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Testing hypotheses about mechanisms for the unknown carbon sink: A time series analysis

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[1] We test hypotheses about the unknown sink for carbon by analyzing time series for the unknown carbon sink, carbon emissions, atmospheric concentrations, and surface temperature between 1860 and 1990. During this period, the time series for the unknown carbon sink is determined by annual changes in carbon emissions and summer land surface temperature in the northern hemisphere. The first difference of carbon emissions indicates that an increase in carbon emissions may generate a short run increase in oceanic uptake that is not simulated correctly by models. The temperature effect may have its greatest impact on terrestrial vegetation in the midlatitudes and high latitudes of Eastern North America and Europe. We also test and reject hypotheses that increases in the atmospheric concentration of CO_2, nitrogen deposition associated with fossil fuel combustion, or uncertainty about the rate at which forests are cut and/or regrow are responsible for changes in the unknown carbon sink over time. *INDEX TERMS:* 0330 Atmospheric Composition and Structure: Geochemical cycles; 1615 Global Change: Biogeochemical processes (4805); 1620 Global Change: Climate dynamics (3309); *KEYWORDS:* carbon cycle, unknown carbon sink

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1. Introduction

[2] Summing the estimates for carbon flows to and from the atmosphere indicates that the atmospheric concentration of carbon dioxide should be greater than observations. This discrepancy implies that some unknown mechanism(s) is removing carbon from the atmosphere and/or a known mechanism is removing carbon faster than believed: the so-called unknown carbon sink. Hypotheses for this unknown sink include uncertainty about oceanic uptake and/or increased uptake by terrestrial vegetation due to changes in climate, elevated levels of atmospheric CO_2, forest regrowth, and/or anthropogenic mobilization of nitrogen [*Schimel et al.*, 2001].

[3] Here we test competing hypotheses for the unknown carbon sink by analyzing time series for anthropogenic carbon emissions, atmospheric carbon concentrations, surface temperature, and uptake by the unknown carbon sink between 1860 and 1990. These time series are not stationary, which means that statistical relations estimated using ordinary least squares (OLS) could be misleading. To avoid this potential source of confusion, we use two techniques that are designed to analyze relations among nonstationary time series. The results indicate that most of the variation in the time series for carbon uptake by the unknown carbon sink is associated with annual changes in carbon emissions and summer temperature in the Northern Hemisphere. These results imply that oceans may increase their uptake of carbon in the short run in response to increased emissions. The effect of temperature implies that summer warming may increase net primary productivity (NPP) faster than heterotrophic respiration: net carbon exchange between the terrestrial biosphere and the atmosphere increases. Conversely, we find no evidence that elevated levels of carbon dioxide, uncertainties about forest regrowth, or nitrogen deposition have a statistically measurable effect on estimates for the unknown carbon sink over the last 130 years.

[4] These results are described in five sections. Section 2 describes the data analyzed. Section 3 describes the differences between stationary and nonstationary time series, how these differences can affect statistical relations estimated by OLS, and techniques that can be used to analyze relations among nonstationary time series. Section 4 describes the results of tests designed to evaluate four mechanisms for the unknown carbon sink: (1) atmospheric concentrations of CO_2, (2) emissions of CO_2, (3) air and/or ocean surface temperature, and (4) uncertainty about forest regrowth and nitrogen deposition. Section 5 discusses these results relative to previous investigations. Finally, we conclude with a description of research that is needed to reconcile differ-

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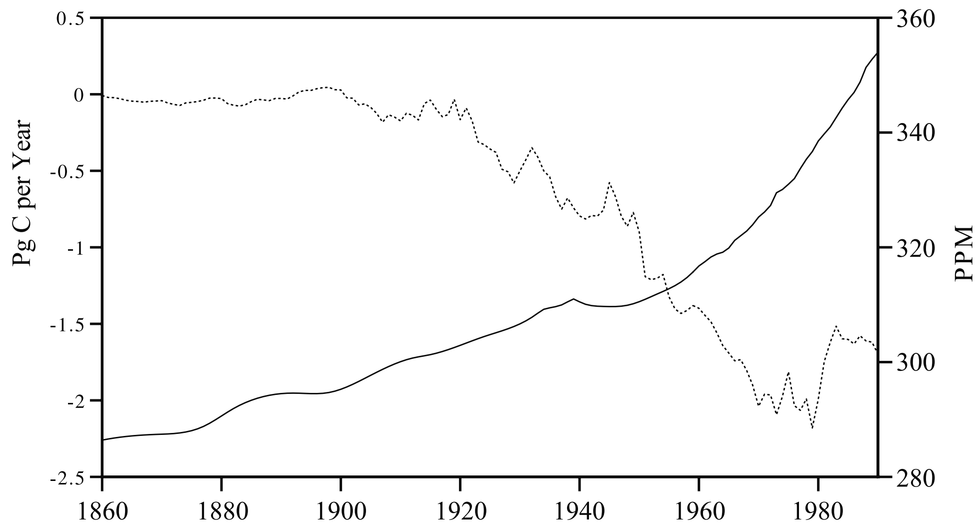

Figure 1. The time series for the unknown carbon sink (dotted line, left axis) and the time series for the atmospheric concentration of carbon dioxide (solid line, right axis).

ences between statistical analyses of the observational record and results generated by simulation models.

2. The Data

[5] To test hypotheses about the mechanisms for the unknown carbon sink, we analyze the time series for the unknown carbon sink calculated by *Houghton et al.* [1998]

$$\Delta CO_2 = \text{carbon emissions} - \text{oceanic uptake} + \text{unknown sink}, \quad (1)$$

in which ΔCO_2 is the change in atmospheric CO_2, carbon emissions is the net annual rate of anthropogenic CO_2 emissions and includes estimates for emissions from fossil fuels and net emissions from land use (deforestation minus uptake due to forest regrowth), oceanic uptake is the rate at which carbon is absorbed by oceans as simulated by models, and unknown sink is the rate by which these flows do not balance. All flows are measured in petagrams of carbon per year. Negative values for the unknown sink indicate that there is less carbon in the atmosphere than indicated by the first three terms in equation (1) (Figure 1).

[6] We use the time series for the unknown carbon sink (MISS) as a dependent variable to estimate models that specify one or more variables (*X*), which represent mechanisms postulated to drive the unknown carbon sink (Table 1). To test the hypothesis that elevated levels of atmospheric CO_2 increase NPP relative to heterotrophic respiration, we use statistical techniques to test for a relation between MISS and the atmospheric concentration of CO_2. If elevated levels of carbon dioxide have increased NPP in a way that affects the ability of equation (1) to balance the flow of carbon to and from the atmosphere, there should be a relation between the time series for the atmospheric concentration of CO_2 and the unknown carbon sink. Similarly, we evaluate the effect of temperature on the net flow of carbon to and from the atmosphere by testing for a relation between MISS and various components of surface temperature. Because the time series for the unknown carbon sink is a book-keeping phenomenon with no physically meaningful effect on concentrations, emissions, or temperature, the models specify MISS as an endogenous variable that is a function of exogenous variables in the **X** vector.

[7] We recognize that the time series for carbon uptake by the unknown sink and the possible explanatory variables (*X*) contain considerable uncertainty. For example, measurements of surface temperature after 1900 are more reliable than measurements between 1860 and 1900 [*Jones*, 1994; *Trenberth et al.*, 1992]. Similarly, the data for atmospheric CO_2 estimated from ice cores have less year-to-year variation than observations from Mauna Loa, which start in 1959 [*Craig et al.*, 1997]. To account for the effects of measurement error, we estimate the statistical models in Table 1 with data from three sample periods: (1) the entire period for which all data are available (1860–1990); (2) the more reliable portion of the temperature data (1900–1990); and (3) the period for which direct measurements of atmospheric CO_2 concentrations are available (1959–1990). If the regression results are consistent across the three sample periods, we can conclude that measurement error in the data has relatively little effect on the results.

