6-15-1998

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Citation/Publisher Attribution:
Maliekal, J.A., (1998) Feedback relations and causal orders between sea surface temperature and convection within the western Pacific warm pool, Geophysical Research Letters, VOL. 25, NO.12, PAGES 2193-2196, JUNE 15,1998

GEOPHYSICAL RESEARCH LETTERS, VOL. 25, NO.12, PAGES 2193-2196, JUNE 15, 1998

Feedback relations and causal orders between sea surface temperature and convection within the western Pacific warm pool

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Abstract. Analysis of time series of standardized anomalies of sea surface temperature and outgoing longwave radiation from the western Pacific warm pool revealed two distinct modes of atmosphere-ocean interaction. A statistically binding positive feedback relationship between convection and ocean temperature exists over the equatorial region surrounding the international date line. Here, the contemporaneous feedback between these two variables is not statistically significant. A causal order from the ocean temperature to outgoing longwave radiation is detected in a region of the Southwest Pacific, where ocean patches with temperatures greater than or equal to 29.75° C form most frequently. Dynamical implications associated with the aforementioned feedback relationship and causal order are illustrated by estimating the impact of a sudden transient increase in convection on future values of sea surface temperature and vice versa.

Introduction

Interaction between the atmosphere and ocean involves complex processes, including feedback and causal associations between sea surface temperature (SST) and radiative properties of convective clouds. Within the western Pacific warm pool, intense convection, weak evaporation, deep thermocline, and reduced insolation compound this complexity. Recent studies have shown that as SST increases above 29.5° C, which is almost always the case in the western Pacific warm pool, convection shows a tendency to decline [*Graham and Barnett, 1987; Waliser and Graham, 1993; Waliser et al., 1993*]. Since areas of active convection in the tropics are surrounded by clear skies, heating of the ocean surface exposed to the sunlight can generate 'hot spots' with SST values in excess of 29.75° C [*Waliser, 1996*]. Ensuing destabilization of the overlying atmosphere shifts convection to these 'hot spots' [*Waliser, 1996*]. Over the warmest waters of tropical oceans, reflection of solar radiation by clouds could prevent monthly mean SSTs from ever exceeding 32° C [*Ramanathan and Collins, 1991*]. Deep convection, which generates these highly reflective clouds, results from the destabilization of the atmosphere on account of the enhanced trapping of the infrared radiation by the atmospheric water vapor advected over to the warmest ocean waters by the convergent low-level winds.

Although several studies [*Fu, et al., 1992; Arking and Ziskin, 1994*] have questioned the importance of the thermostat-like effect of the convective clouds in regulating tropical SST, the topic of feedback involving global oceans and convective clouds is an important one [*Trenberth, 1997*].

Paper number 98GL01526.
0094-8534/98/98GL-01526$05.00

Empirical studies designed to detect and quantify climate feedbacks are at their infancy. To date, such studies have used derivatives of radiative properties of clouds with respect to SST to deduce feedback relations between water temperature and convection [*Ramanathan and Collins, 1991; Fu et al., 1992*]. Scatter diagrams of co-located values of these two variables from a region, such as the western Pacific warm pool, are often used to estimate these derivatives. Devoid of the time dependence, these estimates are 'static' in nature; they simply describe gradients due to spatial variations. To incorporate temporal variability in the estimation of such derivatives, a popular and innovative approach uses observations made before and after the 1987 El Niño event [*Ramanathan and Collins, 1991; Fu et al., 1992*]. Even this procedure fails to specify the true dynamics associated with a feedback process. Time series models can adequately capture the dynamics associated with the interaction between two processes. Additionally, time series model parameters, estimated by assuming different modes of interaction, can be used to detect and quantify the nature of feedback or causal relations between two processes. In this article, I have used such a methodology and examined time series of SST and outgoing longwave radiation (OLR) from the western Pacific warm pool to learn more about the nature of the interaction between ocean temperature and tropical convection. Several studies have justified the use of OLR as a proxy for tropical convection [for example, see *Waliser et al., 1993*].

