A New Method for Identifying the Pacific–South American Pattern and Its Influence on Regional Climate Variability

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ABSTRACT

The Pacific–South American (PSA) pattern is an important mode of climate variability in the mid-to-high southern latitudes. It is widely recognized as the primary mechanism by which El Niño–Southern Oscillation (ENSO) influences the southeast Pacific and southwest Atlantic and in recent years has also been suggested as a mechanism by which longer-term tropical sea surface temperature trends can influence the Antarctic climate. This study presents a novel methodology for objectively identifying the PSA pattern. By rotating the global coordinate system such that the equator (a great circle) traces the approximate path of the pattern, the identification algorithm utilizes Fourier analysis as opposed to a traditional empirical orthogonal function approach. The climatology arising from the application of this method to ERA-Interim reanalysis data reveals that the PSA pattern has a strong influence on temperature and precipitation variability over West Antarctica and the Antarctic Peninsula and on sea ice variability in the adjacent Amundsen, Bellingshausen, and Weddell Seas. Identified seasonal trends toward the negative phase of the PSA pattern are consistent with warming observed over the Antarctic Peninsula during autumn, but are inconsistent with observed winter warming over West Antarctica. Only a weak relationship is identified between the PSA pattern and ENSO, which suggests that the pattern might be better conceptualized as a preferred regional atmospheric response to various external (and internal) forcings.

1. Introduction

The Pacific–South American (PSA) pattern has long been recognized as an important mode of regional climate variability. First named by Mo and Ghil (1987), the pattern was identified in a number of studies of the large-scale Southern Hemisphere (SH) circulation during the late 1980s and early 1990s (e.g., Kidson 1988; Ghil and Mo 1991; Lau et al. 1994). A link between the pattern and Rossby wave dispersion associated with El Niño–Southern Oscillation (ENSO) was soon found (e.g., Karoly 1989), and this work was followed by a number of detailed analyses of the characteristics of the pattern and its downstream impacts (e.g., Mo and Higgins 1998; Mo 2000; Mo and Paegle 2001). In the period since these initial climatological accounts, substantial advances have been made in the methods and datasets used to identify quasi-stationary Rossby wave patterns. Given that the PSA pattern has been implicated in recent Antarctic temperature and sea ice trends, these advances could be employed to better understand the role of the pattern in high-latitude climate variability and its climatological characteristics more generally (e.g., spatial pattern, propagation, seasonal and interannual variability).

The PSA pattern is most commonly analyzed in terms of a pair of empirical orthogonal function (EOF) modes (e.g., Fig. 1). Known as PSA-1 and PSA-2, these modes are in quadrature and depict a wave train extending along an approximate great circle path from the central Pacific Ocean to the Amundsen and Weddell Seas. Some authors interpret these patterns as a single eastward propagating wave (Mo and Higgins 1998), while others argue that variability in the PSA sector is better described as a set of geographically fixed regimes (Robertson and Mechoso 2003). On a decadal time scale, PSA-1 has been related to sea surface temperature (SST) anomalies over the central and eastern Pacific, whereas on an interannual time scale it appears as a response to ENSO (Mo and Paegle 2001). The association of PSA-2 with tropical variability is less clear, with
some authors relating it to the quasi-biennial component of ENSO variability (Mo 2000) and others to the Madden–Julian oscillation (Renwick and Revell 1999). While most of the features of the PSA pattern are consistent with theory and/or modeling of Rossby wave dispersion from anomalous tropical heat sources (e.g., Liu and Alexander 2007; Y. Li et al. 2015), it is recognized that the pattern can also result from internal atmospheric fluctuations caused by instabilities of the basic state (and that both mechanisms likely act in concert; e.g., Grimm and Ambrizzi 2009).