[8] Statistical models do not establish causal relations in a physical sense, but they do allow us to test competing hypotheses for the unknown carbon sink at temporal and spatial scales in ways that field experiments and simulation models cannot. Field experiments are run at a very small scale: extrapolating effects measured from single leaves or eddy flux towers to the flows of the global carbon cycle are fraught with uncertainties such as how limiting factors change with scale [e.g., *Baldocchi and Hanley*, 1995; *Ruimy et al.*, 1996]. At the global scale, process-based models can simulate the effect of climate change, changes in land use, and elevated levels of atmospheric CO_2 on net carbon exchange between the terrestrial biosphere and atmosphere [*McGuire et al.*, 2001]. But these models have not been

Table 1. Time Series Definitions

Models	Time Series in the **X** Vector
Model 1	CO_2
Model 2	$\ln(CO_2)$
Model 3	$MISS_\infty / \left(1 + ae^{bCO_2}\right)$
Model 4	ΔCO_2
Model 5	$\Delta Ln(CO_2)$
Model 6	$\Delta MISS_\infty / \left(1 + ae^{bCO_2}\right)$
Model 7	ECO_2
Model 8	ΔECO_2
Model 9	ΔECO_2 SSTNHEM
Model 10	ΔECO_2 SSTSHEM
Model 11	ΔECO_2 LNDSHEM
Model 12	ΔECO_2 LNDNHEM
Model 13	ΔECO_2 NHWTR
Model 14	ΔECO_2 NHSPR
Model 15	ΔECO_2 NHFALL
Model 16	ΔECO_2 NHSUM
Model 17	$\Delta EFFCO_2$ $\Delta EBIOCO_2$ LNDNHEM

Mnemonic	Definition
CO_2	atmospheric concentrations of carbon dioxide [*Keeling and Whorf*, 1994; *Etheridge et al.*, 1996]
ΔCO_2	first difference atmospheric concentrations of carbon dioxide
ECO_2	anthropogenic emissions of carbon dioxide [*Houghton and Hackler*, 1999; *Marland and Rotty*, 1984]
$MISS_\infty$	asymptote for MISS in the logistic model (estimated parameter)
ΔECO_2	first difference anthropogenic emissions of carbon dioxide
$\Delta EFFCO_2$	first difference emissions of carbon dioxide from fossil fuels [*Marland and Rotty*, 1984]
$\Delta EBIOCO_2$	first difference emissions of carbon dioxide from biotic sources [*Houghton and Hackler*, 1999]
LNDNHEM	land surface temperature Northern Hemisphere [*Nicholls et al.*, 1996; *Parker et al.*, 1994]
LNDSHEM	land surface temperature Southern Hemisphere [*Nicholls et al.*, 1996; *Parker et al.*, 1994]
SSTNHEM	sea surface temperature Northern Hemisphere [*Nicholls et al.*, 1996; *Parker et al.*, 1994]
SSTSHEM	sea surface temperature Southern Hemisphere [*Nicholls et al.*, 1996; *Parker et al.*, 1994]
NHWTR	Northern Hemisphere temperature winter [*Nicholls et al.*, 1996; *Parker et al.*, 1994] (Jan., Feb., March)
NHSPR	Northern Hemisphere temperature spring [*Nicholls et al.*, 1996; *Parker et al.*, 1994] (April, May, June)
NHSUM	Northern Hemisphere temperature summer [*Nicholls et al.*, 1996; *Parker et al.*, 1994] (July, Aug., Sept.)
NHFALL	Northern Hemisphere temperature fall [*Nicholls et al.*, 1996; *Parker et al.*, 1994] (Oct., Nov., Dec.)

validated extensively. Sensitivity analyses indicate that "large uncertainties still exist for mechanistic modeling of global vegetation activity" [*Knorr and Heimann*, 2001].

[9] To avoid these difficulties, we analyze relations among time series using statistical techniques. Following this approach, hypotheses about the mechanisms that underlie the unknown carbon sink are consistent with the historical record if regression results indicate a statistically significant relation between the time series for the unknown carbon sink and the variable used to represent a possible mechanism. Conversely, the lack of a statistically significant relation indicates that the hypothesized mechanism is not consistent with the historical record. The global scale of the time series allows us to avoid the conceptual and practical difficulties associated with scaling results from field experiments. Direct testing against the observational record allows us to avoid the uncertainty in simulation models.

[10] The statistical models used to test the relation between the unknown carbon sink and possible explanatory variable(s) can be estimated most simply using OLS. But results generated by OLS must be interpreted with caution. OLS tends to overstate the statistical significance of the relation among nonstationary variables. The nature of this overstatement and statistical techniques that can cope with it are described in section 3.

3. Time Series Properties and Statistical Techniques

3.1. Time Series Properties

[11] The relation between two variables, x and y, can be specified most simply with a linear model. A linear model is given by:

$$y_t = \alpha + \beta x_t + \mu_t, \tag{2}$$

in which y_t is the value of time series y at time t, x_t is the value of time series x at time t, μ is a normally distributed

Table 2. ADF Tests[a]

Variable	$p = 3$[b]	$p = 4$
MISS	−1.87	−1.83
ΔMISS	**−5.28**	**−4.84**
CO_2	1.11	0.62
ΔCO_2	−0.51	−0.50
$\Delta^2 CO_2$	**−7.53**	**−5.73**
ECO_2	0.62	0.73
ΔECO_2	−3.21	−2.86
$\Delta^2 CO_2$	**−8.42**	**−7.68**
$EFCO_2$	0.29	0.48
$\Delta EFFCO_2$	**−3.58**	−3.31
$\Delta^2 EFFCO_2$	**−7.97**	**−8.26**
$EBIOCO_2$	−1.13	−1.14
$\Delta EBIOCO_2$	**−4.41**	**−3.65**
LNDHEM	−3.25	−2.60
ΔLNDNHEM	**−9.83**	**−7.45**
LNDSHEM	−3.36	−3.07
ΔLNDSHEM	**−8.54**	**−7.49**
SSTNHEM	−3.30	−2.69
ΔSSTNHEM	**−8.47**	**−7.55**
SSTSHEM	−3.13	−2.77
ΔSSTSHEM	**−8.26**	**−6.82**
WINTER	**−3.98**	−3.43
ΔWINTER	**−9.12**	**−7.79**
SPRING	**−3.55**	−2.91
ΔSPRING	**−8.83**	**−8.44**
SUMMER	−2.32	−2.23
ΔSUMMER	**−8.31**	**−7.71**
FALL	**−4.05**	−3.31
ΔFALL	**−9.83**	**−7.21**

[a]Entries are ADF t statistics. Sample: 1866–1990. Values in bold exceed the 0.05 threshold.

[b]The column heading "p = 3" indicates the number of lags used to compute the ADF test. The tests for a unit root in levels include a constant and a linear time trend; the tests for first differences include a constant only. The 5% critical value is −3.45.

random error term with a mean value of zero, and α and β are regression coefficients. Values for α and β can be estimated from observational data using OLS. OLS calculates point estimates for α and β that minimize the sum of the error squared.

[12] One way to evaluate the statistical significance of the relation between x and y is to test whether the OLS estimate for β is statistically different from zero. The null hypothesis that the regression coefficient (β) equals zero is evaluated with a test statistic that is calculated by dividing the OLS estimate for the regression coefficient (β) by its standard error. This ratio (commonly termed a t-test) is evaluated against a t distribution. If the t statistic exceeds the value associated with a critical threshold, usually $p < 0.05$, this result indicates that the null hypothesis is rejected and that the coefficient is not equal to zero. Under these conditions, variables x and y are said to be related in a statistically significant manner.

[13] Interpreting the t statistics (and other diagnostic statistics) generated by OLS is based on several assumptions. Among the most important (for this analysis) is the assumption that the time series (x, y) and/or the regression error (μ) is stationary. A stationary time series has a constant mean. That is, the mean value for a subsample of the time series does not differ from the mean for the entire sample period. If time series being analyzed are stationary (and satisfy the other assumptions that underlie the use of OLS), the t statistic estimated by OLS will falsely reject the null hypothesis $\beta = 0$ at $p < 0.05$ about 5% of the time.

[14] This result can be illustrated using Monte Carlo techniques in which realizations for two time series, x and y, are created by drawing randomly 50 times from a normal distribution that has a mean value of zero and a standard deviation of 1.0. This process can be repeated 100 times to create 100 realizations for the time series for x and y (each realization of x and y has 50 observations). Based on the way in which x and y are created, there should be no relation between x and y: we should not be able to reject the null hypothesis that $\beta = 0$. This hypothesis can be evaluated for each of the 100 time series for x and y by estimating equation (2) using OLS. The OLS estimate for β (and its standard error) is such that there is no statistically meaningful relation between x and y in about 95 of the 100 relations analyzed. This expectation is illustrated by the results for one realization of x and y (Figure 2a). For this realization, the t statistic associated with β is 0.9 ($p < 0.38$).

[15] If we relax the assumption of stationarity, the ability to use the t statistic (and other diagnostic statistics) to evaluate the relation between variables estimated by OLS changes dramatically. To demonstrate this change, we repeat the Monte Carlo simulation using nonstationary time series. A nonstationary time series is defined by changes in its mean over time. That is, the mean value for one subsample is different from the mean value for another subsample. The simplest example of a nonstationary time series is a random walk, which is given as follows:

$$Z_t = \lambda Z_{t-1} + \varepsilon_t, \tag{3}$$

in which Z_t is the value of the time series Z at time t, Z_{t-1} is the value of Z in the previous period, λ is an autoregressive coefficient equal to 1.0, and ε is a number drawn randomly from a normal distribution (normality and randomness are not required to generate the results that follow).