Data and Methodology

Monthly time series of standardized anomalies of SST [*Reynolds, 1988*] and OLR [*Gruber and Winston, 1978*] from the Niño 4 box (5 ° N to 5 ° S; 160° E to 150 ° W), and a Southwest Pacific box (0 ° to 10 ° S; 155 ° E to 175 ° E) for the period from January 1979 through July 1993 are used in this study. The latter region is included in the study, because patches of ocean surfaces with water temperatures in excess of 29.75° C are observed most frequently in this region [*Waliser and Graham, 1993; Waliser, 1996*]. Although the region identified by *Waliser [1996]* is slightly bigger in size, an examination of figure 2 in *Waliser and Graham [1993]* and figure 3 in *Waliser [1996]* suggests that the subregion chosen in this study is quite adequate to elucidate the phenomenology associated with the formation of 'hot spots.'

If two time series are causal to each other, there exists a feedback relationship between the processes that generated them [*Granger, 1963*]. A test for causality can be devised by comparing the residual sum of squares of restricted and unrestricted versions of autoregressive models fitted to time series [*Granger, 1969*]. In the current context, unrestricted models are given by

$$S_t = \sum_{i=1}^{M} \alpha_{1i} S_{t-i} + \sum_{i=1}^{M} \beta_{1i} O_{t-i} + \epsilon_{1t}, \qquad (1)$$

and

$$O_t = \sum_{i=1}^{M} \alpha_{2i} S_{t-i} + \sum_{i=1}^{M} \beta_{2i} O_{t-i} + \epsilon_{2t}, \qquad (2)$$

were, S_t is the SST time series, O_t is the OLR time series, M is the model order, ϵ_{it} s are error terms (also known as innovations), and α_{ij} and β_{ij} are regression coefficients. Let σ_1 and σ_2 represent the residual sum of squares, or variances of error terms. To test whether OLR anomalies cause SST anomalies, a restricted version of the model is fitted by equating β_{1i}s to zero in equation (1), which, in fact, provides a univariate description of S_t. The corresponding residual sum of squares is denoted by τ_1. If the addition of lagged values of OLR in equation (1) does not improve the predictability of SST by reducing the residual sum of squares in a statistically significant manner, the former time series is not causal to the latter time series. Similarly, the error variance τ_2 from another restricted model, obtained by equating α_{2i}s to zero in equation (2), can be compared with the residual sum of squares from the unrestricted model to determine whether SST anomalies cause OLR anomalies.

In general, the linear dependence between S_t and O_t, ($F_{S,O}$), can be expressed as the sum of the linear feedback from O_t to S_t, or O_t is causal to S_t, ($F_{O\rightarrow S}$), the linear feedback from S_t to O_t, or S_t is causal to O_t, ($F_{S\rightarrow O}$), and the instantaneous feedback between S_t and O_t, or S_t is contemporaneously causal to O_t,($F_{S.O}$), [*Geweke, 1982*]. That is,

$$F_{S,O} = F_{O\rightarrow S} + F_{S\rightarrow O} + F_{S.O} \,.$$

If we let σ_{12} represent the covariance between the innovations ϵ_{1t} and ϵ_{2t}, then the covariance matrix is

$$\Gamma = \begin{vmatrix} \sigma_1 & \sigma_{12} \\ \sigma_{12} & \sigma_2 \end{vmatrix} .$$

The following quantities can be used to test the statistical significance of individual interactions [*Geweke, 1982*].

$$F_{O\rightarrow S} = N \times \ln\left(\frac{\tau_1}{\sigma_1}\right), \qquad F_{S\rightarrow O} = N \times \ln\left(\frac{\tau_2}{\sigma_2}\right),$$

and

$$F_{S\cdot O} = N \times \ln\left(\frac{\sigma_1 \times \sigma_2}{|\Gamma|}\right),$$

where N is the length of the time series. These three test statistics follow a χ^2 distribution; corresponding degrees of freedom are M, M, and 1.

The Akaike's Information Criterion (AIC), a likelihood-based subset selection procedure, may be used to examine whether a subset of the unrestricted model exhibits the same binding structure suggested by the test results. For example, when the statistical test indicates that O_t is not causal to S_t, all β_{1i} coefficients in equation (1) must equate to zero. Likewise, when the instantaneous feedback is absent, the parsimonious model ought not contain the contemporaneous interaction term. Statistically speaking, improvement in modeling occurs as the number of regression coefficients, or the model order, increases, which is at the expense of an increase in the model variance. To achieve a tradeoff between the improvement in modeling and the increase in the model variance, AIC adds a penalty term to the likelihood [*Akaike, 1974*]. For a particular model order, $AIC = -2 \ln ML + 2k$, where ML is the maximum likelihood of the model and k is the number of parameters in the model. The AIC-selected model order, which is the model with the minimum AIC, implies that it is the best among competing models in the sense that it gives the closest approximation to reality.

Table 1. Model Orders and Related AIC Values.

Region		AIC M = 5	AIC M = 3	AIC Parsimonious
Niño 4	Eq. (1)	- 406.2	- 404.9	- 406.6
	Eq. (2)	- 309.7	- 311.7	- 314.5
SW Pacific	Eq. (1)	- 209.4	- 213.3	- 219.3
	Eq. (2)	- 144.6	- 145. 7	- 149. 8

At the first stage of this subset selection procedure, regression coefficients are deleted, one at a time, from equation (1), starting with high-lag-end values of O_t. If the deletion of a particular regression coefficient results in the reduction of the AIC, that coefficient is dropped from the model. The end product of this stage is the parsimonious version of equation (1). Before equation (2) is subjected to the same procedure, the term $\alpha_{20} S_t$, is added to it to include the contemporaneous association. Finally, the AIC value is used to decide whether to exclude the contemporaneous regression coefficient from the final version of the model. Parsimonious models are shown in box 1.

Parameters corresponding to M = 5 are used to compute all test statistics. Likelihoods of the fitted models are estimated by assuming a Gaussian distribution for all time series. Examining the AIC values (Table 1), we see that five lags are sufficient to adequately summarize interactions between SST and OLR. In fact, AIC evaluations also indicate that model orders can be reduced from five to one in the case of the Niño 4 box, and five to three in the case of the Southwest Pacific box. Test results, along with probabilities of obtaining test statistics as large as, or even greater than those computed from the data under the assumption that the null hypotheses are true, are summarized in the Table 2.

Results

Proper feedback between SST and OLR is detected in the Niño 4 box; causal associations from OLR to SST ($F_{O\rightarrow S}$ = 14.54, p < 0.012) and from SST to OLR ($F_{S\rightarrow O}$ = 27.75, p < 0.000) are statistically significant. However, the instantaneous feedback is not statistically binding ($F_{S.O}$ = 0.05, p<0.82). When water temperature is above 28° C, increases in SST have limited effect on the intensity of convection [*Graham and Barnett, 1987; Waliser and Graham, 1993*]. Although SST values seldom drop below 28° C in the Niño 4 box, the correlation between the time series of SST and OLR anomalies at lag zero is -0.66, which is statistically significant. Therefore, the failure to detect the instantaneous feedback is in spite of the strong correlation between SST and OLR anomalies! How can one reconcile what appears to be an apparent contradiction?

Persistence, which is related to the inherent memory of a process, is ubiquitous in virtually every climate-related time series. If two time series are each autocorrelated (the larger the magnitude of the lag 1 autocorrelation, the greater the persistence) an artificial cross-correlation may be introduced between them, even when the true cross-correlation is zero [*Jenkins and Watts, 1968*]. Hence, the lag zero negative correlation between SST and OLR may simply indicate that strong persistence is present in both time series, and that persistence in each time series proceeds in opposite directions.

Table 2. Summary of Test Results. Quantities within the Brackets Correspond to Parsimonious Models.

Region		Test Statistic	p-value
Niño 4	$F_{O \rightarrow S}$	14.54 (03.80)	0.01 (0.05)
	$F_{S \rightarrow O}$	27.75 (22.91)	0.00 (0.00)
	$F_{S \cdot O}$	00.05	0.82
SW Pacific	$F_{O \rightarrow S}$	02.75 (00.59)	0.74 (0.44)
	$F_{S \rightarrow O}$	12.02 (09.80)	0.02 (0.03)
	$F_{S \cdot O}$	05.75	0.03

By fitting separate stochastic models to SST and OLR time series and subtracting the component due to these models from individual time series, the effect of univariate dynamics can be eliminated [*Jenkins and Watts, 1968*]. By using the covariance matrix of innovations, which describes the variability unaccounted for by the constrained and unconstrained models, test statistics employed in the present study go beyond the simple point-wise comparison of SST and OLR and examine the presence of feedback and causal associations.

Dynamics associated with the detected feedback relationship can be studied by estimating the impact of a one-time transitory increase in the value of one variable on future values of the other variable. Suppose that OLR and SST values were at their normal levels up to a certain time. A sudden enhancement in convection caused OLR to decrease by one standard deviation. According to equations (3) and (4) in box 1, this scenario yields $O_t = -1 = \epsilon_{2t}$, all other values are zero. The impact of this impulsive increase in convection on a future value of SST, the impulse response, is given by $\partial S_{t+i}/\partial O_t$. If the contemporaneous correlation between ϵ_{1t} and ϵ_{2t} is zero, then the above partial derivative can be estimated in terms of $\partial S_{t+i}/\partial \epsilon_{2t}$ either analytically or through a simple simulation. For the Niño 4 region, this correlation is quite small, hence a simulation by setting $\epsilon_{2t} = -1$, and letting S_{t-1}, O_{t-1}, ϵ_{1t}, and all other future values of ϵ_{1t} and ϵ_{2t} to zero in equations (3) and (4) yields estimates of $\partial S_{t+i}/\partial O_t$ for various i values. Simulated values increase from 0 to 0.16 as i varies from 1 to 5 and decrease thereafter (see Table 3). Thus, an impulsive increase in convection, or a decrease in OLR, causes SST to increase in the following months. By the fifth month, this increase can be as much as 16% of the monthly standard deviation of the SST.

By definition, ϵ_{1t} and ϵ_{2t} in equations (3) and (4) are independently and identically distributed random variables. During simulations their values are treated as deterministic initial conditions. These initial conditions together with coefficients of autoregressive models provide all the information needed to simulate the system's response to a sudden stimulus. An identical approach may be used to estimate $\partial O_{t+i}/\partial S_t$ in terms of $\partial O_{t+i}/\partial \epsilon_{1t}$. Simulations reveal that a sudden increase in SST causes OLR values to decrease in the following months (Table 3). By the fourth month, when this reduction reaches its minimum, OLR anomalies are one-half of the standard deviation below the norm for that month.

In the Niño 4 region the instantaneous value of SST does little to improve the predictability of OLR. As such, convection activation occurs either as a delayed response of the atmosphere to the local forcing by SST or as a result of the large-scale tropical atmospheric dynamics. Previous studies [*Stephens and Slingo, 1992; and others*] have suggested that the later process is quite important. The above result does not minimize the importance of the large-scale processes in understanding the nature of SST-OLR relationship in the tropics. Instead, the implication is that once the low frequency convection is activated in the Niño 4 region, feedback between local SST and OLR can reinforce anomalies in each other. The cooling effect of the convective clouds is not detected in this study. Analysis of data collected during the Tropical Oceans Global Atmosphere Coupled Ocean-Atmosphere Response Experiment (TOGA COARE) indicate that in convective areas precipitation creates freshwater lenses at the surface, which by restricting the vertical mixing within the thermocline prevents the cooling of the ocean surface [*Anderson et al, 1996; Lau and Sui, 1997*]. That a statistically binding contemporaneous causal association between SST and convection may not exist, even when the correlation analysis suggests otherwise, is a significant result. Besides reinforcing the insinuation that simple point-wise comparison of time series of SST and radiative properties of clouds have very little power to detect feedbacks and causal associations [*Stephens and Slingo, 1992*], it warns that such results may even be misleading if persistence is present in each of the two time series.

In a region of the Southwest Pacific, where SST values frequently rises above 29.75° C, instantaneous and delayed causal orders ($F_{S.O} = 5.75$, $p < 0.025$; $F_{S \rightarrow O} = 12.02$, $p < 0.034$) are detected between ocean temperature and convection. Absence of a proper feedback between SST and OLR is also supported by the parsimonious model in box 1. Test statistics obtained by extending the size of the Southwest Pacific box by 10 degrees of longitude to the east, which makes it identical to the box identified by *Waliser [1996]* as the preferred location for the formation of 'hot spots', yielded the same general result. Estimates of $\partial O_{t+i}/\partial S_t$ indicate that the causal association given by equation (6) in box 1 is such that enhancement in convection forced by SST reaches a peak

Box 1. Parsimonious Models

Niño 4: (5° N to 5° S; 160° E to 150° W)

$$S_t = 0.843\ S_{t-1} - 0.088\ O_{t-1} + \epsilon_{1t} \qquad (3)$$
$$O_t = -0.279\ S_{t-1} + 0.667\ O_{t-1} + \epsilon_{2t} \qquad (4)$$

SW Pacific: (0° to 10° S; 155° E to 175° E)

$$S_t = 0.500\ S_{t-1} + 0.176\ S_{t-2} + \epsilon_{1t} \qquad (5)$$
$$O_t = -0.188\ S_t - 0.250\ S_{t-1} + 0.307\ O_{t-2} + 0.206\ O_{t-3} + \epsilon_{2t} \qquad (6)$$

Table 3. Impulse Responses

Time (I)	$\partial S_{t+i}/\partial O_t$	$\partial O_{t+i}/\partial S_t$
1	0.088	- 0. 279
2	0.133	- 0.421
3	0.153	- 0.486
4	0.160	- 0. 506
5	0.159	- 0.505

one month after the stimulus is applied, at which time the reduction in OLR is one-quarter of the standard deviation below the monthly norm. Feedback between SST and convection may still exist on sub-monthly scales, but monthly data are too coarse to resolve such relationships. The instantaneous interaction between SST and OLR points to the potential importance sub-monthly scale processes may have in regulating convection in the Southwest Pacific region. Preferential heating of the ocean surface adjacent to areas of active convection may help generate 'hot spots' capable of activating subsequent convection. Since ocean patches with temperature in excess of 29.75° C form adjacent to convectively active areas, a feedback between SST and OLR is not detected.

Discussion

Autoregressive models fitted to climate-related time series often include a trend term [*Kaufmann and Stern, 1997*], which can be a deterministic time trend or a unit root processes. Since SST and OLR time series do not appear to possess such a demeanor, the deterministic trend term is not included. The prototypical example of a unit root process is the random walk process with a drift. The largest coefficient of the first order autoregressive models fitted to the SST time series is 0.9064. Dickey-Fuller tests [*Dickey and Fuller, 1979*] reject the null hypothesis that this coefficient is equal to one in favor of the alternate hypothesis that it is less than one. Therefore, it is unlikely that time series used in this study possess such a trait.

Sensitivities of the results reported above can be gauged by re-computing test statistics with different model orders. Since $M = 1$ yields the lowest AIC values for both time series in the Niño 4 box, $F_{O \to S}$ and $F_{S \to O}$ can be re-computed using this model order. Similarly, for the Southwest Pacific box, $F_{O \to S}$ can be re-computed using $M = 2$, and $F_{S \to O}$ can be re-computed using $M = 3$. Re-computed test statistics (see Table 2) are in general agreement with the earlier results.

Few empirical studies have attempted to quantify the effect of one variable on another variable in the absence of interactions from other processes [*Lau, et al., 1997*]. Most studies employ variations of the correlation-regression analysis to estimate the rate of change of the dependent variable with respect to the independent variable. When feedback is present, it is difficult to separate the cause from the effect [*Stephens and Slingo, 1992*]; as such, discriminating between dependent and independent variables is impossible. The methodology employed in this study conquers this difficulty with the help of recent developments in time series analysis. Time series models capture the dynamics behind the interaction between two or more processes. Partial derivatives such as the $\partial S_{t+i}/\partial O_t$ and $\partial O_{t+i}/\partial S_t$ obtained using model parameters, estimated by assuming different modes of interaction, are ideally suited to study climate-related feedbacks.

Conclusions

Fluctuations in most meteorological and oceanographic variables arise from several interconnected processes; they include causal orders, simultaneous interactions, and feedback relations. Results from the present study show that over the equatorial western Pacific ocean, in a region surrounding the international dateline, SST and OLR anomalies tend to reinforce each other through a positive feedback mechanism. Effects of this coupled interaction last for several months. Over the tropical southwestern Pacific, in a region where there is a high propensity for SST values greater than 29.75° C to occur, the association between ocean temperature and convection is characterized by the unidirectional causality from SST to OLR. Further research is in progress to document the full extent of the feedback and causal associations between SST and other radiative properties of convective clouds.

Acknowledgments. This work is supported by the NOAA grant NA46GP0219.

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(Received December 15, 1997; revised March 19, 1998; accepted April 9, 1998)