It has been shown that the PSA pattern plays a role in blocking events (Sinclair et al. 1997; Renwick and Revell 1999) and South American rainfall variability (Mo and Paegle 2001) and is also closely related to prominent regional features such as the Amundsen Sea low (Turner et al. 2013), Antarctic dipole (Yuan and Martinson 2001), Antarctic Circumpolar Wave (Christoph et al. 1998), and southern annular mode (SAM; e.g., Ding et al. 2012; Fogt et al. 2012). While these are all important mid-to-high-latitude impacts and relationships, in recent years the PSA pattern has been mentioned most frequently in the literature in relation to the rapid warming observed over West Antarctica and the Antarctic Peninsula (Nicolas and Bromwich 2014). In particular, it has been suggested that seasonal trends in tropical Pacific SSTs may be responsible, via circulation trends resembling the PSA pattern, for winter (and to a lesser extent spring) surface warming in West Antarctica (Ding et al. 2011), spring surface warming over the western Antarctic Peninsula (Clem and Fogt 2015), and autumn surface warming across the entire Antarctic Peninsula (Ding and Steig 2013). The pattern has also been associated with declines in sea ice in the Amundsen and Bellingshausen Seas (Schneider et al. 2012) and glacier retreat in the Amundsen Sea Embayment (Steig et al. 2012).

In identifying the PSA pattern as a possible contributor to these trends, the aforementioned studies looked through the lens of the variable(s) of interest. For instance, Ding et al. (2011) performed a maximum covariance analysis to examine the relationship between central Pacific SSTs and the broader SH circulation (the 200-hPa geopotential height). The second mode of that analysis revealed a circulation resembling the PSA pattern (and that brings warm air over West Antarctica), and atmospheric model runs forced with the associated central Pacific SSTs produced a PSA-like wave train. While this is certainly a valid research methodology, the result would be more robust if a climatology of PSA pattern activity also displayed trends consistent with warming in West Antarctica. This concept of teleconnection reversibility was recently invoked to question the relationship between Indian Ocean SSTs and heat waves in southwestern Australia (Boschat et al. 2016).

A climatology that addresses issues such as recent trends is currently lacking in the literature, so this study will present an update on our somewhat dated...
climatological understanding of the PSA pattern (Mo and Higgins 1998; Mo and Paegle 2001). Not only will it utilize a longer, higher-quality reanalysis dataset than previous studies, it will also develop and apply a methodology that fully exploits the capabilities of Fourier analysis, as opposed to relying on a traditional EOF-based approach. This alternative methodology was adapted from a recent climatology of SH zonal wave activity (Irving and Simmonds 2015) and seeks to avoid the issues associated with the stationary nature of spatial EOF modes, which can be problematic when trying to capture phase variations in a wave pattern of interest. This updated climatology will provide new insights into the variability, propagation, and downstream impacts of the PSA pattern, including its role in recent high-latitude trends.

2. Data

Data from the European Centre for Medium-Range Weather Forecasts interim reanalysis (ERA-Interim; Dee et al. 2011) were used in this study. In particular, the 6-hourly 500-hPa zonal and meridional wind, surface air temperature, sea ice fraction, sea surface temperature, and mean sea level pressure analysis fields were used, from which daily mean time series were calculated for the 36-yr period 1 January 1979 to 31 December 2014. For precipitation, the “total precipitation” forecast fields were used. Each forecast field represents the accumulated precipitation since initialization, so the daily rainfall total was calculated as the sum of the two 12-h post-initialization accumulation fields for each day. The horizontal resolution of the ERA-Interim data was 0.75° latitude × 0.75° longitude.

Relative to the other latest-generation reanalysis datasets, ERA-Interim is thought to best reproduce the precipitation variability (Bromwich et al. 2011; Nicolas and Bromwich 2011), vertical temperature structure (Screen and Simmonds 2012), and mean sea level pressure and 500-hPa geopotential height at station locations (Bracegirdle and Marshall 2012) around Antarctica. While these are encouraging findings, it is worth noting that the sparsity of observational data in the mid-to-high southern latitudes means that ERA-Interim data (like all reanalysis data) still need to be interpreted with caution. There are also well-known difficulties with the representation of low-frequency variability and trends in reanalysis data, due to factors such as changes in the observing system over time (Dee et al. 2014). These issues are highly relevant to the PSA pattern trends discussed in this study, but are somewhat less critical for the results pertaining to seasonal and interannual variability.