[16] The data generating process given by equation (3) creates a time series Z which does not have a constant mean. Instead, Z may meander away from its mean for extended periods. These movements may make it appear as though the time series contains a trend. Such trends are termed stochastic trends because their movements are generated by the cumulative effects of stochastic changes.

[17] Movements in nonstationary time series are generated by the fact that the variable Z has memory. The autoregressive coefficient of $\lambda = 1.0$ implies that the time series' memory extends back ad infinitum. That is, the value of a nonstationary variable at any point of time depends on the entirety of its history.

[18] The ability of "memory" to generate a stochastic trend can be illustrated by using equation (3) to generate nonstationary time series. To do so, we sum the normally distributed random variables x and y using equations (4) and (5)

$$X_t = X_{t-1} + x_t = \sum_{t=0}^{T} x_t \tag{4}$$

$$Y_t = Y_{t-1} + y_t = \sum_{t=0}^{T} y_t, \tag{5}$$

in which X and Y are nonstationary variables that contain a stochastic trend. Two realizations of a nonstationary time series, which are generated from the random variables in Figure 2a, are shown in Figure 2b. A nonstationary variable with a stochastic trend is said to be integrated order 1 (i.e., $I(1)$). An $I(1)$ variable must be differenced one time to make it stationary $I(0)$. That is, the first difference of X and Y will generate x and y, which are stationary. Similarly, an $I(2)$ variable must be differenced two times to make it stationary.

3.2. Spurious Regressions

[19] The presence of stochastic trends in X and Y undermines the results generated by OLS. Repeating the Monte Carlo experiment with 100 realizations of X and Y generates results remarkably different from those obtained from the 100 realizations of stationary variables x and y. Using OLS to estimate the relation between X and Y from Figure 2b as follows:

$$Y_t = \alpha + \beta X_t + \mu_t \tag{6}$$

generates a t value for $\beta(-0.45)$ of 5.2, which has a significance level of $p < 0.00001$ when evaluated against a standard t distribution. This rejection of the null hypothesis is not a fluke. About 80 of the 100 regressions of X and Y generate a t statistic for β that exceeds the 0.05 threshold.

[20] The tendency of standard diagnostic statistics to overstate the significance of regression results estimated by OLS from nonstationary variables is described by *Granger and Newbold* [1974]. They term such results as

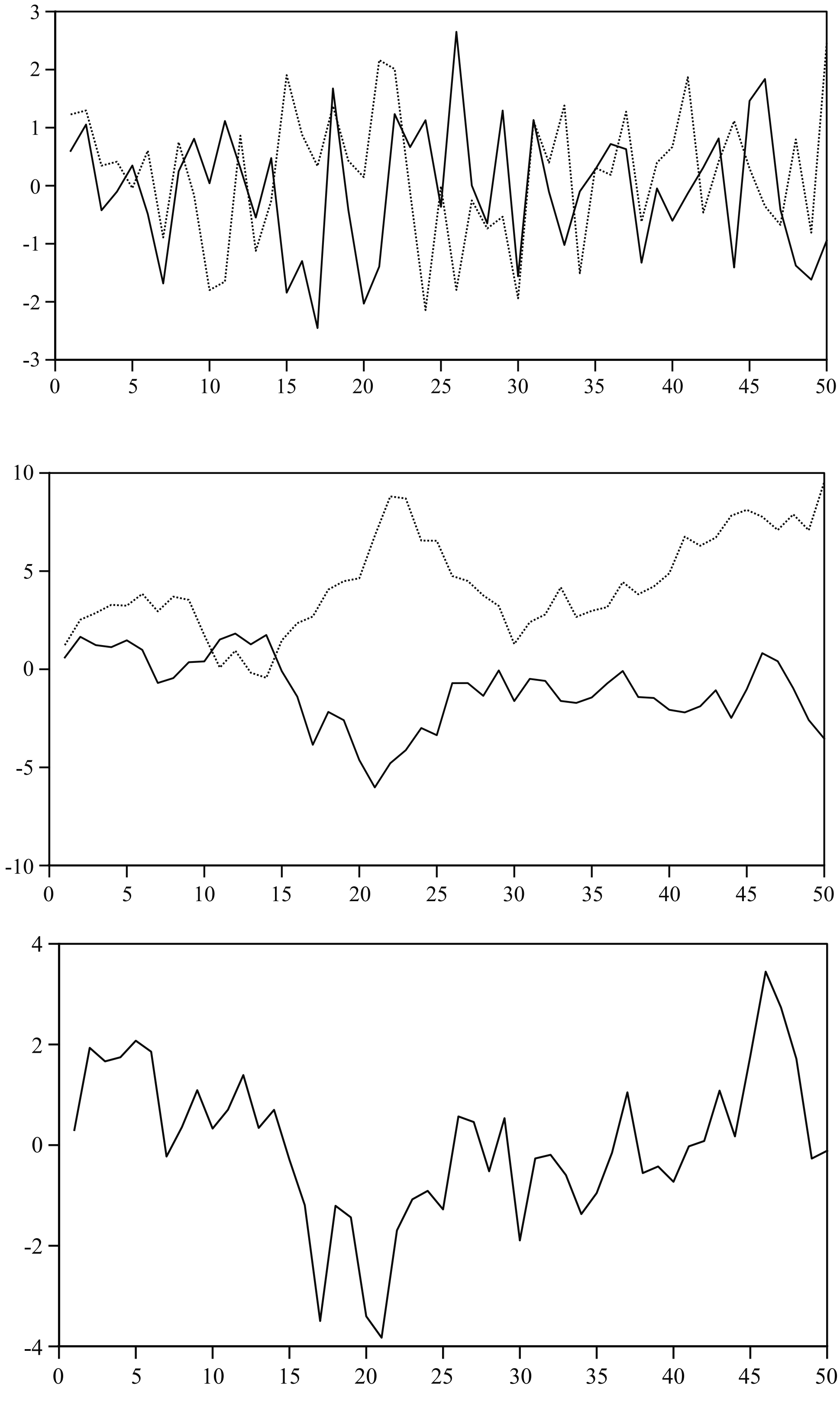

Figure 2. (a) Realizations for two normally distributed random variables x (solid line) and y (dotted line). (b) Realizations for two variables with a stochastic trend X (solid line) and Y (dotted line) that are calculated from the x and y variables in Figure 2a using equations (4) and (5). (c) The residual from an OLS regression of X and Y as given by equation (6).

spurious regressions. When evaluated against standard distributions, the correlation coefficients and t statistics for a spurious regression are likely to indicate a significant relation among variables when none may exist.

[21] To avoid misinterpreting spurious regression results, *Engle and Granger* [1987] define the notion of cointegration. A group of nonstationary variables is said to cointegrate if there is at least one linear combination of the variables that is stationary. That is, if X and Y are related to one another, they will share the same stochastic trend. If they share the same stochastic trend, there will be at least one way to combine X and Y such that the residual from equation (6) is stationary. But if X and Y are not truly related (or if the regression omits a statistically meaningful nonstationary variable), the residual will contain a stochastic trend. Returning to our example, the residual from the regression of X and Y in Figure 2b seems to contain a stochastic trend (Figure 2c). This implies that X and Y are not related even though the t statistic suggests that they are related. The presence or lack of cointegration allows analysts to use stochastic trends as "fingerprints" to detect relations among nonstationary variables.

3.3. Statistical Analysis of Cointegrating Relations

[22] The need to establish cointegration adds several steps to the statistical analysis of nonstationary time series. In the first step, analysts use the Augmented Dickey Fuller statistic (ADF) to determine whether the time series contain a stochastic [*Dickey and Fuller*, 1979]. Other test statistics are available, but the ADF performs well relative to other test statistics [*Stock*, 1994]. The model for the ADF test is:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{I=1}^{s} \delta_i \Delta y_{t-i} + \varepsilon_t, \tag{7}$$

in which y is the variable under investigation, Δ is the first difference operator (i.e., $y_t - y_{t-1}$), t is a linear time trend (which is used to represent a possible deterministic trend), s is the number of lags for Δy used to correct for possible serial correlation, ε is a random error term, and the coefficient γ is equivalent to $\lambda - 1$ in equation (3).

[23] The null hypothesis for the ADF test is that the series contain a stochastic trend. The ADF test evaluates the null, $\gamma = 0$, i.e., $\lambda = 1$ by comparing the t statistic for γ against a nonstandard distribution that was developed specifically for the ADF test [*MacKinnon*, 1994]. If the null hypothesis for the undifferenced series is rejected, then the original series y is $I(0)$: it is stationary. If the hypothesis for the differenced series is rejected, then the original series y is $I(1)$: it is nonstationary. Similarly, a series y is $I(2)$ if only the second difference of the series Δy is found to be $I(0)$.

[24] Results of the ADF test indicate that the time series for MISS and possible explanatory variables contain a stochastic trend (Table 2). This result may be surprising. Traditionally, climate models do not model temperature as a variable that contains a stochastic trend because the effects of innovations do not fade over time. As such, the temperature in the control simulations would be inherently unstable with no tendency to return to a long-run mean.

[25] This seeming contradiction with the historical record is reconciled by identifying the source of the stochastic trend in temperature. The stochastic trend in temperature simulated by climate models is introduced with processes that are driven by human activity and processes by which the atmosphere accumulates CO_2. Anthropogenic emissions of CO_2 are determined by economic activity. The economic literature is replete with studies that indicate gross domestic product and its components contain a stochastic trend; therefore carbon emissions embody these stochastic trends. Similarly, the long residence time of CO_2 implies that the atmosphere integrates emissions. This can introduce a stochastic trend in the time series for atmospheric CO_2, the corresponding values for radiative forcing, and ultimately surface temperature [*Kaufmann and Stern*, 2002].

[26] Because the time series for MISS and its possible explanatory variables contain a stochastic trend, the presence or absence of a statistically meaningful relation between variables is evaluated by whether they cointegrate. Following a well-established method to determine whether two (or more) variables cointegrate [*Engle and Granger*, 1987], OLS is used to estimate equation (6). The residual (μ) is analyzed for a stochastic trend using the ADF. If the ADF fails to reject the null hypothesis, the residual contains a stochastic trend. This result indicates one of two possibilities: (1) the variables in the regression are not related to each other in a statistically meaningful way; or (2) the variables share a stochastic trend (and are related) but do not cointegrate (eliminate the stochastic trend) because the dependent variable contains one or more stochastic trends that are not present in the regressors. Regardless of the cause, a nonstationary residual indicates that the regression is spurious. Continuing with the analysis of the relation between X and Y from Figure 2b, the ADF tests fails to reject the null hypothesis that the residual in Figure 2c contains a stochastic trend (ADF 2.26, $p < 0.65$). This result implies that X and Y do not cointegrate. Without cointegration, the relation between X and Y indicated by the OLS estimate of equation (6) is spurious, which is consistent with how the time series are generated.

[27] If the residual does not contain a stochastic trend (i.e., it is stationary), OLS can be used to estimate the relation between MISS and its explanatory variable. The OLS estimate for β in equation (6) represents the long-run relation among the nonstationary variables, which is termed the cointegrating relation, and will be "superconsistent" [*Stock*, 1987]. That is, the OLS estimate for β converges to its true value faster than usual. Nonetheless, the OLS estimate of the cointegrating vector will contain a small sample bias and the limiting distribution is nonnormal with a nonzero mean [*Stock*, 1987].

[28] Because of this bias, we supplement OLS results with those generated by statistical techniques that are designed to analyze the relation among nonstationary variables. These techniques include the dynamic ordinary least squares (DOLS) estimator developed by *Stock and Watson* [1993] and the full information maximum likelihood estimator of a vector error correction model developed by *Johansen*

[1988] and *Johansen and Juselius* [1990]. DOLS generates asymptotically efficient estimates of the regression coefficients for variables that cointegrate using the following specification:

$$\mathrm{MISS}_t = \alpha + \beta X_t + \sum_{i=-s}^{s} \theta_s \Delta X_{t+s} + \mu_t, \tag{8}$$

in which the elements of β represent the long-run relation among variables. The number of lags and leads (s) for the first differences of the dependent variables are chosen using the Akaike Information criterion [*Akaike*, 1973]. Equation (8) can be estimated using either OLS (DOLS) or generalized least squares (DGOLS). Monte Carlo experiments indicate that estimates for β have less bias than the OLS estimate of equation (6), but still have some bias, especially in small samples. Furthermore, the lags and leads of the first differences are nuisance parameters. As such, the DOLS estimator does not represent the short-run dynamics of the relation between MISS and the variables in the **X** vector (This is not necessary for an asymptotically efficient estimation of the cointegrating relation).

[29] To estimate both the long- and short-run relation between MISS and its explanatory variables, we use a full information maximum likelihood procedure to estimate a vector error correction model (VECM):

$$\Delta\mathrm{MISS}_t = \alpha(\beta_1 \mathrm{MISS}_{t-1} + \beta_2 X_{t-1}) + \sum_{i=1}^{s} \lambda_i \Delta\mathrm{MISS}_{t-i} + \sum_{i=0}^{s} \phi_i \Delta X_{t-i} + \mu_t, \tag{9}$$

in which the short-run relation between MISS and the nonstationary explanatory variables is represented by their first differences.

[30] Equation (9) specifies the first difference of MISS, which is stationary, as a function of linear lagged values of the first difference of the nonstationary variables, which also are stationary, and stationary combinations of the nonstationary variables, which represent the long-term relations among variables. The long-run relation among variables is given by the elements of β (β_1, β_2), and is termed the cointegrating vector. The rate at which MISS responds to disequilibrium in the long-run relation is given by α. For example, a value of -0.25 would indicate that 25% of disequilibrium in the long-run relation between MISS and the variables in X is eliminated each period.

[31] We chose the number of lagged first differences to include in equation (9) using the Schwartz and Hannon-Quinn information criteria [*Hansen and Juselius*, 1995]. We test for the presence of a cointegrating relation using the λ_{trace} and $\lambda_{\max}$ statistics [*Johansen*, 1988; *Johansen and Juselius*, 1990]. To evaluate whether elements of β are equal, we impose restrictions that are evaluated with a likelihood ratio test, which is distributed as a χ^2 with degrees of freedom equal to the number of restrictions.

[32] Monte Carlo simulations indicate that no single efficient estimator, DOLS, or the maximum likelihood estimator of the VECM, is best [*Stock*, 1994]. Rather than rely on a single estimation technique, we evaluate the degree to which the results are robust by using both efficient estimators and OLS to estimate the relation between MISS and explanatory variables (X) for models in which the variables cointegrate. If MISS and the variables in the **X** vector cointegrate (i.e., are related in a statistically meaningful fashion), the estimates for the long-run relation should be similar across the three estimation techniques.

[33] Using cointegration to identify relations among variables allows us to avoid pitfalls that are associated with analyzing time series that contain considerable uncertainty. This uncertainty may take two forms. If the uncertainty in the time series is stationary (e.g., white noise), it will not affect tests for cointegration, and therefore will not affect our conclusions about the presence of a statistically meaningful relation among variables. Systematic errors in the data (e.g., stochastic trends) will tend to prevent cointegration because there will be no way to eliminate the stochastic trends associated with the errors. Under these conditions, systematic errors will obfuscate statistical estimates of physically meaningful relations rather than create relations where none exist. Systematic errors will falsely indicate cointegration only if the same systematic error is present in the time series for MISS and its explanatory variables, such as anthropogenic carbon emissions, atmospheric concentrations of CO_2, and temperature. Given the very different methods used to measure and compile these time series, it is highly unlikely that these series contain the same systematic error (it is possible that the measure for the unknown carbon sink and measurement errors in emissions are correlated: the effect of this possible correlation is described in section 4.4). Thus it is highly unlikely that the cointegrating relations described in the next section are created by stationary and/or nonstationary errors in the data. Indeed, the emphasis on cointegration, the use of three estimation techniques, and three sample periods provide a series of safeguards against bad data and spurious regression results. If the relation between MISS and the variables in the **X** vector is meaningful, the statistical results will be similar across the three sample periods and three estimation techniques.

4. Results

4.1. Elevated Levels of Atmospheric CO_2

[34] Elevated concentrations of atmospheric CO_2 may drive the unknown carbon sink by increasing terrestrial NPP and/or by increasing oceanic uptake in a way not simulated by models. We test these hypotheses by examining the relation between MISS and the atmospheric concentration of CO_2. Visual inspection indicates that there is no clear relation between the atmospheric concentration of CO_2 and the unknown carbon sink (Figure 1). Notably, the atmospheric concentration of CO_2 rises rapidly between 1970 and 1990. During this period, there is little increase (in absolute terms) in carbon uptake by the unknown carbon sink.

[35] This visual impression is tested statistically by estimating the relation between MISS and the atmospheric

Table 3. Tests of Cointegration: Entries are ADF Statistics

$p = 2$[a]	$p = 3$	$p = 4$	Sample Period
		Model 1	
−1.87	−2.07	−2.05	1866–1990
−1.27	−1.79	−1.66	1900–1990
−1.76	−2.21	−1.80	1959–1990
		Model 2	
−1.91	−2.09	−2.05	1866–1990
−1.40	−1.92	−1.78	1900–1990
−1.77	−2.22	−1.80	1959–1990
		Model 3	
0.074	−0.15	−0.17	1866–1990
0.02	−0.06	−0.16	1900–1990
−1.79	−2.24	−1.81	1959–1990
		Model 4	
−2.47	−1.86	−1.76	1866–1990
−1.96	−1.26	−1.00	1900–1990
−3.84[b]	−3.58	−3.03	1959–1990
		Model 5	
−2.62	−2.14	−2.08	1866–1990
−2.16	−1.51	−1.27	1900–1990
−4.04[b]	−3.84[b]	−3.28	1959–1990
		Model 6	
−3.11	−2.45	−2.29	1866–1990
−3.26	−2.48	−2.34	1900–1990
−2.42	−1.85	−1.75	1959–1990
		Model 7	
0.20	−0.59	−0.66	1866–1990
0.82	0.18	0.25	1900–1990
−1.76	−2.13	−1.79	1959–1990
		Model 8	
−5.10[c]	−4.96[c]	−4.81[c]	1866–1990
−4.61[c]	−4.59[c]	−4.51[c]	1900–1990
−2.17	−2.97	−3.02	1959–1990

[a]The column heading "$p = 2$" indicates the number of lags used to compute the ADF test.
[b]Value exceeds the 0.05 threshold. Significance level computed from *MacKinnon* [1994].
[c]Values exceed the 0.01 threshold. Significance level computed from *MacKinnon* [1994].

concentration of CO_2. The relation may be specified using three functions; linear, logarithmic, and logistic [*Moore and Braswell*, 1994]. Analysis of the regression errors for a linear relation between MISS and CO_2 (model 1) indicates that the time series for the atmospheric concentration of CO_2 does not cointegrate with the time series for the unknown carbon sink. The ADF statistic fails to reject the null hypothesis that the residual from model 1 has a stochastic trend regardless of the sample period (Table 3). The lack of cointegration indicates that: (1) the atmospheric concentration of CO_2 is not related linearly to the unknown carbon sink; or (2) there is a relation, but it cannot be estimated reliably because model 1 omits some other nonstationary variable(s).

[36] Alternatively, model 1 may not cointegrate because it is specified incorrectly. The effect of elevated concentrations of carbon dioxide may saturate at higher levels if NPP becomes limited (in a Liebigian sense) by a factor other than atmospheric CO_2 as the concentration of CO_2 rises. To evaluate this possibility, we specify the atmospheric concentration of carbon dioxide using a natural log. According to this specification (model 2), the effect of an increase in atmospheric CO_2 diminishes as its concentration increases. The results of the ADF test indicate that we cannot reject the null hypothesis and that the residual from model 2 has a stochastic trend (Table 3). Again, this indicates that there is no statistically meaningful relation between atmospheric concentration of carbon dioxide and the unknown carbon sink or some other nonstationary variable has been omitted from model 2.

[37] Alternatively, we estimate the relation between CO_2 and MISS using a logistic function (model 3). Due to its nonlinear nature, the asymptote for the logistic equation ($MISS_\infty$) is estimated using an iterative grid search procedure [*Kaufmann*, 1991]. Regardless of the asymptote chosen or sample period, none of the ADF tests reject the null hypothesis that the regression residual contains a stochastic trend (Table 3). These results indicate that a logistic function cannot be used to represent a statistically meaningful relation between CO_2 and the unknown carbon sink.

[38] Finally, elevated levels of atmospheric CO_2 may not have a long-run effect on net carbon uptake by the terrestrial biosphere and/or the ocean. Rather, the vegetation, ocean, and/or soil pools may acclimate to elevated concentrations of carbon dioxide such that there is only a short-run effect. To test whether atmospheric CO_2 has a short-run effect on unknown carbon sink, we check for cointegration between the first difference of concentrations and MISS (model 4). Using the first differences to represent the short-run effects of atmospheric CO_2 is based on the error correction model. As described in the previous section, the VECM (equation (9)) specifies short-run effects using first differences of the variables. As indicated by the results of Table 3, there is no consistent evidence that the unknown carbon sink cointegrates with the first differences of atmospheric concentrations of CO_2 regardless of how the atmospheric concentration of CO_2 is specified: linear (model 4), logarithmic (model 5), or logistic (model 6). Together, these results indicate that there is no statistical evidence to support the hypothesis that the atmospheric concentration of CO_2 is related to the mechanism for the unknown carbon sink at the global scale in the long or short run.

4.2. Carbon Emissions

[39] Carbon emissions may drive the unknown carbon sink by changing the rate at which carbon flows from the atmosphere to the ocean. A simplified response function indicates that oceanic carbon uptake can be represented by the atmospheric concentration of CO_2 and the size of the pulse (i.e., carbon emissions) to the atmosphere [*Joos et al.*, 1996]. The effect of emissions on oceanic carbon uptake is thought to be small. *Bruno and Joos* [1997] find that emissions have a relatively minor effect on the rate of carbon uptake simulated by ocean models. If the effect of carbon emissions is larger than indicated by models, this component of ocean uptake would appear as part of the unknown carbon sink in equation (1).

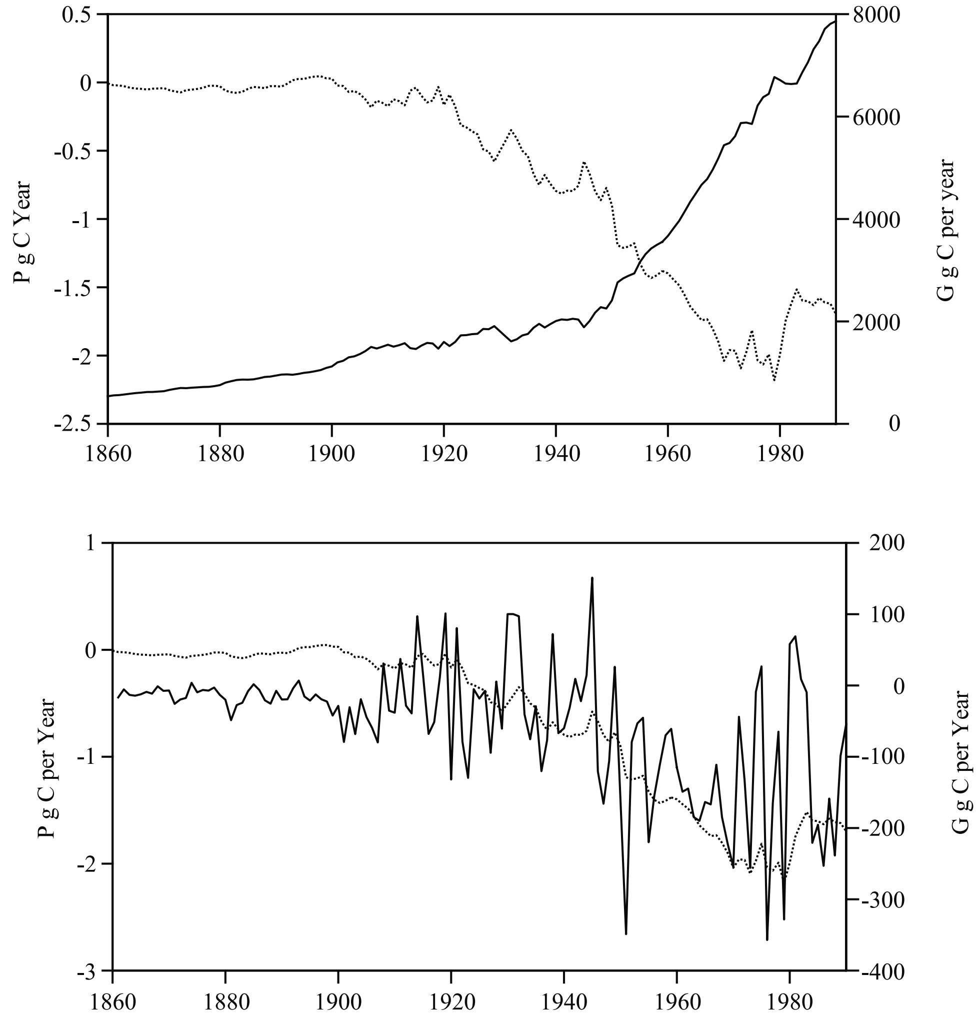

Figure 3. (a) The time series for the unknown carbon sink (dotted line, left axis) and the time series for the anthropogenic emissions of carbon dioxide (solid line, right axis). (b) The time series for the unknown carbon sink (dotted line, left axis) and the time series for the negative values for the first difference of anthropogenic CO_2 emissions (solid line, right axis). Negative values are used to highlight the relation between variables.

[40] We evaluate the relation between carbon emissions and the unknown carbon sink using model 7. Visual inspection of the time series indicates that the unknown carbon sink is not related to carbon emissions (Figure 3a). Carbon emissions increase rapidly between 1970 and 1990, but the absolute rate of uptake by the unknown carbon sink does not increase significantly during this period. Consistent with this visual impression, carbon emissions do not cointegrate with the unknown carbon sink regardless of the sample period used to estimate model 7 (Table 3). This result indicates that there is no long-run relation between carbon emissions and the unknown carbon sink or that model 7 fails to include a statistically important nonstationary explanatory variable.

[41] On the other hand, it appears that there is a short-run relation between carbon emissions and the unknown carbon sink. Visual inspection indicates that the first difference of emissions (ΔECO_2) is similar to carbon uptake by the unknown carbon sink (Figure 3b). The unknown carbon sink and negative values (negative values are used to ease the visual comparison) for the first difference in carbon emissions increase between 1930 and 1960. Since 1960, both series are relatively stable.

[42] Consistent with this visual interpretation, the first difference of carbon emissions (ΔECO_2) cointegrates with MISS (model 8). The ADF statistic strongly rejects the null hypothesis that the residual from model 8 has a stochastic trend for the 1860–1990 and 1900–1990 periods (Table 3). The results for the 1959–1990 period fail to reject the null hypothesis that the residual from model 8 contains a stochastic trend.

[43] The lack of cointegration during the most recent period probably is related to the failure of the ADF test in small samples, and not to the changes in the frequency of emissions data. The 1959–1990 sample has 31 observations. For such small samples, the ADF test does not

Table 4. Regression Results[a]

	ΔECO_2			Temperature		
Period	OLS	DOLS	FIML	OLS	DOLS	FIML
			Model 9			
1850–1990	−6.75[b]	**−11.94**	**−15.66**	−0.30	−0.30	−0.36
1900–1990	−6.78[b]	**−12.02**	**−15.60**	−0.32	−0.14	−0.07
1959–1990	−8.19[b]	**−13.03**	**−14.20**	−0.05	**3.49**	−1.24
			Model 10			
1850–1990	−6.72[b]	**−11.93**	**−16.02**	−0.05	**−0.31**	−0.30
1900–1990	−6.73[b]	**−11.90**	**−15.96**	0.01	−0.28	−0.05
1959–1990	−8.17[b]	**−13.31**	**−14.24**	−0.32	**−2.83**	−1.41
			Model 11			
1850–1990	−6.70[b]	**−12.01**	**−16.08**	0.01	−0.35	−0.54
1900–1990	−6.70[b]	**−11.86**	**−15.98**	0.12	−0.19	−0.26
1959–1990	−8.19[b]	**−13.21**	**−14.12**	−0.20	−2.16	−0.01
			Model 12			
1850–1990	−6.84[b]	**−12.05**	**−15.60**	*−0.35*	**−0.47**	**−0.70**
1900–1990	−6.91[b]	**−12.06**	**−15.54**	−0.59	**−0.61**	*−0.90*
1959–1990	−8.27[b]	**−13.13**	**−14.11**	−1.23	**−1.14**	**−2.86**
			Model 13			
1850–1990	−6.79[b]	**−12.04**	**−15.93**	−0.14	−0.27	−0.39
1900–1990	−6.83[b]	**−11.94**	**−15.74**	−0.15	−0.14	−0.15
1959–1990	−8.30[b]	**−13.43**	**−14.61**	−0.48	**−0.46**	−1.63
			Model 14			
1850–1990	−6.74[b]	**−11.91**	**−15.49**	−0.39	**−0.51**	−0.70
1900–1990	−6.76[b]	**−11.93**	**−15.47**	−0.49	−0.39	−0.47
1959–1990	−7.95[b]	**−12.71**	−13.13	−1.77	*−2.91*	*−7.56*
			Model 15			
1850–1990	−6.77[b]	**−12.01**	**−15.73**	−0.21	**−0.37**	−0.43
1900–1990	−6.80[b]	**−12.03**	**−15.70**	−0.28	−0.36	−0.23
1959–1990	−8.27[b]	**−13.00**	**−14.09**	−0.93	−0.01	0.052
			Model 16			
1850–1990	−6.57[b]	**−11.65**	**−15.10**	−0.94[b]	**−0.87**	**−1.15**
1900–1990	−6.55[b]	**−11.74**	**−14.81**	−1.12[b]	**−0.81**	−1.06
1959–1990	−7.65[b]	**−13.10**	**−13.46**	−1.93	0.60	−2.30

[a]Bold values exceed the 0.05 threshold. Values in italics exceed the 0.10 threshold.

[b]Values that exceed the threshold when evaluated against a standard t distribution, but OLS cannot be evaluated reliably against the t distribution when the variables contain a stochastic trend. Significance level DOLS estimates are calculated from standard errors that are calculated using the procedure of *Newey and West* [1987] with four lags. Significance levels for the FIML estimates for the elements of β are evaluated by restricting its value to zero. These restrictions are evaluated with a χ^2 test with one degree of freedom. The cointegrating vector estimated by the FIML procedure is normalized by the element of β associated with MISS (β_1). This cointegrating relation is "solved" for MISS to derive the signs on the elements of β that can be compared to the OLS and DOLS results.

perform reliably [*Stock*, 1994]. On the other hand, the frequency of the emission data increases in the 1959–1990 period relative to the 1860–1990 and 1900–1990 periods. The reduction in temporal resolution of the emission data during the earlier periods would tend to obfuscate stochastic trends. This would cause ADF tests to reject cointegration for model 8 during earlier periods, rather than falsely indicating cointegration. Finally, estimates for β associated with ΔECO_2 for the 1959–1990 period are very similar to the corresponding values for the 1860–1990 and 1900–1990 periods, for which the lack of cointegration is clearly rejected (results not shown in Table 4 to save space). This similarity implies that MISS probably cointegrates with ΔECO_2 and that the lack of cointegration for the 1959–1990 period is a statistical artifact.

[44] Together, these results indicate that there is a statistically meaningful relation between the unknown carbon sink and the first difference of carbon emissions. No other variables are needed to eliminate the stochastic trend in the unknown carbon sink. This implies that models 1–3 fail to cointegrate because atmospheric concentrations of CO_2 are not related to the unknown carbon sink. Consistent with this hypothesis, the regression coefficients associated with the atmospheric concentration of CO_2 (linear, logarithmic, or logistic) generally are not statistically significant when added to model 8 (results not shown to save space).

4.3. Temperature

[45] Changes in temperature can drive the unknown carbon sink by causing models to misstate oceanic uptake or by altering net carbon exchange between the terrestrial biosphere and the atmosphere. We test hypotheses about the effect of temperature on the unknown carbon sink by estimating models that specify the first difference in carbon emissions and various components of sea and land surface temperature. These models retain the first difference in carbon emissions to ensure cointegration: without ΔECO_2, there is no cointegration and the regression results would be spurious.

[46] Global temperature is separated into spatial (by hemisphere and land/sea) and temporal (by season) components to test competing hypotheses regarding the effect of temperature on the unknown carbon sink. Sea surface temperature is specified to represent the effect of ocean temperature on oceanic uptake. If ocean models do not simulate the effect of ocean temperature on the rate of carbon uptake accurately, changes in sea surface temperature will be associated with the models' errors, and these errors will be part of the unknown carbon sink. Under these conditions, sea surface temperature for the Northern and/or Southern Hemisphere will correlate with the unknown carbon sink. This hypothesis is tested by estimating models 9 and 10. For both models, the regression coefficient associated with sea surface temperature in the Northern or Southern Hemisphere generally is not statistically different from zero and varies by estimation technique and sample period (Table 4). These results indicate that the unknown carbon sink probably is not associated with the inability of ocean models to simulate the effect of temperature on carbon uptake.

[47] Land surface temperature may affect net carbon exchange between the terrestrial biosphere and the atmosphere by altering rates of net primary production and/or heterotrophic respiration. The net effect of these two processes is represented by including land surface temperature in the Southern or Northern Hemisphere in models 11 and 12. The regression coefficient associated with land surface temperature in the Southern Hemisphere is not statistically significant and varies by estimation technique and sample period (Table 4). These results indicate that land surface temperature in the Southern Hemisphere does not have a measurable affect on net carbon exchange between the

terrestrial biosphere and the atmosphere. The lack of a relation is consistent with the distribution of land between hemispheres. Only a small portion of the total landmass is in the Southern Hemisphere, which implies that any changes in NPP and/or heterotrophic respiration would have a relatively small effect on the global concentration of carbon dioxide. Furthermore, most of the land in the Southern Hemisphere is located at low latitudes where surface temperature probably is not a limiting factor and therefore probably has relatively little effect on NPP or heterotrophic respiration.

[48] The regression coefficient associated with land surface temperature in the Northern Hemisphere (model 12) generally is statistically significant and is similar across estimation techniques and sample periods (Table 4). This result indicates that surface temperature affects net carbon exchange between the terrestrial biosphere and the atmosphere in a way that is partially responsible for the unknown carbon sink. The nature of this effect is indicated by the sign on the regression coefficient that is associated with Northern Hemisphere land surface temperature. For all models and periods, the regression coefficient associated with LNDNHEM is negative. The negative sign indicates that higher temperatures make MISS increasingly negative, which implies that the unknown carbon sink increases the amount of CO_2 it removes from the atmosphere and/or slows the rate at which carbon flows to the atmosphere. Because heterotrophic respiration generally increases with temperature, the negative sign implies that higher temperatures increase NPP relative to heterotrophic respiration such that increases in net carbon exchange by the terrestrial biosphere remove carbon from the atmosphere. The effect of land surface temperature in the Northern Hemisphere on the unknown carbon sink via the terrestrial biosphere is consistent with the distribution of land between hemispheres: most of the world's landmass is located in the Northern Hemisphere and much of this land is located at midaltitudes and high altitudes where temperature is likely to be a limiting factor.

[49] The hypothesis that the statistical relation between the unknown carbon sink and land surface temperature in the Northern Hemisphere represents the effect of temperature on net carbon exchange between the terrestrial biosphere and the atmosphere can be evaluated further by identifying the seasonal components (winter, spring, summer, or fall) of Northern Hemisphere (monthly data for land surface temperature in the Northern Hemisphere are not available) that are related to the unknown carbon sink. Results estimated using models 13–15 indicate that the coefficients associated with winter, spring, or fall temperature generally are not statistically different from zero (Table 4). Winter, spring, and/or fall temperatures probably have little relation to MISS if the unknown carbon sink is driven in part by temperature-induced increases in NPP by terrestrial vegetation.

[50] On the other hand, if the unknown carbon sink is driven by changes by temperature-induced increases in NPP relative to heterotrophic respiration, the effect of temperature should be largest during the summer, when NPP is greatest. Consistent with this hypothesis, the regression coefficient associated with summer temperature generally is statistically significant for the 1860–1990 and 1900–1990 sample period, regardless of the specification or estimation technique (Table 4). On the other hand, the temperature effects are not statistically significant during the 1959–1990 period. For the two longer periods, the estimate for the regression coefficient associated with summer temperature ranges between -0.81 and -1.15. This range of values indicates that a 1°C increase in Northern Hemisphere summer surface temperature increases net carbon exchange between the terrestrial biosphere and the atmosphere by about 1 Pg C annually in the long run.

4.4. Forest Dynamics and Nitrogen Deposition

[51] Forest dynamics and/or nitrogen deposition may drive the unknown carbon sink. If scientists systematically understate reforestation and/or overstate deforestation, they may systematically overstate biotic carbon emissions and thereby create the unknown carbon sink term in equation (1). Alternatively, the unknown carbon sink may be related to nitrogen deposition. Burning fossil fuels generates nitrogen oxides, and their deposition may alleviate limits imposed by nitrogen, which is the limiting nutrient in many terrestrial ecosystems. According to this hypothesis, increased rates of fossil fuel combustion increase NPP, which increases the rate at which terrestrial vegetation removes carbon from the atmosphere.

[52] We evaluate these hypotheses by disaggregating the $\Delta E\mathrm{CO_2}$ term from model 8 and testing whether the first difference in emissions from fossil fuels ($\Delta E\mathrm{FFCO_2}$) and the terrestrial biota ($\Delta E\mathrm{BIOCO_2}$) contribute equally to the unknown carbon sink. This test assumes that the unknown sink does not discriminate between carbon emitted by fossil fuel and biotic sources. Based on this assumption, the sink will take up the carbon emitted by fossil fuels and changes in land use in proportion to the first differences of their respective emissions. On the other hand, nitrogen deposition is associated with carbon emissions from fossil fuels while measurement errors for deforestation and/or forest regrowth are associated with biotic carbon emissions. If these mechanisms are an important component of the unknown carbon sink, these emission-specific mechanisms will disrupt the proportional relation between the unknown carbon sink and the first difference of fossil fuel and biotic carbon emissions.

[53] We can differentiate between the effects of the first difference of biotic and fossil fuel carbon emissions on the unknown carbon sink because these two time series are different (Figure 4). The first difference in carbon emissions from fossil fuels generally increases while there is no overall movement in the first difference of carbon emissions from biotic sources. These differences allow statistical techniques to separate the effects of changes in fossil fuel and biotic carbon emissions if their effects on the unknown carbon sink are different.

[54] We test the null hypothesis that the first difference in carbon emissions from fossil fuels and the terrestrial biota

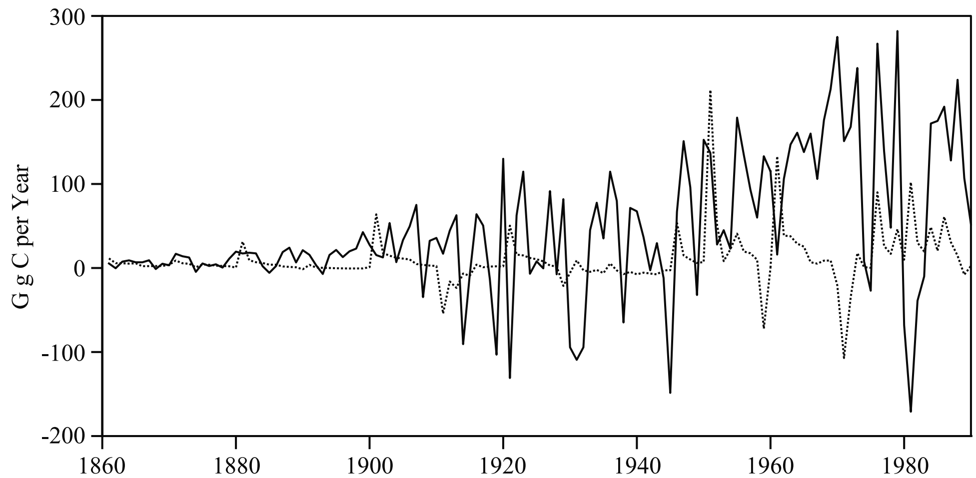

Figure 4. Time series for the first difference of carbon emissions from fossil fuels (solid line) and the first difference of carbon emissions from biotic sources (dotted line).

contribute equally to the unknown carbon sink by using DOLS to estimate the follow equation (model 17):

$$\mathrm{MISS} = \beta_1 \Delta E\mathrm{FFCO_2} + \beta_2 \Delta E\mathrm{BIOCO_2} + \beta_3 \mathrm{LNDHEM} + u_t. \tag{10}$$

The null hypothesis $\beta_1 = \beta_2$ is evaluated with a *t*-test (standard errors estimated using the method of *Newey and West* [1987]) that is described by *Stock and Watson* [2002]. We cannot reject the null hypothesis $\beta_1 = \beta_2$ for the 1866–1990 ($t = -0.20$, $p > 0.84$), 1900–1990 ($t = -0.35$, $p > 0.73$), or 1959–1990 ($t = 0.48$, $p > 0.64$) periods. The failure to reject the restriction $\beta_1 = \beta_2$ indicates that a unit of carbon emitted from biotic and fossil fuel sources contributes equally to the unknown carbon sink.

[55] Equal contributions from the first difference of fossil fuel and biotic emissions imply that anthropogenic mobilization of nitrogen is not largely responsible for the unknown carbon sink. If nitrogen deposition were largely responsible for the unknown carbon sink, the sink would be correlated with changes in fossil fuel carbon emissions, which have large amounts of nitrogen oxides as by-products, and would be uncorrelated with changes in biotic carbon emissions, which generate relatively small amounts of nitrogen oxides. Under these conditions, we would reject $\beta_1 = \beta_2$.

[56] The inability to reject $\beta_1 = \beta_2$ also indicates that the unknown carbon sink is not generated largely by measurement errors for biotic carbon emissions. If measurement errors in deforestation and/or forest regrowth were largely responsible for the unknown carbon sink, these measurement errors would be present in both the observed values for biotic carbon emissions and the unknown carbon sink, which would create a strong correlation between these variables. On the other hand, there would be no correlation between the unknown carbon sink and the first difference in fossil fuel carbon emissions because it is highly unlikely that fossil fuel carbon emissions contain the measurement error for biotic carbon emissions.

[57] It is also unlikely that nitrogen deposition and measurement errors for biotic carbon emissions are jointly responsible for the unknown carbon sink. If both nitrogen deposition and measurement errors for biotic carbon emissions were responsible, we would fail to reject $\beta_1 = \beta_2$ “only if” nitrogen deposition and the measurement error for biotic carbon emissions shared the same stochastic trend. This is highly unlikely given the difference between these two processes.

[58] The failure to reject $\beta_1 = \beta_2$ also indicates that there is a physical process (as opposed to measurement error) that prevents scientists from balancing carbon flows to and from the atmosphere. The failure to reject $\beta_1 = \beta_2$ implies that β_1 is nonzero. A nonzero value for β_1 indicates that the unknown carbon sink probably is not “created” entirely by measurement errors for deforestation and/or forest regrowth. If the unknown carbon sink is created entirely by measurement error for biotic carbon emissions, it is highly unlikely that there would be any correlation between the first difference in fossil fuel carbon emissions and the measurement error for biotic carbon emissions, which would be equivalent to the unknown carbon sink. The failure to reject $\beta_1 = \beta_2$ also indicates that cointegration between MISS and $\Delta E\mathrm{CO_2}$ in model (8) is not caused solely by measurement error: $\beta_1 = \beta_2$ only if the measured value for the unknown carbon sink and the first difference of carbon emissions from fossil fuels and terrestrial biota contain the same measurement error. This is highly unlikely because the estimates for carbon emissions from fossil fuels and the terrestrial biota are compiled from very different sources of data.

5. Discussion

[59] Our statistical analysis of the observational record for the last 130 years provides little evidence to support the hypothesis that increases in the atmospheric concentration of carbon dioxide is even partially responsible for the inability to balance the flows of carbon to and from the atmosphere at the global scale. The lack of cointegration in

models 1–3 is consistent with an analysis by *Bruno and Joos* [1997]. They find that the temporal trend in their estimate for a CO_2 fertilization effect is substantially different from the trend in their estimate for the unknown carbon sink. Based on this difference, they conclude that the unknown carbon sink cannot be explained by CO_2 fertilization.

[60] The conclusion that CO_2 fertilization is relatively small is also consistent with other analyses of observational data at large scales. A statistical analysis of satellite measures for surface greenness indicates that the Normalized Difference Vegetation Index (NDVI) of forested areas in North America and Eurasia increased between 1981 and 1999 [*Zhou et al.*, 2001] and that this increase in surface greenness is associated with an increase in biomass that is consistent with estimates for the size of the unknown carbon sink [*Myneni et al.*, 2001]. There is no evidence, however, that the increase in satellite measures of surface greenness is associated with elevated levels of CO_2. Increases in surface greenness are correlated with atmospheric concentrations of CO_2 [*Ahlbeck*, 2002]. But more sophisticated analysis indicates that this correlation is spurious. Adding a time trend to the regression equation for the relation between NDVI and atmospheric CO_2 eliminates the statistical significance of atmospheric CO_2 [*Kaufmann et al.*, 2002]. Together, these results cast doubt on results generated by process-based vegetation models and small-scale field experiments which imply a large CO_2 fertilization effect.

[61] This lack of support for a significant CO_2 effect is surprising because its effects are believed to be significant at the global scale. A comparison of four process-based terrestrial biosphere models indicates that elevated levels of carbon dioxide during the 1980s increased carbon uptake by terrestrial vegetation between 0.9 and 3.1 Pg C yr^{-1} [*McGuire et al.*, 2001]. These rates are about the same size as values for the unknown carbon sink during the 1980s. Because their sizes are similar, statistical techniques should be able to detect a relation between the time series for the atmospheric concentration of CO_2 and the unknown carbon sink if elevated levels of atmospheric CO_2 increase net carbon exchange between the terrestrial biosphere and the atmosphere. That is, the effect of elevated atmospheric CO_2 concentrations on NPP is not so small as to be undetectable.

[62] The statistical results reported here also contradict another result generated by the four process-based terrestrial biosphere models: that climate has a small absolute effect on net carbon exchange between the terrestrial biosphere and the atmosphere. The importance of the spatial (Northern Hemisphere land) and temporal (summer) components of surface temperature suggests that temperature-induced changes in net carbon exchange between the terrestrial biosphere and the atmosphere are a component of the unknown carbon sink. This suggestion is consistent with analysis of satellite imagery. Satellite measures of NDVI indicate an elongation in the growing season and an increase in the peak values of NDVI in midlatitudes and high latitudes in the Northern Hemisphere [*Myneni et al.*, 1997]. These increases are associated with changes in temperature at the continental scale [*Zhou et al.*, 2001].

[63] The results of the statistical models may help clarify uncertainty regarding the effect of higher temperature on net carbon exchange between the terrestrial biosphere and the atmosphere. Higher temperatures and longer growing seasons may increase NPP, which would increase the rate at which carbon flows from the atmosphere to the terrestrial biosphere. Conversely, higher temperatures may increase heterotrophic respiration, which would increase the rate at which carbon flows from the terrestrial biosphere to the atmosphere. The size of the temperature effect (i.e., the Q_{10}) associated with these two flows is uncertain. Consistent with this uncertainty, the effect of temperature on net carbon exchange between the terrestrial biosphere and the atmosphere varies among the four process-based terrestrial biosphere models analyzed by *McGuire et al.* [2001]. The Terrestrial Ecosystems Model (TEM) indicates that climate variations reduced carbon stored in the terrestrial vegetation by an average of 0.2 Pg C yr^{-1} during the 1980s. Conversely, the high resolution biosphere model (HRBM), the integrated biosphere simulator (IBIS), and the Lund-Potsdam-Jena dynamic global vegetation model (LPJ) indicate that variations in climate increased carbon storages by an average of 0.0–0.9 Pg. C yr^{-1} during the 1980s.

[64] The negative sign that is associated with Northern Hemisphere land temperature (model 12) and Northern Hemisphere summer temperature (model 16) indicates that higher temperatures increase NPP relative to heterotrophic respiration. Consistent with this balance, changes in temperature and precipitation are the greatest single explanatory variables for interannual variations in seasonal values of NDVI [*Zhou et al.*, 2003]. Temperature seems to have a smaller effect on soil respiration. *Giardina and Ryan* [2000] find that soil decomposition rates are relatively unaffected by temperature. Similarly, *Luo et al.* [2001] observed that soils in temperate grasslands acclimate to higher temperatures. As such, our results are inconsistent with claims that the Q_{10} of heterotrophic respiration is greater than the Q_{10} of NPP [*Valentini et al.*, 2000; *Vukicevic et al.*, 2001].

[65] The results of model 8 imply that the ocean model used by *Houghton et al.* [1998] to calculate the unknown carbon sink may not simulate accurately the short-run dynamics of the relation between carbon emissions and oceanic uptake. The negative regression coefficient associated with ΔECO_2 (Table 4) indicates that an increase in carbon emissions generates a short-run increase in oceanic uptake. To assess the size of this effect, we use the VECM estimated for the 1860–1990 period (model 8) to calculate the change in ocean carbon uptake that is implied by changes in carbon emissions. The results indicate that increases in carbon emissions increased oceanic uptake by an average of 1.8 Pg C yr^{-1} in the 1980s. It is difficult to assess this affect relative to the uncertainty in different ocean models. For example, the scenario used by *Prentice et al.* [2001] to show the rate of ocean uptake by several models [Figure 3.8 (a) of *Prentice et al.*, 2001] represents the effect of changes in atmospheric concentrations only:

the effect of changes in emissions are ignored. Our results suggest that it may be worthwhile to simulate the models using scenarios that represent interannual variability in carbon emissions.

6. Conclusion

[66] Statistical analysis of global data for the atmospheric concentration of CO_2, anthropogenic emissions, and surface temperature allows us to test competing explanations for the inability to balance the atmospheric storage of carbon dioxide in ways that field experiments and simulation models cannot. Although these approaches suggest physiological/ecological mechanisms by which increased concentrations of CO_2 and anthropogenic mobilization of nitrogen can increase the rate at which carbon flows from the atmosphere, there is little statistical evidence to indicate that these responses have had a globally measurable effect over the last 130 years. Nor is there much evidence that scientists have systematically erred in estimating areas where terrestrial ecosystems are cut and/or regrow. Instead, the statistical results indicate that annual increases in carbon emissions and higher temperature may increase the rate at which carbon is removed from the atmosphere by the ocean and/or the terrestrial biosphere.

[67] Inconsistencies between model simulations and this statistical analysis regarding the effect of elevated levels of carbon dioxide and temperature may tempt some to dismiss the statistical analysis of the historical record as flawed due to uncertainties in the data. We respond that uncertainties in the data probably are not responsible for the results described above. The emphasis on cointegration allows the statistical techniques to avoid spurious regression results. Furthermore, errors in measurement are far more likely to hide statistically meaningful relations than to create false relations. To create false relations, the same errors must be present in the time series for the unknown carbon sink, emissions of carbon dioxide, and temperature (but only in the Northern Hemisphere and during the summer). A common source of error seems highly unlikely given the differences in the methodologies that are used to compile these time series. This suggests that the process-based models should be validated against the observational record using statistically rigorous techniques. Preliminary evidence indicates that these models are biased and fail to include the effects of temperature accurately (R. K. Kaufmann, A statistical validation of four process-based models for the terrestrial biosphere, submitted to *Global Biogeochemical Cycles*, 2002.). Based on these preliminary results, it is too soon to dismiss either the results generated by simulation models or statistical analyses of the observational record.

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