares
Date: 08/15/09 Time: 10:46
Sample: 1960 2000
Included observations: 41

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-562.2999	84.22411	-6.676234	0.0000
PDL01	0.000981	0.005897	0.166385	0.8688
PDL02	0.001057	0.001201	0.879767	0.3850
PDL03	-6.96E-05	5.58E-05	-1.246580	0.2208
PDL04	-1.45E-07	5.33E-08	-2.729881	0.0098
PDL05	7.42E-08	6.37E-08	1.163774	0.2524

R-squared	0.644030	Mean dependent var	20.75417
Adjusted R-squared	0.593177	S.D. dependent var	0.175022
S.E. of regression	0.111634	Akaike info criterion	-1.412725
Sum squared resid	0.436174	Schwarz criterion	-1.161958
Log likelihood	34.96086	Hannan-Quinn criter.	-1.321410
F-statistic	12.66458	Durbin-Watson stat	1.688949
Prob(F-statistic)	0.000000		



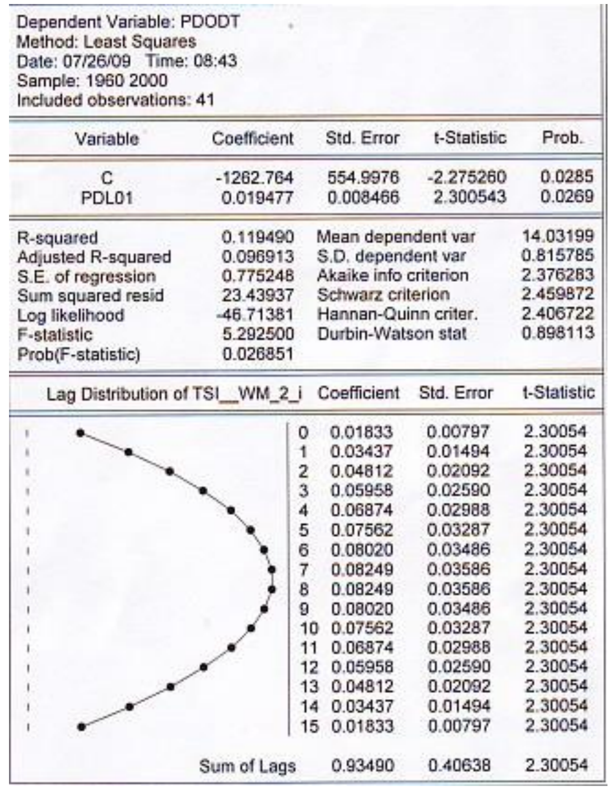
Lag Distribution of TSI__WM_2_i	Coefficient	Std. Error	t-Statistic
0	0.00197	0.00478	0.41212
1	0.00563	0.00754	0.74658
2	0.01057	0.00867	1.22002
3	0.01638	0.00854	1.91866
4	0.02262	0.00760	2.97645
5	0.02889	0.00645	4.47961
6	0.03477	0.00586	5.93588
7	0.03984	0.00636	6.26619
8	0.04368	0.00759	5.75512
9	0.04588	0.00881	5.20957
10	0.04602	0.00944	4.87621
11	0.04367	0.00913	4.78539
12	0.03843	0.00784	4.90242
13	0.02987	0.00668	4.47551
14	0.01759	0.00925	1.90221
15	0.00115	0.01683	0.06830
Sum of Lags	0.42697	0.06167	6.92297



Lag Distribution of TSI_DVI i	Coefficient	Std. Error	t-Statistic
0	-2.3E-07	9.3E-08	-2.44560
1	-1.5E-07	5.3E-08	-2.72988
2	-8.0E-08	6.7E-08	-1.19999
3	-3.1E-08	5.4E-08	-0.58054
Sum of Lags	-4.8E-07	1.8E-07	-2.72988

Per Don Easterbrook, "The paper will be in a special vol
Climate Science" published by Elsevier."

Figure 10. PDO Temperature Equation Estimation with AMO Functional Form.



Dependent Variable: PDODT
Method: Least Squares
Date: 07/26/09 Time: 08:43
Sample: 1960 2000
Included observations: 41

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1262.764	554.9976	-2.275260	0.0285
PDL01	0.019477	0.008466	2.300543	0.0269

R-squared	0.119490	Mean dependent var	14.03199
Adjusted R-squared	0.096913	S.D. dependent var	0.815785
S.E. of regression	0.775248	Akaike info criterion	2.376283
Sum squared resid	23.43937	Schwarz criterion	2.459872
Log likelihood	-46.71381	Hannan-Quinn criter.	2.406722
F-statistic	5.292500	Durbin-Watson stat	0.898113
Prob(F-statistic)	0.026851		

Lag Distribution of TSI__WM_2_i		Coefficient	Std. Error	t-Statistic
	0	0.01833	0.00797	2.30054
	1	0.03437	0.01494	2.30054
	2	0.04812	0.02092	2.30054
	3	0.05958	0.02590	2.30054
	4	0.06874	0.02988	2.30054
	5	0.07562	0.03287	2.30054
	6	0.08020	0.03486	2.30054
	7	0.08249	0.03586	2.30054
	8	0.08249	0.03586	2.30054
	9	0.08020	0.03486	2.30054
	10	0.07562	0.03287	2.30054
	11	0.06874	0.02988	2.30054
	12	0.05958	0.02590	2.30054
	13	0.04812	0.02092	2.30054
	14	0.03437	0.01494	2.30054
	15	0.01833	0.00797	2.30054
Sum of Lags		0.93490	0.40638	2.30054

Figure 10 shows the estimation of the PDO temperature equation using the same form as the AMO equation.[19] Note that while the TSI variable is statistically significant, the interaction term is not and the equation has extremely poor explanatory power (an adjusted R-square of 0.1). This result is not surprising, given the low correlation between PDO and the AMO and US time series. (See Table 3.)

Some assume that solar activity and a disturbance of the Earth's magnetic field may be considered as an external force for excitement of ENSO variability, for example as measured by the Southern Oscillation Index (SOI). The SOI is a function of the standardized data of Sea Level Pressure (SLP) difference between Tahiti and Darwin (Australia). As noted in Nuzhdina [5][20], "cyclic dynamics of ENSO phenomena are due to solar activity and geomagnetic variations. It is background long-period variations on which high frequency oscillations are imposed." Since these individual exogenous impacts are not well understood, the Southern Oscillation Index (SOI)[21] is used here as a proxy, or instrumental variable, to capture this complex solar/magnetic field influence on temperatures. The correlation between SOI and the temperature series are given in Table 4. Note that this exogenous variable's impact is insignificant for the AMO and the U.S., but critical regarding both the PDO and NINO 3.4.

Table 4. Correlation between SOI and Various Temperature Series.

	AMO	PDO	NINO3.4	US
SOI	**-.077**	**-.543**	**-.925**	**-.084**

The impact of SOI is modeled as a "Central Tendency," that is, a dummy variable depending on whether the SOI series is indicating a La Nina central tendency (0) or an El Nino tendency (+1). If the central tendency is La Nina, then La Nina conditions are more frequent/important and vice versa. The dummy variable is presented with the SOI series in Figure 11.

Figure 11. SOI and “Central Tendency”

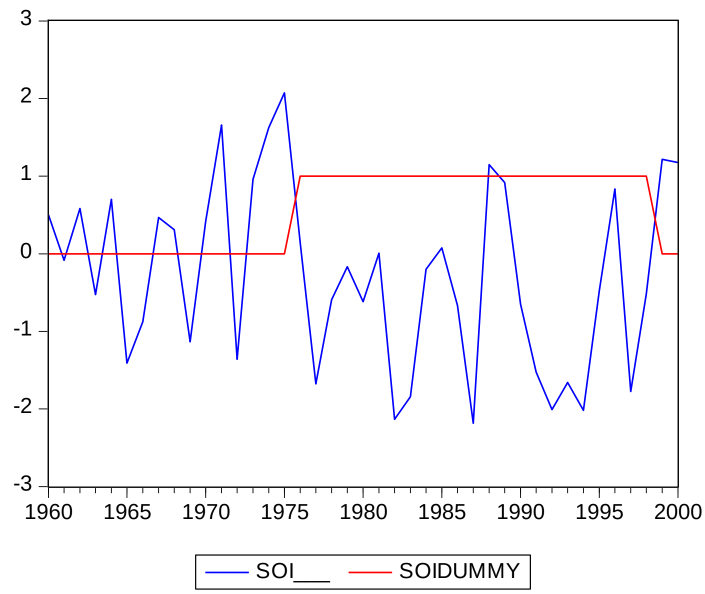


Figure 12. PDO Temperature Equation Estimation Using SOI Dummy.

Dependent Variable: PDODT
Method: Least Squares
Date: 08/03/09 Time: 12:46
Sample: 1960 2000
Included observations: 41

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	13.33949	0.126495	105.4548	0.0000
SOIDUMMY	1.234459	0.168889	7.309297	0.0000

R-squared	0.578040	Mean dependent var	14.03199
Adjusted R-squared	0.567221	S.D. dependent var	0.815785
S.E. of regression	0.536672	Akaike info criterion	1.640692
Sum squared resid	11.23267	Schwarz criterion	1.724281
Log likelihood	-31.63419	Hannan-Quinn criter.	1.671131
F-statistic	53.42582	Durbin-Watson stat	1.620538
Prob(F-statistic)	0.000000		

Note: the SOI Dummy = 1 from 1976-1998, 0 elsewhere. The alternative using values of 1 for 1999 and 2000 has poorer statistical properties, e.g. adjusted-R squared.[22]

Using the SOI Dummy as a proxy for such complex solar/magnetic field influences, the PDO temperature equation estimation is shown in Figure 12.[23]

The adjusted-R squared is at roughly the same level as for the AMO equation and the coefficient sign is correct with a very high t statistic. It should be noted that CO_2Fit was not statistically significant if added to this model formulation or any other considered.

CO_2 Equation Estimation adding the Pacific Ocean (PDO) Impact.

In the CO_2 model estimation shown in Figure 13 below the SOI Dummy has been added as the only change from the estimate in Figure 8. The adjusted-R squared is slightly higher (.56 vs. .53) suggesting this is the preferred model. All the signs are as expected and statistically significant, particularly with a DW statistic of 1.92. When the equilibrium atmospheric CO_2 concentration is repeated, the result is a nearly identical 301 vs. 299 ppm! Another interesting result of this formulation is that it allows estimation of the impact of a shift in Central Tendency; the impact is 8 PPM.

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

Figure 13. CO_2 Equation Estimation with Pacific Impact.

Dependent Variable: DELTA_C_CMAN
Method: Least Squares
Date: 11/12/09 Time: 12:39
Sample: 1960 2000
Included observations: 41

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-28.60176	7.073216	-4.043671	0.0003
AMO_RAW	1.838641	0.366190	5.020997	0.0000
CO2_LAG	-0.031697	0.005141	-6.165855	0.0000
SOIDUMMY	0.253568	0.152008	1.668126	0.1037

R-squared	0.588933	Mean dependent var	-1.033377
Adjusted R-squared	0.555603	S.D. dependent var	0.551963
S.E. of regression	0.367955	Akaike info criterion	0.930758
Sum squared resid	5.009476	Schwarz criterion	1.097936
Log likelihood	-15.08054	Hannan-Quinn criter.	0.991635
F-statistic	17.66990	Durbin-Watson stat	1.929856
Prob(F-statistic)	0.000000		

US Temperature Equation

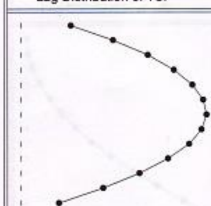
As mentioned in Section 4, it was expected that the U.S. surface temperature could be successfully modeled using the same basic structure as for AMO, but that different lag structure would result. For example, it would be expected that the solar influences would occur more rapidly with air than water temperature – which is exactly the result obtained. The impact of volcanic action is similar in lag structure but more muted than was the case for the AMO. Given the on going controversy regarding errors of observation in this data set, it is not surprising that this result has an adjusted-R squared less than half that of AMO and PDO. And, it should again be noted that when CO_2Fit was added to this or any other formulation tested, it was not statistically significant. (See Figure 14.)

Figure 14. Estimation of US Temperature Equation..

Dependent Variable: GISS_US_TEMP
Method: Least Squares
Date: 09/11/09 Time: 09:40
Sample: 1960 2000
Included observations: 41

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1701.104	476.2577	-3.571814	0.0010
PDL01	0.040946	0.015432	2.653330	0.0117
PDL02	-0.002977	0.001578	-1.886781	0.0671
PDL03	-4.27E-07	2.80E-07	-1.523951	0.1360

R-squared	0.300036	Mean dependent var	57.38659
Adjusted R-squared	0.243282	S.D. dependent var	0.789190
S.E. of regression	0.686513	Akaike info criterion	2.178085
Sum squared resid	17.43811	Schwarz criterion	2.345263
Log likelihood	-40.65074	Hannan-Quinn criter.	2.238962
F-statistic	5.286611	Durbin-Watson stat	1.879781
Prob(F-statistic)	0.003901		



Lag Distribution of TSI	i	Coefficient	Std. Error	t-Statistic
	0	0.03797	0.01391	2.73025
	1	0.06998	0.02479	2.82311
	2	0.09604	0.03270	2.93672
	3	0.11615	0.03774	3.07738
	4	0.13030	0.04006	3.25233
	5	0.13849	0.03996	3.46591
	6	0.14074	0.03801	3.70263
	7	0.13702	0.03541	3.86924
	8	0.12736	0.03449	3.69251
	9	0.11174	0.03841	2.90866
	10	0.09016	0.04896	1.84165
	11	0.06263	0.06555	0.95546
	12	0.02914	0.08706	0.33477
Sum of Lags		1.28772	0.34874	3.69251

Lag Distribution of TSI_DVI	i	Coefficient	Std. Error	t-Statistic
	0	-5.7E-07	3.7E-07	-1.52395
	1	-4.3E-07	2.8E-07	-1.52395
	2	-2.8E-07	1.9E-07	-1.52395
	3	-1.4E-07	9.3E-08	-1.52395
Sum of Lags		-1.4E-06	9.3E-07	-1.52395

6. KISS Model Forecasts and Validation.

While all of the rules for model development and validation spelled out above have thus far been followed and with success, a critical step remains; testing whether or not the KISS Model has any hope of providing forecasts that are truly useful as input for policy makers. In this test, the model, as estimated over the period 1960 -2000, is examined regarding its ability to forecast the period 2001-2008. This is a far more stringent test than simply undertaking a within-sample test.

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

In this analysis, actual values of the exogenous variables for the out-of-sample period, 2001-2008 are used as model input. In Section 7, KISS Model forecasts will be made using an array of likely exogenous variable that might have reasonably been constructed in the year 2000.

Substituting known values for TSI and DVI, the forecasts for AMO are shown in Figure 15. The expected value of the forecast is for a decline in temperature, much like what actually happened. How the KISS Model does relative to a simple naïve models is also a crucial test. The naïve models used here are: a linear time trend fitted to the period 1960 to 2000 and a linear trend fitted to the period 1976 to 2000. Figure 15 shows that the KISS Model outperformed both of these naïve models.[24] Figures 16-18 show the same performance for the other dependent variables in the KISS Model.

Figure 15. Forecast of AMO Temperature vs. Naïve Models.

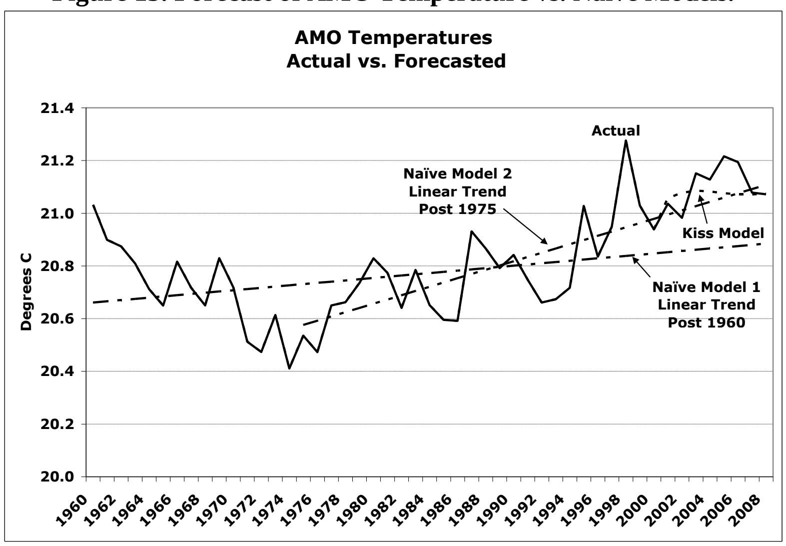
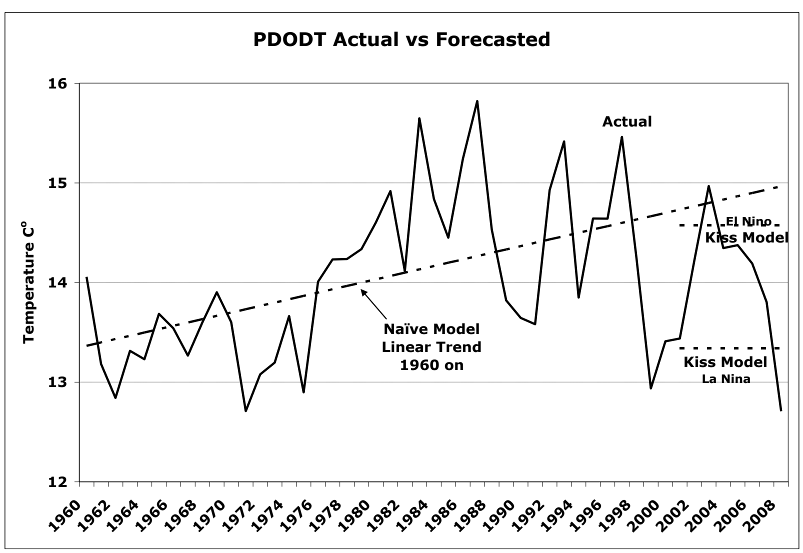


Figure 16. Forecast of PDO Temperature vs. Naïve Models.



Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

Figure 17. Forecast of GISS US Temperature vs. Naïve Models.

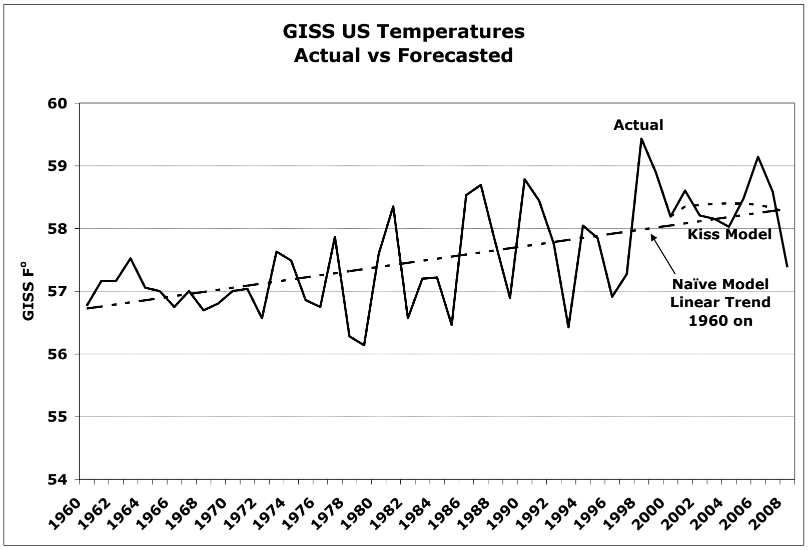


Figure 18. Forecast of CO_2 Concentration vs. Naïve Models.

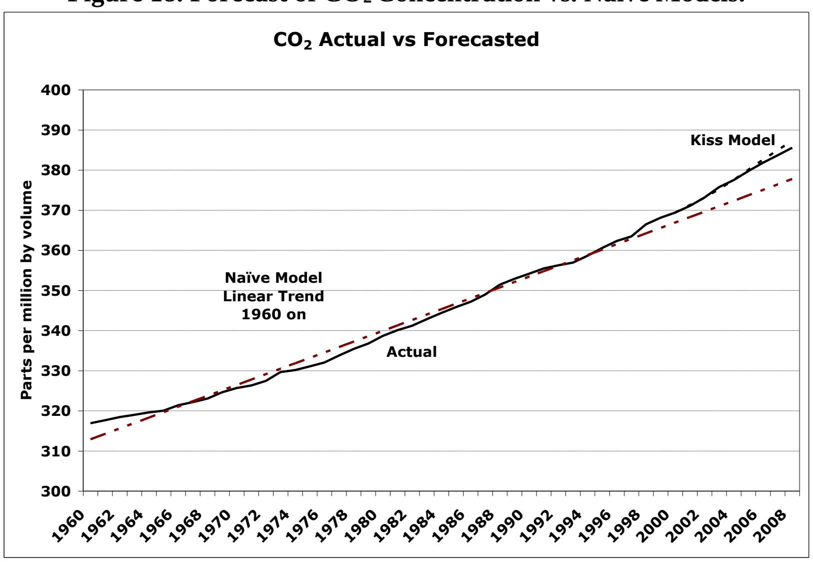


Table 5 compares the KISS Model forecasts with the various naïve or benchmark model forecasts on the basis of three widely used evaluation metrics: the Bias (how close were the forecasts on average), the Mean Absolute percent Error (MAPE)[25], and turning point errors (did the forecast capture the turning point, if there was one). For all endogenous variables, the KISS Model outperformed the naive models on the basis of Bias and MAPE. The model also correctly captured the turning point in all three temperature series, whereas the naïve models did not. As expected, the MAPE for the chaotic temperature, PDO, is significantly higher than for the other temperatures. The ranking of the MAPE measures correspond to the coefficient of variation hierarchy identified earlier.

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

Table 5. Comparison of KISS Model Forecasts with Naïve Models.

	BIAS		MAPE		Captured Turning Point	
	KISS Model	Naïve Model (Trend '60-'00)	KISS Model	Naïve Model (Trend '60-'00)	KISS Model	Naïve Model (Trend '60-'00)
AMO	.033	.239 .056*	.294	1.13 .355*	Yes	No
PDO La Nina	.667	-.842	5.796	6.542	Yes	No
PDO El Nino	-.568	-.842	4.491	6.542	Yes	No
GISS US	-.075	.124	.636	.680	Yes	No
CO_2	-.459	5.534	.156	1.457	NR	NR

***=Trend from 1975-2000**

7. KISS Model 2001 -2030 Simulations

This section illustrates the use of the KISS Model for policy analysis purposes. Note that, in doing this, the KISS Model is subjected to a strong validation test, by starting the forecasts in the year 2000, not in the year 2008. The model was simulated for the thirty-year period 2001-2030, using a plausible set of exogenous variables specified using only information available when year 2000 was published.

The first exogenous variable, TSI, has an observed *solar seasonal* pattern of about 11 years superimposed on a longer term trend cycle. To represent a High Side TSI case, using data from 1960 to 2000 only, a trend-cycle that would continue upward for the thirty years after 2000 would seem plausible. Alternatively, as a Base Case, a trend-cycle using a longer set of historical data, from 1910-2000 say, would support *a no linear trend* outlook with only the solar seasonal pattern superimposed. Finally, a simulated return of a Maunder Minimum –type pattern is not inconceivable.[26] These three scenarios are shown in Figure 19.

The second exogenous variable, volcanic activity, if any, would tend to decrease temperatures. For these scenarios, this interaction term was set equal to zero in all three scenarios. Significant volcanic action reduces the average temperatures somewhat. If the volcanic activity of the early 1990s (Pinatubo) coupled with the behavior of TSI at that time (coming off an 11-year cycle peak) were to occur again, the average AMO temperature , over the four year period, would fall about 0.16^o C.

The third exogenous variable, c_{fossil}, emissions form fossil fuel burning, is assumed to grow at its historical rate of 2.5% per annum in all three scenarios. If technological change or policy actions reduce this rate of growth of fossil fuel emissions, the forecasted CO_2 concentrations would be overstated. **According to the KISS Model, the effects of**

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

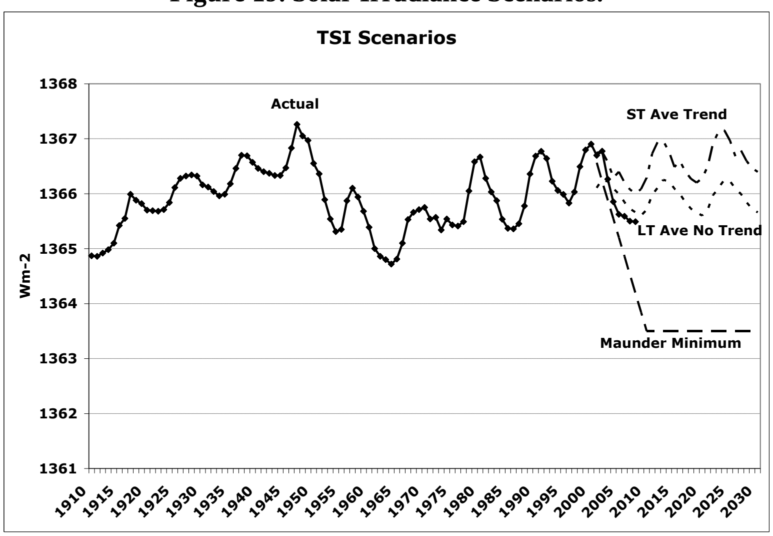
such policy action will have no impact on the AMO, PDO and U.S. temperature outlooks.

The final exogenous variable, the Central Tendency in the Pacific, is assumed to be La Nina for all three scenarios. If the tendency were to revert to the El Nino Central Tendency, the temperatures in the Pacific would be about 1.2 ^{o} C higher. These cases are summarized in Table 6.

Table 6. Exogenous Assumptions, 2001-2030

	High Side Case	**Base Case**	**Maunder Minimum**
Exogenous Variable			
Total Solar Irradiance	**Trend-cycle calculated over 1960-2000. (Has a trend)**	**Cycle calculated over 1910-2000 time period (Does not have a trend)**	**TSI corresponding to 1363.37, the lowest observable point in the time series (in 1890)**
Volcanic Activity	**No significant volcanic activity**		
Fossil Fuel Emissions	**Historical growth rate = 2.5% per year**		
Pacific Central Tendency	**La Nina Central Tendency**		

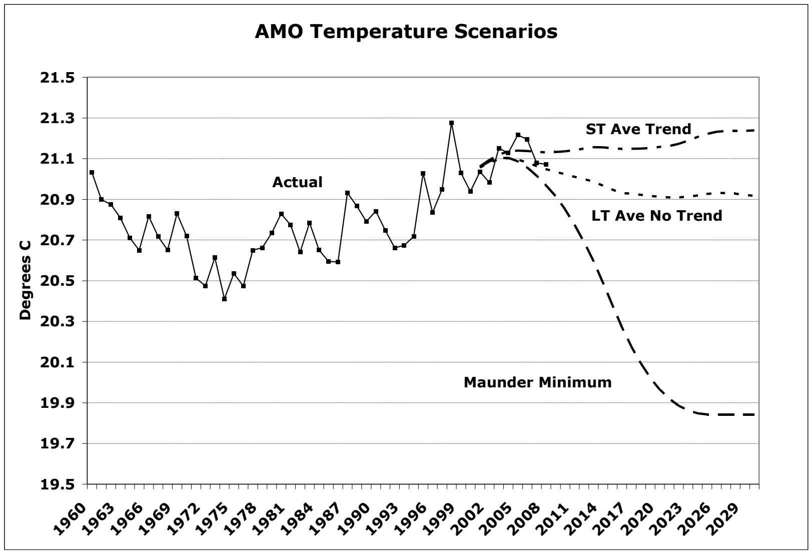
Figure 19. Solar Irradiance Scenarios.



As shown in Figure 20, under the Base Case assumptions, AMO temperatures would fall over the forecast period and flatten out at 20.9^{o} C, or about 0.15^{o} C above the average for 1960-2000. In the High Case, AMO temperature rises to 21.2^{o} C, or 0.4^{o} C above the average over the estimation period. In the Maunder Minimum Case, AMO temperature falls precipitously to 19.9^{o} C, which is below any point in the 1960-2000 period.

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

Figure 20. AMO Temperature Simulations.



In the KISS Model, the forecast for PDO depends solely on the assumption as to the SOI Central Tendency in the Pacific. As shown in Figure 21, using the assumption of a continuation of the "La Nina" Central Tendency, Pacific temperatures are forecast to average 12.2^{o} C under all scenarios. If that were to prove wrong and the Central Tendency be El Nino, the PDO would be 1.2 C higher.

Figure 21. PDO Temperature Simulations.

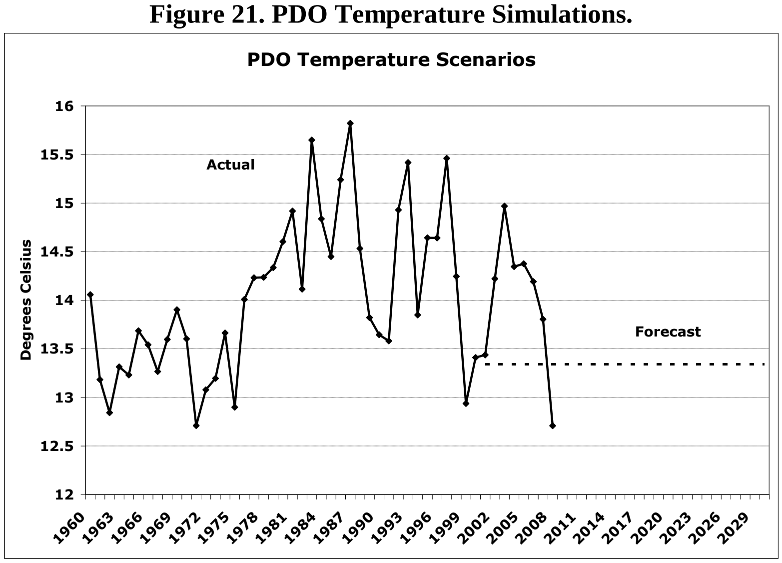
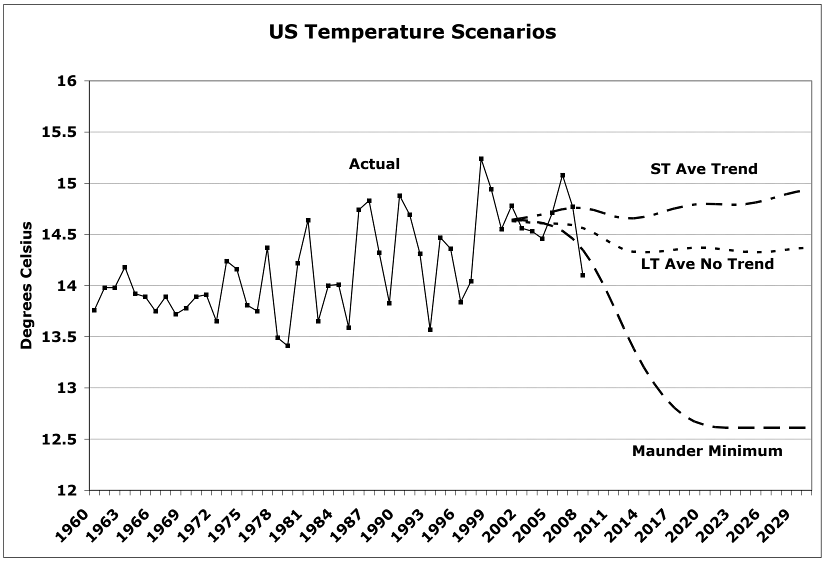


Figure 22 shows the U.S. temperature outlook under each of the three scenarios.
If these scenarios, adequately bracket the outlook, there would certainly not seem to suggest serious upside temperature risk.

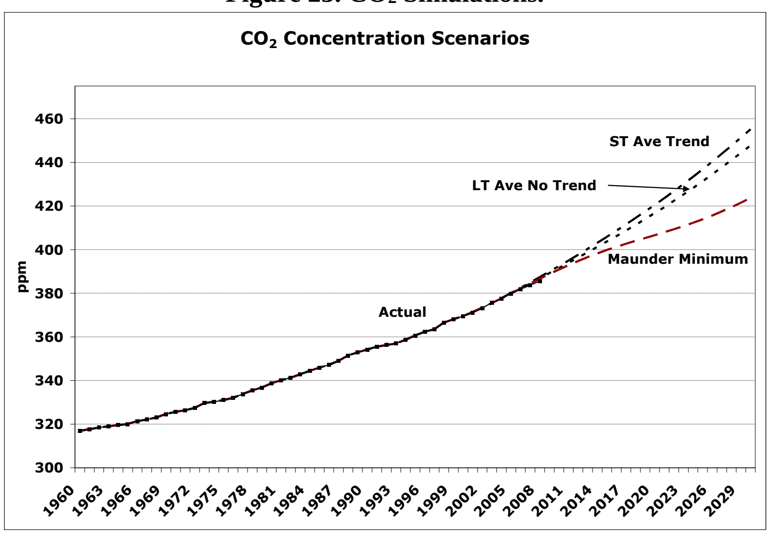
Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

Figure 22. US Temperature Simulations.



Under all three scenarios, given that man-made fossil fuel emissions continue unabated by assumption, as shown in Figure 23, CO_2 concentrations continue to rise. But they stay under 460 ppm through 2030.

Figure 23. CO_2 Simulations.



8. Conclusions and Ramifications

Our analysis suggests the following conclusions and ramifications:

The simplest model that can characterize the relationship between atmospheric CO_2 concentration levels and temperature levels must contain at least two simultaneous

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

equations, one for each of these two state variables. Therefore, the climate system must be analyzed using simultaneous equation estimation techniques. Otherwise the parameter estimates of any structural equations will be both biased and inconsistent, which implies they are useless for policy analysis purposes. The existence of a robust atmospheric CO_2 equation has been amply demonstrated, thus guaranteeing that **ANY** modeling system designed to forecast temperature must include at least two equations.

Using the KISS Model and seeking to link temperature to CO_2 concentrations, the null hypothesis that atmospheric CO_2 levels have a statistically significant impact on temperature levels is rejected. In fact, it is rejected three times, i.e. for the AMO, PDO and US temperatures.

The KISS climate modeling system is recursive. It has been shown that Ocean and US. Surface temperatures may be modeled and forecast reasonably well using only exogenous variables that relate to solar/magnetic activity, volcanic activity, and ocean oscillations. Then, atmospheric CO_2 concentrations can be modeled and forecast reasonably well using these forecast ocean temperatures as well as forecast fossil fuel CO_2 emissions.

The KISS Model forecasts of AMO, PDO and US surface temperatures and CO_2 concentrations for the period 2001-2008, using the model parameters estimated over the period from 1960-2000, and with actual exogenous variable values through 2008, capture the observed decline in ALL THREE temperatures and capture the continued upward movement in CO_2. The KISS Model forecasts outperform all naïve model forecasts over the same period for all four dependent variables.

Since the KISS Model was developed and estimated following the fundamental professional guidelines spelled out in Section 2, and passed all of the standard statistical tests, it can be used for policy analysis to simulate alternative AMO, PDO and U.S. temperature and CO_2 concentration futures. Since the geographic coverage is at least 70%, it is highly unlikely that *actual* global average temperatures rise beyond that which would be consistent with reasonable KISS Model simulations. Under the assumptions that solar irradiance follows its linear trendless 1910-2000 historical trend cycle or continues falling to its 200-year minimum and the PDO exhibits a La Nina Central Tendency, all three temperatures are expected to decline through 2030, even as CO_2 concentrations continue to rise. Under the assumption that solar irradiance rises at its 1975 to 2000 trend-cycle rate and volcanic activity is again benign, US temperatures rise modestly, on the order of 1^o Celsius through 2030. However, given the recent behavior of the sun spot activity this scenario seems highly unlikely.

Finally, it seems extremely critical to note that, over the period 1975 through roughly 1998, there were only two significant volcanic eruptions, the TSI trend cycle was upward sloping and the SOI was in its Hot El Nino Central Tendency Mode. This situation led to rising AMO, PDO and U.S. temperatures. Because CO_2 was also rising, some analysts claimed causation. The KISS Model results categorically refute this claim. Despite the continued rise in CO_2, the KISS Model forecasts the 2000-2008 decline in temperature for all three regions of the world, which together cover over 70% of its surface area.

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

Another ramification of all this is that any rational modeling activity, designed to provide a global average surface temperature outlook, would need to develop and validate separate temperature equations covering the bulk of the surface area of the Earth, including both polar regions. In this paper, a means of selecting and estimating the parameters of the appropriate functional form of the temperature equations for additional geographic areas was indicated by the PDO analysis. Follow on work might include determining a reasonable mutually exclusive, collectively exhaustive set of regions that meet the KISS model development and validation rules set as outlined in Section 2.

Bibliography

1. Feng, Song and Qi Hu,"How the North Atlantic Multidecadal Oscillation may have influenced the Indian summer monsoon during the past two millennia," Geophysical Research Letters, 2008, 35, L01707.

2. Hoyt, D.V. and K.H. Schatten, „A discussion of plausible solar irradiance variations,“ J. Geophys. Res., 1993, 98A, 18895-18906.

3. Abdussamatov, Habibullo, "The Sun Defines the Climate," (translated from Russian by Lucy Hancock), November 2008.

4a. Lamb, H. H., 'Volcanic Dust in the Atmosphere; With a Chronology and Assessment of its Meteorological Significance.' Philosophical Transactions of the Royal Society of London, Series A, 1970, 266, 425-533.

4b. Lamb, H. H., 'Supplementary Volcanic Dust Veil Assessments.' Climate Monitor, 1977, 6, 57-67.

4c. Lamb, H. H., 'Update of the Chronology of Assessment of the Volcanic Dust Veil Index.' Climate Monitor, 1983, 12, 79-90.

5. Nuzhdina, M.A., "Connection between ENSO phenomena and solar and geomagnetic activity," Natural Hazards and Earth Sciences, 2002, 2, 83-89.

End Notes

---

[1]. Dr. James P. Wallace, III jwallace39@aol.com is President of Jim Wallace and Associates, LLC, Dr Anthony Finizza afinizza@uci.edu is principal at AJF Consulting and Lecturer, University of California, Irvine, and Joseph D'Aleo is Certified Consulting Meteorologist and Fellow of the American Meteorological Society…

The authors wish to thank Dr. William Niskanen for his review of the paper.

[2] A complete data set is available upon request.

[3] These can be found at www.forecastingprinciples.com. These represent the work of 120 experts.

[4] NINO34 is the NINO 3.4 time series of East Central Tropical Pacific SST (5N-5S)(170-120W) -- http://www.cdc.noaa.gov/data/correlation/nina34.data.

[5] PDO is the PDO Index which is standardized values for the leading PC of monthly SST anomalies in the North Pacific, poleward of 20°N -- http://jisao.washington.edu/pdo/PDO.latest.

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

[6] AMO_Raw is the raw Atlantic Multi-decadal Oscillation; that is, not detrended -- http://www.cdc.noaa.gov/data/correlation/amon.us.long.mean.data
[7] GISS-US are from http://data.giss.nasa.gov/gistemp/graphs/Fig.D.txt and are anomalies for the US only. Converted to level form.
[8] Feng and Hu, page 1.
[9] Wikipedia.
[10] Total Solar Irradiance (TSI) data are from Willie Soon (Hoyt and Schatten [2], scaled to fit ACRIM).
[11] There are two competing variables that describe volcanic activity, the Dust Veil Index (reported as a positive number) due to Mann and Volcanic due to NOAA (reported as a negative number). Since, volcanic activity is expected to reduce temperature, other things being equal, the expected coefficient in the equation is negative for the first of the pair and positive for the second of the pair. DVI is the ' Weighted' Dust Veil Index from Mann et al 1998. http://bobtisdale.blogspot.com/2008/04/mann-et-al-weighted-dust-veil-index.html. The alternative series, volcanic, is the forcing (Wm-2) due to volcanic activity -- ftp://ftp.ncdc.noaa.gov/pub/data/paleo/gcmoutput/crowley2000/forc-total-4_12_01.txt
[12] Global CO2 Emissions from Fossil-Fuel Burning, Cement Manufacture, and Gas Flaring: 1751-2005. http://cdiac.ornl.gov/ftp/ndp030/global.1751_2005.ems. Conversion to CO_2 was calculated on the basis of the carbon content of each fossil fuel.
[13] SOI is the Southern Oscillation Index, the Tahiti minus Darwin Pressure anomalies -- ftp://ftp.cpc.ncep.noaa.gov/wd52dg/data/indices/soi.his and http://www.cpc.ncep.noaa.gov/data/indices/soi.
[14] See Theil, Henri. *Introduction to Econometrics*, Prentice-Hall, 1978, pages 328-342. and Goldberger, A.S., *Econometric Theory*, 1964, pages 329-348.
[15] See Theil, Henri. *Introduction to Econometrics*, Prentice-Hall, 1978, pages 346-349 and Goldberger, A.S., *Econometric Theory*, 1964, pages 354-355. The model was estimated in EVIEWS. For a description of Polynomial Distributed Lags, see Batten, Dallas and Daniel Thornton, “Polynomial Distributed Lags and the Estimation of the St. Louis Equation,” St. Louis Review, April 1983, pages 13-25.
[16] This is a robust test of goodness-of-fit whenever the equations compared have the same dependent variable. For example,

Example of Determination of Order and lag in AMO Temperature Equation

Lag of TSI Variable	Order of Polynomial	Adjusted R-squared
13	3	.598
14	3	.593
15	3	.593
16	3	.590
17	3	.581
12	2	.587

[17] The authors wish to acknowledge a major contribution to the formulation of this equation and the following footnote resulting from discussions with A.J. Meyer. (ajmeyer@optonline.net)
[18] The number of carbon atoms on/in the Earth is fixed, except for a small percentage that arrive from extraterrestrial sources via bombardment of comets, meteors and space dust. This means that essentially a fixed amount of carbon is continually traveling back and forth at various rates between the biosphere (flora and fauna, including mankind), the oceans, lakes, land (on or under the Earth’s crust), and the atmosphere via the processes of photosynthesis, respiration, combustion, decay, weathering, subduction and volcanism.

The published data on the amount of CO_2 flowing between the sources and sinks of the carbon cycle is not in balance. There should be more CO_2 in the atmosphere. Where is it all going? The deep oceans are the primary candidates as extra carbon sinks. But in addition to the oceans, it appears that the forests of the northern hemisphere are fixing carbon at a much faster rate than has previously been estimated. To gain some perspective, just the annual seasonal CO_2 flux, driven by the deciduous trees in the northern hemisphere, **due only to leaves** sprouting in the spring and falling in the fall, is equal to about 220 billion tonnes of CO_2 per year.

If the atmospheric concentration of CO_2 increases, then the rate at which CO_2 is extracted from the atmosphere by the Earth’s flora will also increase. In many if not most climate models, variable

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

carbon fixing rates, especially the rates of the Northern Hemisphere's forests, have either been ignored altogether or greatly underestimated. (co2science.org, has a list of references to peer reviewed publications on Carbon sequestration in forests. See, http://www.co2science.org//subject/c/carbonforests.php. "Thus, it would appear that elevated CO_2 typically reduces or has no effect upon plant litter decomposition rates. In addition, it is important to note that none of these decomposition studies looked at wood, which can sequester carbon for long periods of time, even for millennia **(Chambers et al., 1998),** provided it is not burned. Based upon several different types of empirical data, a number of researchers have concluded that current rates of carbon sequestration are robust and that future rates will increase with increasing atmospheric CO_2 concentrations. In **Fan et al. (1998)** based on atmospheric measurements, for example, the broad-leaved forested region of North America between 15 and 51°N latitude was calculated to possess a current carbon sink that can annually remove all the CO_2 emitted into the air from fossil fuel combustion in both Canada and the United States. On another large scale, **Phillips et al. (1998)** used data derived from tree basal area to show that average forest biomass in the tropics has increased substantially over the last 40 years and that growth in the Neotropics alone can account for 40% of the missing carbon of the entire globe. And in looking to the future, **White et al. (2000)** have calculated that coniferous and mixed forests north of 50°N latitude will likely expand their northern and southern boundaries by about 50% due to the combined effects of increasing atmospheric CO_2, rising temperature, and nitrogen deposition."

It is important to note that young forests on recently cleared land fix atmospheric carbon (grow) at a rate at least an order of magnitude faster than do forests in a later (a decade or so) stage of re-growth, whilst tropical old growth forests fix carbon at essentially the same rate as they emit it back into the atmosphere, primarily through insect (termite) flatulence and rapid soil bacterial metabolism. (A study, published in ***Science*** in the early 1980's, indicated that the annual amount of CO_2, emitted by termite flatulence is over twice the amount produced by all anthropogenic carbon emissions. **[Science, Vol. 218, Nov. 5, 1982, Zimmerman et al.]** As is well known, termites emit prodigious amounts of methane. However, what may be less well known is that termites also annually emit about 52.4 billion tonnes of CO_2, equivalent to around 14.3 billion tonnes of combusted carbon. Whereas humanity's annual atmospheric contribution is about 6 billion tonnes of carbon or 22 billion tonnes of CO_2.) That is, tropical old growth rain forests are in a state of quasi-equilibrium. In northern forests, due to colder temperatures, more of the annual carbon detritus (dead wood, leaves, etc,) is fixed in the soil, or drops into in anoxic bogs, which can slowly reduce the detritus to peat (another long term carbon sink). Much of the carbon that is harvested does not return to the atmosphere, since it becomes stored in building materials, furniture etc., or ends up in the form of paper and packaging material buried in landfills which are essentially anoxic carbon sinks. Also, all plastic products, packaging material and plastic bags, unless incinerated are practically 'eternal' carbon sinks.

In addition, greater atmospheric concentrations of CO_2 along with any minimal warming, due to whatever cause, should trigger greater forest growth rates and should also extend the tree line of the Boreal forest further north into the tundra. ("The boreal forest is a major carbon sink, absorbing an average of between 700 million and 1.3 billion metric tonnes of carbon each year between 1970-1990. This is the equivalent of the net addition of 750 million cubic meters of wood each year. This sink is 13-24 percent of the 5.5 billion tonnes of carbon released annually from the burning of fossil fuels during 1980-1989." http://archive.greenpeace.org/climate/arctic99/reports/forests.html)

A rough back-of-the-envelope-calculation quickly shows that an extension of the northern boundary between forests and tundra by one-degree latitude will result in an annual reduction of about .5 ppmv in atmospheric CO_2 concentration. This, of course, does not include the increased carbon fixing response rates due to a greater atmospheric concentration of CO_2 by the rest of the world's flora.

[19] All temperature equations were initially estimated by TSLS, using the appropriate set of exogenous variables. None of the variables for the fitted values of CO_2 were statistically significant.

[20] Nuzhdina [5], page 88.

[21] SOI is the Southern Oscillation Index, the Tahiti minus Darwin Pressure anomalies -- ftp://ftp.cpc.ncep.noaa.gov/wd52dg/data/indices/soi.his and http://www.cpc.ncep.noaa.gov/data/indices/soi

[22] This method of determining whether a switch in Central Tendency may have happened seems worth further analysis since looking at the 2001-2008 seems to confirm the switch. Since this PDO behavior is

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."

clearly chaotic and independent of CO2, some means selecting at least the near term outlook the SOI Dummy is always needed.

[23] It should be noted that only a detrended version of the PDO time series was available to the authors. Adding any reasonable trend, however, had no impact on the lack of statistical significance of CO_2.

[24] The AMO time series was stationary of order one, so a linear trend is a reasonable naïve model.

[25] The MAPE is used to compare among different variables.

[26] Abdussamatov [3], page 4.

Per Don Easterbrook, "The paper will be in a special volume entitled "Evidence-based Climate Science" published by Elsevier."