3. Computation

A number of different software packages were used in generating the key results presented in this paper. Simple editing of netCDF file attributes and routine data analysis tasks (e.g., anomalies, running means) were performed using a collection of command line utilities known as the NetCDF Operators (NCO) and Climate Data Operators (CDO) respectively, while a Python distribution called Anaconda was used for more complex analysis and visualization. With respect to specific Python libraries, xarray was used for data analysis and the reading/writing of netCDF files, which is a library that builds upon the Numerical Python (NumPy; van der Walt et al. 2011), Pandas, and Scientific Python (SciPy) libraries that come installed with Anaconda. Similarly, Iris, Cartopy, and Seaborn build upon Matplotlib (the default Python plotting library; Hunter 2007) and were used to generate many of the figures. Iris was also used for rotating the global coordinate system and meridional wind (via the PROJ.4 Cartographic Projections Library), and the pyqt_fit, eofs (Dawson 2016a), and windpharm (Dawson 2016b) libraries were used for kernel density estimation, for EOF analysis, and for calculating the streamfunction, respectively.

An accompanying Figshare repository has been created to document the computational methodology in more detail (Irving 2016b). It contains the specifics of the software packages discussed above (i.e., version numbers, release dates, web addresses) as well as a supplementary log file for each figure in the paper. Those log files outline the computational steps performed from initial download of the ERA-Interim data through to the final generation of the plot, and a version-controlled repository of the relevant code can be found at https://github.com/DamienIrving/climate-analysis. The rationale behind this approach to computational reproducibility is explained by Irving (2016a).

4. Methodology

While EOF analysis has been useful in highlighting the existence of the PSA pattern, it may not be the best tool for detailed climatological investigation. A particularly problematic shortcoming is that EOF analysis allows for only a crude representation of variations in wave phase (via the PSA-1 and PSA-2 modes, which are 90° out of phase), which makes it difficult to interpret characteristics such as the propagation of the pattern. This issue is further compounded by the degenerate (North et al. 1982) nature of the PSA-2 mode (e.g., Fig. 1; Mo 2000), which means the true second mode is some random combination of the apparent second and third modes.
To obtain more detailed information on variations in wave phase, existing studies of Rossby wave activity have tended to apply Fourier analysis along lines of constant latitude (e.g., Glatt and Wirth 2014). More sophisticated methods have recently been considered for identifying and tracking nonzonal waves (e.g., Zimin et al. 2006; Souders et al. 2014); however, a key insight of the method developed here is that unlike the generalized case of all possible nonzonal propagation, analysis of the PSA pattern can make use of the fact that the waveform follows an approximate great circle path (Hoskins and Karoly 1981). By rotating the global coordinate system such that the equator (itself a great circle) traces the approximate path of the PSA pattern, we were able to simply apply Fourier analysis along the “equator” in the new zonal direction. Such grid rotation is commonly used in ocean modeling to avoid coordinate singularities caused by the convergence of meridians at the poles (i.e., the grid is rotated to place the north pole over land; e.g., Bonaventura et al. 2012) but has not previously been applied in the context of tropospheric planetary wave activity. This new approach to PSA pattern identification is described below, along with the other more general data analysis techniques used in the study.

a. Identification algorithm

1) GRID ROTATION

To align the new equator with the approximate path of the PSA pattern, a global 0.75° latitude × 0.75° longitude grid was defined (i.e., the same resolution as the original ERA-Interim data) with the north pole located at 20°N, 260°E. The 500-hPa zonal and meridional wind data were used to calculate the meridional wind relative to the new north, and then the temporal anomaly of this new meridional wind was linearly interpolated to the rotated grid for use in the Fourier analysis (e.g., Fig. 2). It should be noted that existing zonal wave studies (e.g., Irving and Simmonds 2015) tend to skip this final step of calculating the anomaly, because in the case of zonal waves the temporal mean of the meridional wind is typically close to zero (and hence waveforms defined by the meridional wind already oscillate about zero).

On this rotated grid, the search region of interest was defined as the area bounded by 10°S–10°N, 115°–235°E (this approximate area is referred to as the PSA sector at times throughout the paper). This region was selected via visual comparison with existing definitions of the PSA pattern (e.g., Fig. 1); however, the final results were not sensitive to small changes in pole location or search region bounds.

2) FOURIER ANALYSIS

To prepare the meridional wind anomaly for Fourier analysis, the meridional mean was calculated over 10°S–10°N (in order to eliminate the latitudinal dimension) and then values outside of 115°–235°E were set to zero. Zero padding is a commonly used technique in signal processing when the waveform of interest does not complete an integer number of cycles in a given domain, and is equivalent to multiplying the original signal (in this case the meridional mean meridional wind anomaly) by a square window function. This multiplication (or convolution) of two waves has consequences in frequency space, such that even a perfectly sinusoidal signal that would repeat exactly six times (for example) over the zero padded domain would show power at more than one frequency. This phenomenon is known as spectral leakage (into the side lobes of the frequency spectrum) and arises from the fact that a square window
function is not square in frequency space. In analyses where excessive leakage is undesirable, a Hanning or Hamming window can be used instead. In the frequency space these windows do not display as much spread into the side lobes, but this comes at the expense of the magnitude of the main lobes. Since our selection process (see below) focuses on identifying the main lobes, a square window function was considered most appropriate.

3) IDENTIFICATION AND CHARACTERIZATION OF PSA-LIKE VARIABILITY

Given that the PSA pattern completes approximately 1.6 to 2.0 cycles (depending on the specific EOF mode) over the 120° search area (see Fig. 1), our analysis focused on data times where a Fourier transform revealed wavenumber 5 and 6 as dominant frequencies over the zero padded 360° domain. In particular, a data time was said to display PSA-like variability (and hence was selected for further analysis) if the amplitude of the wavenumber 5 and 6 components of the Fourier transform were ranked in the top three of all frequencies. The vague “PSA-like” descriptor is used because a number of features besides the PSA pattern (e.g., Antarctic dipole, Amundsen Sea low) can exhibit wavenumber 5–6 variability in the PSA sector.

Once these data times were selected, additional information from the Fourier transform was used to characterize the phase and amplitude of the PSA-like variability. With respect to the former, it can be seen from Fig. 3 that within the search area the phase of the wavenumber 5 and 6 components of the transform (and usually also adjacent frequencies like wavenumber 4 and 7) tend to align both with each other and also with the phase of the actual signal. The phase of the wavenumber 6 component of the Fourier transform was therefore used as a proxy for the phase of the signal as a whole, and this information was used to separate data times displaying the actual PSA pattern from the larger population of PSA-like variability (note that similar results were obtained using wavenumber 5). The details of this separation process (e.g., the phase ranges used to define the PSA pattern) are discussed below. To quantify the amplitude of PSA-like variability, the wave envelope construct pioneered (in the atmospheric sciences) by Zimin et al. (2003) and recently applied by Irving and Simmonds (2015) was used. The envelope is obtained by performing a Fourier transform, followed by an inverse Fourier transform for only the wavenumbers of interest (this is known as a Hilbert transform in digital signal processing). The complex number amplitude of the resulting waveform represents the envelope. Since the envelope of the complete signal (i.e., with all wavenumbers retained) can be quite noisy, the amplitude of PSA-like variability was defined as the maximum value of the envelope when only wavenumbers 4 to 7 are retained (see Fig. 3 for an example envelope).

4) TIME-SCALE CONSIDERATIONS

In applying the identification algorithm to the ERA-Interim dataset, we focus on monthly time-scale data at 500 hPa. This represents a mid-to-upper tropospheric level that is below the tropopause in all seasons and at all latitudes of interest. Given the equivalent barotropic nature of the PSA pattern (i.e., the wave amplitude increases with height but phase lines tend to be vertical) the results do not differ substantially for other levels of the troposphere. Monthly mean data were used for consistency with most previous studies and were obtained by applying a 30-day running mean to the daily (i.e., diurnally averaged) ERA-Interim data, in order to maximize the available monthly time-scale information. As noted by previous authors (e.g., Kidson 1988), potentially useful information may be lost if only 12 (i.e., calendar month) samples are taken every year. Dates were labeled as the middle day of the 30-day period and this middle day was used to determine which season a given data time belonged to (e.g., the labeled date “1979–02–16” spans the period 1 Feb 1979 to 2 Mar 1979 and belongs to DJF).
To explore the implications of this time-scale selection, the Fourier transform used in the identification process was applied to the 500-hPa rotated meridional wind anomaly data (Fig. 4). That analysis revealed wavenumber 7 as the most dominant frequency for daily time-scale data in the PSA sector, with wavenumber 6 dominating the frequency spectrum for a 10–90-day running window. Given that the PSA pattern is itself characterized by wavenumber 5–6 variability in the PSA sector, this result suggests that the PSA pattern is a dominant regional feature on weekly through to seasonal time scales, and by extension the climatological results obtained from 30-day running mean data also be relevant at those time scales.

b. Data analysis techniques

The general data analysis techniques described below are similar to those employed in the zonal wave analysis of Irving and Simmonds (2015). The following text is derived from there with minor modifications.

1) ANOMALIES

All anomaly data discussed in the paper represent the daily anomaly. For instance, in preparing the 30-day running mean surface air temperature anomaly data series, a 30-day running mean was first applied to the daily surface air temperature data. The mean value for each day in this 30-day running mean data series (over the entire 1979–2014 study period) was then calculated to produce a daily climatology (i.e., the multiyear daily mean). The corresponding climatological daily mean value was then subtracted at each data time to obtain the anomaly.

2) COMPOSITES

Composite mean fields are presented throughout the paper for various temporal subsets (e.g., all data times corresponding to the positive or negative phase of the PSA pattern). For the composite mean anomalies of surface temperature, precipitation, and sea ice, two-sided, one-sample t tests were applied at each grid point to examine the null hypothesis that the composite mean anomaly had been drawn from a population centered on zero. To account for autocorrelation in the data (which was substantial due to the 30-day running mean applied to the daily time-scale data), the sample size (i.e., the number of data times used in calculating the composite; denoted n) was reduced to an effective sample size (n_{\text{eff}}) according to

\[ n_{\text{eff}} = \frac{n}{1 + 2 \sum_{k=1}^{n-1} \frac{n-k}{n-\rho_k}}. \]

where \( \rho_k \) represents the autocorrelation for a given time lag k (Zieba 2010).

3) PERIODOGRAM

The characteristics of data series that have been Fourier-transformed are often summarized using a plot known as a periodogram or Fourier line spectrum (Wilks 2011). These plots are also referred to as a power or density spectrum, and most commonly display the squared amplitudes \( C_k^2 \) of the Fourier transform coefficients as a function of their corresponding frequencies \( \nu_k \). As an alternative to the squared amplitude, we have chosen to rescale the vertical axis and instead use the \( \mathcal{R}_k^2 \) statistic commonly computed in regression analysis. The \( \mathcal{R}_k^2 \) for the kth harmonic is

\[ \mathcal{R}_k^2 = \frac{(n/2)C_k^2}{(n-1)s_y^2}. \]

where \( s_y^2 \) is the sample variance and \( n \) the length of the data series. This rescaling is particularly useful as it shows the proportion of variance in the original data series accounted for by each harmonic (Wilks 2011).

4) CLIMATE INDICES

Two of the major modes of SH climate variability are the SAM and ENSO. To assess their relationship with the PSA pattern, the Antarctic Oscillation Index (Gong and Wang 1999) and the Niño-3.4 index (Trenberth and...
Stepaniak 2001) were calculated from 30-day running mean data (i.e., the same time scale that was used for the PSA pattern analysis). The former represents the normalized difference of zonal mean sea level pressure between 40° and 65° S, while the latter is the sea surface temperature anomaly (relative to the 1981–2000 base period) for the region in the central tropical Pacific Ocean bounded by 5° S–5° N, 190°–240° E.

5. Results

a. General PSA-like variability

Before attempting to isolate the PSA pattern using the phase information obtained from the identification algorithm, it is worth considering the characteristics of all PSA-like variability. In total, 55% (7163 of 13120) of data times were identified as displaying PSA-like variability (i.e., wavenumbers 5 and 6 were among the top three ranked frequencies), which is consistent with the fact that wavenumber 6 dominates the Fourier spectrum at the monthly time scale (Fig. 4). Grouping consecutive identifications into discrete events revealed a mean event duration of 19.7 data times, with a distribution depicted in Fig. 5a. While interpretation of these duration data is complicated by the 30-day running mean applied to the original data (e.g., an event that lasted 10 data times could be said to span anywhere between 10 and 40 days) and the occurrence of short events immediately before or after a long event (i.e., they could conceivably be considered as a single event), it appears that PSA-like variability often persists for up to a few months at a time. Building on this baseline duration data, the life cycle of events lasting longer than 10 data times was investigated in more detail. As depicted in Fig. 5b, the amplitude of these events tended to peak midevent with some longer-lasting events peaking more than once during their lifetime (perhaps suggesting that some events simply merge into the next). The mean (±1 standard deviation) linear phase trend across all events lasting longer than 10 data times was 0.12° ± 0.38° E per data time, which indicates that while there was a tendency for events to propagate to the east, a substantial proportion moved very little (or even to the west) during their lifetime.

Important insights were also obtained by considering the phase distribution across all individual PSA-like data times (Fig. 6). On an annual basis the distribution is clearly bimodal, with the two maxima of the kernel density estimate located at 12.75° and 45.0° E. Since the phase was defined as the location of the first local maximum of the wavenumber 6 component of the Fourier transform, this approximate 30° phase separation indicates a pair of spatial patterns that are exactly out of phase (Fig. 7). Taken together these patterns clearly represent the single most dominant mode of variability in the PSA sector, and closely resemble the PSA-1 mode identified by previous authors. On the basis of this finding, it appears that filtering the PSA-like data times according to the location of the two local maxima represents a simple and valid technique for isolating the PSA pattern from the larger population of PSA-like variability.

The spatial patterns corresponding to the local minima of the phase distribution are also shown in Fig. 7, as a way to summarize the characteristics of the remaining PSA-like variability. The three anomaly centers associated with these composite mean circulation patterns have different amplitudes (the middle anomaly has a larger amplitude than the others), which indicates that it was often not a coordinated wave pattern that the identification algorithm was picking up (i.e., not the coordinated PSA-2 waveform discussed by previous authors, despite the similarity in wave phase). Looking at the individual data times corresponding to those minima (not shown), they appear to be a mixture of the hemispheric zonal wave 3 pattern (Raphael 2004; Irving and Simmonds 2015), a more meridionally oriented wave train extending from the tropical Pacific to the Amundsen Sea (e.g., Clem and Fogt 2015; Clem and Renwick 2015), and isolated Amundsen Sea low variability.

b. The PSA pattern

In defining the PSA pattern according to the peaks of the PSA-like phase distribution, it was necessary to account for seasonal variations in the location of those peaks (Fig. 6). A spread of 15° was considered sufficient to capture these variations and hence the 15° interval about each local maximum containing the highest mean values (taken from the annual kernel density estimate) was determined. This approach was used to account for the fact that the phase histograms were not symmetrical about the local maxima and it yielded two intervals corresponding to the positive (4.5°–19.5° E) and negative (37.5°–52.5° E) phase of the PSA pattern. Both intervals represented approximately 15% of all data times (14.8% for the positive phase vs 15.8% for the negative), which suggests that the two phases have a similar frequency of occurrence. With this definition in place, it was possible to investigate variability and trends in the PSA pattern as well as its influence on surface temperature, precipitation, and sea ice.

1) Trends and Variability

During autumn and winter in particular, the middle years of the study period (1991–2002) were characterized by a predominance of positive PSA pattern activity,
whereas negative phase activity was more common in recent years (Fig. 6). This variability is reflected in the linear trends observed over 1979–2014, with negative phase activity showing a statistically significant increasing trend (at the $p < 0.05$ level) on an annual basis and smaller nonsignificant increasing trends for summer, autumn, and winter (Fig. 8). Positive phase activity showed a nonsignificant decreasing trend on an annual basis and also during autumn and winter, with an increasing trend observed for summer (Fig. 9). Consistent with previous studies, both phases of the PSA pattern were most active during winter and spring (Figs. 8 and 9).
In attempting to explain annual and decadal variability in PSA pattern activity, previous authors have suggested that coupling between the SAM and ENSO is important (e.g., Fogt and Bromwich 2006). While some degree of coupling is evident in Fig. 10 (e.g., the positive phase of the PSA pattern was most common when positive/warm ENSO events and negative SAM events coincided), it is clear that the SAM has a much stronger association with PSA pattern activity than ENSO. Recent positive trends in the SAM during summer, autumn, and to a lesser extent winter (the latter being smaller and not statistically significant; e.g., Simmonds 2015) are also broadly consistent with the negative trends observed in the PSA pattern during those seasons.

![Fig. 6. Phase distribution for all data times displaying PSA-like variability. The bars show the total count for each 0.75°E interval over the period 1979–2014, while the lines represent kernel density estimates for a series of different time periods. Gray shading indicates the phase groupings taken to represent the positive (4.5°–19.5°E) and negative (37.5°–52.5°E) phase of the PSA pattern.](image-url)
2) **INFLUENCE ON SURFACE VARIABLES**

To assess the influence of the PSA pattern on regional climate variability, the composite mean surface air temperature anomaly, precipitation anomaly, and sea ice concentration anomaly was calculated for both the positive and negative phase (Fig. 11). On the western flank of the central composite mean streamfunction anomaly associated with positive phase activity, anomalously warm conditions were evident over the Ross Sea, Amundsen Sea, and interior of West Antarctica, particularly during autumn and winter (seasonal composites not shown). The northerly flow responsible for those warm conditions also induced large precipitation increases along the West Antarctic coastline and reduced sea ice in the Amundsen Sea. On the eastern flank, anomalously cool conditions were evident over the Antarctic Peninsula, Patagonia, and the Weddell Sea during all seasons (winter and spring especially; not shown), with the latter also experiencing large increases in sea ice. Anomalously dry conditions were also seen over the Antarctic Peninsula in association with the weaker westerly flow.

The anomalies associated with the negative phase of the PSA pattern were essentially the reverse of the positive phase (Fig. 11). It is also noteworthy that while the hemispheric composite mean streamfunction anomaly associated with the PSA pattern gives the impression of a hemispheric zonal wavenumber 3 pattern, the phase of that pattern and the unremarkable anomalies either side of the Indian Ocean anomaly are inconsistent with the characteristics of the dominant SH zonal wavenumber 3 mode (e.g., Raphael 2004; Irving and Simmonds 2015).

6. Discussion

A novel methodology has been presented for objectively identifying the PSA pattern. By rotating the global coordinate system such that the equator (a great circle path) traces the approximate path of the PSA pattern, the method was able to utilize Fourier analysis to quantify the phase and amplitude of wavelike variability in the PSA sector. In reconciling the results of this Fourier analysis with existing EOF-based definitions of the PSA pattern, a strong resemblance was found between the existing PSA-1 mode and the spatial pattern corresponding to the bimodal phase peaks of wavenumber 5–6 dominant variability in the PSA sector. The lack of a higher-order, multimodal phase distribution questions the physical reality of the existing PSA-2 mode, and may explain the difficulty that researchers have had in identifying a tropical driver for that mode.

These bimodal phase peaks were used as a means to define the positive and negative phase of the PSA pattern. The climatology arising from this definition revealed that the PSA pattern is most active during winter and spring, often persisting for months at a time. It propagates to the east on average, but a substantial number of events remain relatively stationary or even propagate to the west. The pattern was also shown to have a strong influence on regional temperature, precipitation, and sea ice variability. With respect to the former, our results confirm existing relationships established between pattern and station temperatures over the Antarctic Peninsula (e.g., