NOTES AND CORRESPONDENCE

Interdecadal Trend and ENSO-Related Interannual Variability in Southern Hemisphere Blocking

LI DONG

Department of Earth and Atmospheric Sciences, Cornell University, Ithaca, New York, and WindLogics, Inc., Grand Rapids, Minnesota

TIMOTHY J. VOGELSANG

Department of Economics, Michigan State University, East Lansing, Michigan

STEPHEN J. COLUCCI

Department of Earth and Atmospheric Sciences, Cornell University, Ithaca, New York

(Manuscript received 14 July 2006, in final form 7 September 2007)

ABSTRACT

The interdecadal trend and ENSO-related interannual variability in the frequency and intensity of atmospheric blocking in the Southern Hemisphere are analyzed by a statistical model that takes account of serial correlation in the datasets. Results suggest that an autoregressive process AR(1) fits the error term of the Southern Hemisphere blocking occurrence series, and a white-noise process AR(0) fits the error term of the Southern Hemisphere blocking intensity series reasonably well. It is found that the Southern Hemisphere blocking days have decreased over the past 52 yr (1948–99) but with an enhanced intensity. In addition, the Southern Hemisphere atmospheric blocking is found to occur more frequently in the warm phase of ENSO cycles, whereas the intensity of the Southern Hemisphere atmospheric blocking does not appear to be affected by ENSO cycles.

1. Introduction

Atmospheric blocking is a weather phenomenon that is characterized by a splitting of the normal westerly jet stream of midlatitudes into two distinct, widely separated currents, embedded within the westerly dominant background circulation. Because of the importance of atmospheric blocking in affecting the regional short-term climate, it is imperative to study this atmospheric phenomenon. Many theoretical and observational studies have investigated the onset of atmospheric blocking from distinct perspectives (Rex 1950; Egger 1978; Charney and De Vore 1979; Tung and Lindzen 1979a,b; Hoskins and Karoly 1981; Austin 1980; Colucci et al. 1981; Frederiksen 1982; Shutts 1983; Tsou and Smith 1990; Tracton 1990; Alberta et al. 1991; Colucci 2001; Dong and Colucci 2005, 2007). Despite the extensive diagnostic and theoretical studies of atmospheric blocking over the last several decades, the current prediction skill of blocking by comprehensive numerical models is still far from satisfactory (Tracton 1990; Tibaldi et al. 1994; Watson and Colucci 2002).

Interannual variability in the frequency of blocking events within a season may, however, be predictable in a statistical sense, although the details of individual cases may not be well forecast. Renwick and Wallace (1996) found a statistically significant relationship between El Niño–Southern Oscillation (ENSO) variability and the frequency of wintertime blocking events over the Alaskan region such that blocking is suppressed during the warm phase of ENSO. In contrast to the Northern Hemisphere (NH), Renwick (1998) found that the number of days of blocking tends to increase
on average during the warm phase of ENSO cycle, particularly over the southeast Pacific during the southern spring and summer, using a 16-yr record of 500-hPa height field data. This result is not only confirmed by the updated work of Renwick and Revell (1999), using a 39-yr record of 500-hPa height dataset, but also consistent with other investigations (Rutllant and Fuenzalida 1991; Marques and Rao 2000; Wiedenmann et al. 2002). Furthermore, by using a linearized, barotropic vorticity equation model, Renwick and Revell (1999) revealed that linear Rossby wave propagation provides an important link between anomalous convection in the tropics and the occurrence of blocking over the southeast Pacific Ocean. Rao et al. (2000) further provided observational evidence to show that the Rossby wave propagation similar to the one noted by Renwick and Revell (1999) is in fact stronger and better organized in austral spring than in other seasons. In addition to the ENSO-related interannual variability in Southern Hemisphere (SH) blocking occurrence addressed by the aforementioned work, numerous studies have also been carried out to investigate the long-term trend in SH blocking occurrence and intensity (Wiedenmann et al. 2002; Renwick and Revell 1999; Marques and Rao 2000). The corresponding long-term trend could, however, vary given different lengths of datasets used in each study.

A number of definitions of atmospheric blocking exist in the literature to objectively identify blocking. Several studies identified blocking events as persistent positive anomalies from the 500-hPa geopotential height field (Dole and Gordon 1983; Renwick and Wallace 1996; Renwick and Revell 1999). Several climatological studies of blocking over the SH (Tibaldi et al. 1994; Tibaldi and Molteni 1990) have used the blocking index of Tibaldi and Molteni (1990) modified from that of Lejenä and Økland (1983). The index is local and instantaneous, which isolates regions of the geostrophic easterly flow at 500 hPa associated with midlatitude blocks. In the present study, a modified version of the Tibaldi and Molteni index is used to identify atmospheric blocking days in the SH. In comparison with the Tibaldi and Molteni index, the modified Tibaldi and Molteni index (MTI) includes a height gradient calculation on the equatorward side of the system and increases the poleward reach of the index (Watson and Colucci 2002). Simply speaking, the MTI provides a minimum westerly flow on the poleward and equatorward side of the easterly flow, similar to the original Rex (1950) definition that requires equivalent flow on the poleward and equatorward sides. The MTI improves the original Tibaldi and Molteni index by rejecting strong closed lows and enhancing its ability to identify blocking highs located farther poleward. An instantaneous blocking is defined to occur where and when the MTI is met and a blocking system is defined to take place when the instantaneous blocking persists for at least 5 consecutive days spanning 20 or more degrees of longitude.

To the best of the authors' knowledge, most previous studies addressing the long-term trend and ENSO-related interannual variability in blocking occurrence assumed a white-noise process in the error term of their statistical models, that is, no serial correlation. However, for the aggregate meteorological time series, it is a common feature for the error term to have serial correlation. For example, global temperatures are well known to be serially correlated over time (Bloomfield 1992; Zheng et al. 1997; Gordon 1991; Woodward and Gray 1993, 1995; Fomby and Vogelsang 2002). Therefore, if serial correlation is present in the error term, the usual ordinary least squares (OLS) standard errors and t statistics computed by most statistical software programs are no longer valid. This could accordingly lead to the wrong inference.

The present study is aimed at investigating the long-term trend and ENSO-related interannual variability in the SH blocking occurrence and intensity, using a 52-yr (1948–99) 500-hPa geopotential height dataset. Moreover, the generalized least squares (GLS) estimate, which is not as popular as the OLS estimate commonly employed in many meteorological studies partly because its statistical inferences and computational routines are not well known, is used in the present study so that the GLS standard errors and t statistics will permit inference that is robust to serial correlation.

The remainder of the present study is organized as follows. A detailed explanation of the fundamental statistical model that takes account of serial correlation in the error term is presented in section 2. Section 3 describes the datasets utilized to identify atmospheric blocking in the SH. Estimation and inference of the regression parameters in the statistical model are extensively discussed in section 4, followed by a summary and discussion in section 5.

2. Statistical models

The fundamental statistical model used in this study is

\[ Y_t = \alpha + \beta_1 t + \beta_2 \text{soi}_t + u_t, \quad (t = 1, 2, \ldots, T), \]

(1)

where \{Y_t\} is the time series of standardized annual SH blocking occurrence and intensity over \( T \) years, \( \beta_1 \) is the
coefficient for trend, $\beta_2$ is the coefficient for the explanatory variable, Southern Oscillation index (soi), and $\{u_t\}$ is the regression error. Details of each term in the model [(1)]—namely, the trend term, explanatory variable, and regression error—are discussed in the following.

a. Trend term

A trend term in general can be represented by a variety of forms such as linear and exponential trends (Zheng et al. 1997; Bloomfield 1992). For simplicity, a linear trend $\beta_2 t$ is utilized here. It is important to note that the trend term concerned in the present study is a long-term linear trend on the interdecadal time scale.

b. Explanatory variable

The soi is taken as an explanatory variable in the model [(1)], which helps to explain the variations in blocking occurrence and intensity around their trends. Moreover, in order to avoid the contamination of the long-term trend in blocking variability by the possible long-term trend in soi, it is necessary to remove the long-term trend in soi before fitting it to the model [(1)] so that the confidence interval of the long-term trend estimate of blocking occurrence and intensity can be improved. This means that the long-term trend $\beta_2 t$ in the model [(1)] generally accounts for interdecadal variability in SH blocking, whereas the detrended soi explains interannual variability in SH blocking. In the present study, we remove the long-term trend in soi using two methods: (i) fitting a linear trend to soi by OLS and removing the fitted trend, and (ii) filtering soi using a high-pass filter that removes low-frequency components that include zero-frequency components such as a linear time trend.

c. Error term

It is likely for the regression error term $\{u_t\}$ in the model [(1)] to have serial correlation, which is a common feature of aggregate meteorological and climate data. If $\{u_t\}$ has serial correlation, then OLS estimates of the model [(1)] will be unbiased (if an estimator is unbiased, then its probability distribution has an expected value equal to the parameter it is supposed to be estimating), but they will not be efficient because the Gauss–Markov theorem requires $\{u_t\}$ to be uncorrelated over time [here efficient means that, if $W_1$ and $W_2$ are two unbiased estimators of $\theta$, $W_1$ is efficient relative to $W_2$ when $\text{var}(W_1) \leq \text{var}(W_2)$ for all $\theta$, with strict inequality for at least one value of $\theta$ (Wooldridge 1999)]. More importantly, the usual OLS standard errors and $t$ statistics computed by most statistical software programs are no longer valid when $\{u_t\}$ has serial correlation. There are two ways to handle serial correlation in $\{u_t\}$. The first option is to use the OLS estimates but compute standard errors that are robust to serial correlation (Bloomfield 1992). The second option is to model the serial correlation and estimate the model [(1)] using GLS, which is equivalent to using maximum likelihood estimation (MLE) under the assumption that $\{u_t\}$ follows a Gaussian distribution (Woodward and Gray 1993). In the present study, we proceed with the second option because in principle, the GLS estimates will be more efficient than OLS if the model of serial correlation is reasonably accurate. As the MLE estimates incorporate serial correlation into the estimation, GLS standard errors and $t$ statistics will permit inference that is robust to serial correlation in $\{u_t\}$. A convenient model of serial correlation that is sufficiently flexible to represent $\{u_t\}$ is the autoregressive process of order $p$ [AR($p$); Box and Jenkins 1976], namely,

$$u_t = \phi_1 u_{t-1} + \phi_2 u_{t-2} + \ldots + \phi_p u_{t-p} + e_t, \quad (2)$$

where $p$ is a nonnegative integer, $\{\phi_1, \phi_2, \ldots, \phi_p\}$ are the autoregressive coefficients, and $\{e_t\}$ is a white-noise process with zero mean and variance of $\sigma^2$. The autoregressive lag length $p$ is required to estimate the model [(2)] by MLE. In the present study, we estimate the model using the values of $p = 0, 1, 2, 3,$ and 4.

3. Data

In the present study, we use 4-times-daily 500-hPa geopotential height fields from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) global reanalysis datasets during the period 1948–99, with a $2.5^\circ \times 2.5^\circ$ spatial resolution (Kalnay et al. 1996). Following Watson and Colucci (2002) and Sáez de Adana and Colucci (2005), the daily 500-hPa geopotential height datasets were first searched for all longitudes where the MTI is met for instantaneous blocking. Then all selected instantaneous blocking days were further screened with a 3-day-duration threshold for 3-day blocking events. Finally, all datasets of instantaneous blocking days were screened to find blocking systems that spanned at least 20° longitude and lasted for at least 5 consecutive days.

The climatology of NH and SH atmospheric blocking derived from long-term NCEP–NCAR reanalysis is thoroughly described by Watson and Colucci (2002) and Sáez de Adana and Colucci (2005), respectively. According to Watson and Colucci (2002), in the NH the maximum blocking frequencies dominate over two re-
regions, that is, the central Pacific Ocean and eastern Atlantic Ocean, with a peak relative blocking frequency of about 5%. Contrastingly, in the SH, Sáez de Adana and Colucci (2005) found that the maximum blocking frequency occurs only over one region, that is, the southeast Pacific Ocean, with a peak relative blocking frequency about 1.6% for the 1-day blocking (instantaneous blocking) and 0.7% for the 5-day blocking, as shown in Fig. 1. In addition, Sáez de Adana and Colucci (2005) have also comprehensively addressed the interannual variability of SH atmospheric blocking in relation to different phases of ENSO, as illustrated in their Figs. 2 and 3. In general, they found that the number of blocked days per year is highest during the warm phase of ENSO and the overall blocked days peak in the late autumn and winter austral seasons [May–September (MJJAS)].

Three time series of annual SH blocking occurrence, with 1-, 3-, and 5-day duration thresholds, are presented in Fig. 2. Mere visual inspection reveals that all three
time series closely resemble each other with all three experiencing a downward trend (a step change around 1960 is observed, with lower values after 1970). This suggests that the blocking index MTI utilized in the present study is capable of identifying atmospheric blocking signatures even without the duration threshold. For simplicity, in the present study we primarily focus our analysis on the 1-day blocking (instantaneous) time series. Nevertheless, analysis upon the 3- and 5-day blocking occurrence series, discussed in the following section, has shown that estimation and inference derived from these two series are very close to those from the 1-day blocking series. Therefore, in the present study conclusions drawn from the instantaneous blocking should generally apply to the commonly defined blocking events with duration threshold. Here the 1-day blocking occurrence series is standardized by removal of its mean (15 days yr\(^{-1}\)) and division by its standard error (11 days yr\(^{-1}\)).

The annual SH instantaneous blocking intensity series is shown in Fig. 3, which indicates a slight upward trend. Here the blocking intensity is calculated as the maximum of the meridional gradient of heights within the blocking center, which is equivalent to the maximum of easterly wind within the blocking center. The instantaneous blocking intensity series is standardized by its mean (55 meters per degree latitude) and standard error (3 meters per degree latitude). As the duration threshold increases to 3 and 5 days, respectively, there are several years during which no blocking events are identified. This makes the blocking intensity evaluation impossible during these years. Therefore, only the instantaneous blocking intensity series is discussed in the present study.

The explanatory variable, soi, is obtained from the Climatic Research Unit, University of East Anglia, United Kingdom, during 1866–2005. It is defined as the normalized sea level pressure difference between Tahiti and Darwin, Australia. More specifically, the annual cycle of sea level pressure at Tahiti and Darwin is removed by forming anomalies from the long-term monthly averages, and these monthly anomalies are then normalized by the appropriate monthly standard deviations to produce standardized values, that is, zero mean and unit variance (Ropelewski and Jones 1987).

In this study, the annual mean of monthly soi is employed, as shown in Fig. 4a, during 1948–99, with a fitted linear trend by OLS. As pointed out earlier, the explanatory variable soi is subject to a trend removal before being fitted to the statistical model [(1)]. One way to obtain the detrended soi is by removing the fitted linear trend, as shown in Fig. 4b. Another way is by applying a high-pass filter to soi such that it removes the low-frequency components. Here we use a Gaussian filter with a cutoff frequency at 7 yr, which is the upper bound of the periodical length of an El Niño event. The derived low- and high-frequency soi are shown in Figs. 4c and 4d, respectively. The low-frequency soi is observed to experience a downward trend that is consistent with the linear trend in Fig. 4a.

A visual inspection of Figs. 4b and 4d reveals that the time series of detrended soi and high-frequency soi qualitatively agree with each other. It is worth noting that the low-frequency soi in Fig. 4c exhibits an abrupt shift from positive values (cold phase of ENSO) to negative values (warm phase of ENSO) in the late 1970s. This is nicely coincident with the shift of the Pacific decadal oscillation (PDO) in 1976 from dominantly negative values (cold phase of the PDO) for the 25-yr time period 1951–75 to dominantly positive values (warm phase of the PDO) for the period 1977–2001 (Hartmann and Wendler 2005; Mantua et al. 1997). It implies that the warm phase of the PDO becomes in harmony with the warm phase of ENSO in 1976 such that the incidents of El Niño events are reinforced after late 1970s. This may provide evidence that the ENSO and PDO climate patterns are closely related, both spatially and temporally, to the extent that the PDO may be viewed as ENSO-like interdecadal climate variability (Mantua et al. 1997). Nevertheless, there is still considerable uncertainty about whether the PDO is truly independent of ENSO (Zhang et al. 1997).

4. Estimation and inference

When the errors are assumed to be AR(0), GLS and OLS estimates are identical and the OLS estimates can
be obtained by many statistical software programs such as S-PLUS, which is used in this study. The null hypotheses of interest [refer to the model (1)] are no trend in blocking,

\[ H_0: \beta_1 = 0, \]

and no impact on blocking from ENSO,

\[ H_0: \beta_2 = 0. \]

The OLS estimates of \( \beta_1 \) and \( \beta_2 \) for SH blocking occurrence and intensity are presented in the AR(0) row of Tables 1 and 2, respectively. Each table contains two panels. The top panel uses high-frequency soi, and the bottom panel uses detrended soi. For the instantaneous blocking occurrence in the SH, a slight downward trend \((-0.029 \text{ yr}^{-1})\) is found to be highly significant with a \( p \) value less than 0.001. This is consistent with our visual inspection of Fig. 2 as discussed previously. In addition, the estimate of \( \beta_2 \) is found to be -0.68 for high-frequency soi and -0.57 for detrended soi, both of which are highly significant. These results suggest that SH instantaneous blocking tends to occur more frequently in the warm phase of ENSO, which is in agreement with Sáez de Adana and Colucci (2005), Renwick (1998), and Wiedenmann et al. (2002). For the SH instantaneous blocking intensity, a significant upward trend is found \((0.021 \text{ yr}^{-1})\) as shown in Table 2, which is consistent with visual inspection of Fig. 3. However, the OLS estimate of \( \beta_2 \) is found to be insignificant \(( p \text{ value} = 0.8234 \) for high-frequency soi and \( p \text{ value} = 0.9615 \) for detrended soi). This indicates that we cannot reject the null hypothesis that there is no linear relationship between ENSO and SH instantaneous blocking intensity.

The regression error \( \{ u_t \} \) potentially has serial correlation, which is a common feature of aggregate meteorological data. In principle, the GLS estimates are more efficient than the OLS estimates if the serial correlation in the model (1) is reasonably represented. The GLS standard errors and \( t \) statistics permit inference that is valid when there is serial correlation in the error term. We model the serial correlation in the error term by AR(1), AR(2), AR(3), and AR(4) processes. The GLS estimates are obtained using MLE as follows. First, the OLS residuals \( \{ \hat{u}_t \} \) are calculated and AR models are fit to the residuals using Yule–Walker estimates to obtain initial values for the MLE optimization routine. Then the MLE estimates of autoregressive coefficients and

![Figure 4](https://example.com/figure4.png)

**FIG. 4.** Time series of (a) soi, (b) detrended soi, (c) low-frequency soi, and (d) high-frequency soi during 1948–99. The dashed line in (a) is the fitted linear trend of soi by ordinary least squares.
Table 1. Comparisons of various regression models consisting of trend \((t)\), explanatory variables (high-frequency soi and detrended soi), and residual models \((u_t)\) with or without serial correlation, for the SH instantaneous blocking occurrence series. The GLS estimates (with \(p < 0.05\) in boldface) and corresponding standard errors are provided. The values of the LRT for the paired autoregressive residual models (with the lag length against the lag length being one smaller) are listed in the last column.

| Model | \(\hat{\beta}_1\) | Std error | \(p(>|t|)\) | \(\hat{\beta}_2\) | Std error | \(p(>|t|)\) | LRT |
|-------|------------------|-----------|------------|------------------|-----------|------------|-----|
| AR(0) | -0.029           | 0.0076    | 0.0004     | -0.68            | 0.1957    | 0.0011     | —   |
| AR(1) | -0.029           | 0.0093    | 0.0035     | -0.63            | 0.1788    | 0.0009     | 3.23 |
| AR(2) | -0.029           | 0.0097    | 0.0047     | -0.63            | 0.1772    | 0.0008     | 0.13 |
| AR(3) | -0.028           | 0.0100    | 0.0063     | -0.60            | 0.1722    | 0.0010     | 0.28 |
| AR(4) | -0.028           | 0.0100    | 0.0065     | -0.62            | 0.1734    | 0.0007     | 0.38 |

\[ Y_t \sim \hat{\beta}_1 t + \hat{\beta}_2 (\text{detrended soi}) + u_t \]

| Model | \(\hat{\beta}_1\) | Std error | \(p(>|t|)\) | \(\hat{\beta}_2\) | Std error | \(p(>|t|)\) | LRT |
|-------|------------------|-----------|------------|------------------|-----------|------------|-----|
| AR(0) | -0.029           | 0.0075    | 0.0004     | -0.57            | 0.1582    | 0.0007     | —   |
| AR(1) | -0.028           | 0.0093    | 0.0037     | -0.56            | 0.1532    | 0.0006     | 3.36 |
| AR(2) | -0.028           | 0.0096    | 0.0048     | -0.56            | 0.1524    | 0.0005     | 0.11 |
| AR(3) | -0.028           | 0.0099    | 0.0063     | -0.55            | 0.1513    | 0.0007     | 0.22 |
| AR(4) | -0.028           | 0.0099    | 0.0071     | -0.56            | 0.1493    | 0.0005     | 0.18 |

Table 2. Same as in Table 1, but for the SH instantaneous blocking intensity series.

| Model | \(\hat{\beta}_1\) | Std error | \(p(>|t|)\) | \(\hat{\beta}_2\) | Std error | \(p(>|t|)\) | LRT |
|-------|------------------|-----------|------------|------------------|-----------|------------|-----|
| AR(0) | 0.021            | 0.0089    | 0.0233     | -0.05            | 0.2303    | 0.8234     | —   |
| AR(1) | 0.021            | 0.0081    | 0.0131     | -0.05            | 0.2331    | 0.8251     | 0.19 |
| AR(2) | 0.020            | 0.0067    | 0.0045     | -0.10            | 0.2433    | 0.6825     | 2.08 |
| AR(3) | 0.020            | 0.0071    | 0.0064     | -0.10            | 0.2375    | 0.6814     | 0.52 |
| AR(4) | 0.020            | 0.0063    | 0.0030     | -0.07            | 0.2314    | 0.7713     | 0.64 |

\[ Y_t \sim \hat{\beta}_1 t + \hat{\beta}_2 (\text{detrended soi}) + u_t \]

The regression parameters are obtained. Note that the GLS fitting procedure can be readily performed by the GLS program provided in S-PLUS software package.

The GLS estimates for SH instantaneous blocking occurrence series are presented in Table 1. Examining the AR(1) results we see that the GLS estimates are very similar in magnitude to the OLS estimates and are statistically significant, although the \(p\) value for \(\hat{\beta}_1\) is an order of magnitude smaller in the AR(1) case. The standard error of \(\hat{\beta}_1\) obtained by GLS (0.0093) is greater than the OLS estimate (0.0076), whereas the standard error of \(\hat{\beta}_2\) obtained by GLS (0.1788) is smaller than the corresponding OLS estimate (0.1957). These differences in standard errors are potentially induced by serial correlation, which is not taken account in the OLS estimation. The last column in Table 1 reports the likelihood ratio test (LRT) for testing the AR model in that row against the null hypothesis that the model in the previous row is the correct model. Each LRT is approximately distributed chi-square with one degree of freedom under the respective null. The LRT reported in the AR(1) row is also a test that there is no serial correlation. Given the LRT of 3.23, we can reject the null of no serial correlation in the errors at the 10% level but not the 5% level. Thus, there is evidence of serial correlation in the errors but the evidence is not strong. The other GLS estimates and standard errors are nearly identical to the AR(1) results, showing that our results are robust to the choice of lag length. The LRT results for lags 2, 3, and 4 confirm that the AR(1) model is not rejected in favor of a higher lag model.

The GLS estimates for SH instantaneous blocking intensity series are presented in Table 2. Here we see that the OLS and GLS estimates and standard errors are very similar regardless of lag length. The LRT results suggest that the AR(0) model cannot be rejected and it is reasonable to conclude that the regression errors have no serial correlation. Our findings of a slight, but statistically significant, upward trend in the SH instantaneous blocking intensity series, and no significant linear relationship between ENSO and blocking intensity, are robust to the choice of lag length.
5. Conclusions and discussion

The interdecadal trend and ENSO-related interannual variability in the frequency and intensity of atmospheric blocking in the SH are analyzed by a statistical model that takes account of serial correlation in the datasets. Results suggest that an autoregressive process AR(1) fits the error term of the SH blocking occurrence series and a white-noise process AR(0) fits the error term of the SH blocking intensity series reasonably well. It is found that the SH blocking days have decreased over the past 52 yr (1948–99) but with an enhanced intensity. In addition, the SH atmospheric blocking is found to occur more frequently in the warm phase of ENSO cycles, whereas the intensity of the SH atmospheric blocking does not appear to be affected by ENSO cycles.

As it is difficult to determine whether a series is white noise merely by visual inspection, it is important to perform formal tests as to whether the errors have serial correlation. In the present study, regression parameter estimates are found to be insensitive to the choice of error model. This is a robust finding and shows that our empirical findings are not driven by the choice of lag. It is not surprising that the OLS estimates are similar to the GLS estimates because OLS is unbiased even when the error terms have serial correlation. However, as we have described previously, OLS standard errors and t statistics are not valid when serial correlation is present in the error terms as is the case for the blocking occurrence regression, and it is more appropriate to base inference about the regression parameters using the GLS estimates.

The downward long-term trend in the annual number of SH blocking days found in the present study is generally consistent with other studies (Renwick and Revell 1999; Wiedenmann et al. 2002). This downward trend could be attributable to a warming climate associated with enhanced anthropogenic activities. The study of the effect of doubled CO₂ concentration on the frequency of SH blocking conducted by Bates and Meehl (1986) using a general circulation model found that, in general, with the increased tropospheric temperatures due to doubled CO₂, mean 500-hPa heights are higher, particularly near regions where sea ice has retreated, and the number of blocking events are reduced in magnitude. They noted that as the ice margin moved poleward with a doubling of CO₂, the meridional temperature gradient at the surface was reduced and baroclinic eddy activity was suppressed. Thus, this is associated with a decrease in blocking frequency. Interestingly, the studies of Simmonds and Keay (2000) and Simmonds et al. (2003), using 40-yr (1958–97) and 21-yr (1979–99) NCEP-NCAR reanalysis datasets, respectively, found that the annually averaged number of extratropical cyclones in the SH, in general, exhibits a downward trend whereas the annual mean activity of extratropical cyclones (such as cyclone intensity, radius, and depth) has increased instead. They suggest that the downward trends in extratropical cyclone numbers are associated with a warming SH due to decreased eddy activity. A further study is worthwhile to explore the similar response of SH blocking anticyclone and extratropical cyclone interdecadal variability to a warming climate.

The result that the SH blocking occurrence tends to be enhanced in the warm phase of ENSO cycles is nicely consistent with many other similar investigations (Rutllant and Fuenzalida 1991; Renwick and Revell 1999; Marques and Rao 2000; Wiedenmann et al. 2002; Sáez de Adana and Colucci 2005). Renwick and Revell (1999) suggest that linear Rossby wave propagation provides an important link between anomalous convection in the tropics and the occurrence of blocking over the southeast Pacific Ocean. In addition, using a full divergence tendency equation, Sáez de Adana and Colucci (2005) show that divergence anomalies prior to the formation of the block, perhaps partially induced by ENSO activity, could generate anticyclonic vorticity that may be advected toward the incipient block by transient eddy activity. More efforts are, nevertheless, needed to further explore the dynamical impacts of ENSO cycles on SH blocking occurrence so a better prediction skill of atmospheric blocking by medium-range forecasting models can be achieved.

Furthermore, the study of Chen and Yoon (2002) reveals a noticeable impact on the North Pacific blocking exerted by the PDO through a streamfunction budge analysis. Meanwhile, in the SH, Garreaud and Battisti (1999) identified an ENSO-like interdecadal variability with a structure qualitatively similar to ENSO, but at lower frequencies than ENSO. Hence, it would be worthwhile to further study the ENSO-like interdecadal variability of SH atmospheric blocking.

Acknowledgments. The authors are grateful to two anonymous reviewers for their constructive comments, which helped to improve this paper substantially. Also, the authors thank Dr. Daniel Graybeal for carefully proofreading an earlier draft of this paper. This work was in part supported by National Science Foundation Grants ATM-0220009 (Colucci) and SES-0525707 (Vogelsang). The reanalysis data for the SH were provided by the Climate Diagnostics Center of the National Oceanic and Atmospheric Administration, and analyzed by S-PLUS software package from Insightful Inc.
REFERENCES


Garreaud, R. D., and D. S. Battisti, 1999: Interannual (ENSO) and interdecadal (ENSO-like) variability in the Southern Hemisphere tropospheric circulation. J. Climate, 12, 2113–2123.


Wiedenmann, J. M., A. R. Lupo, I. I. Mokhov, and E. A.


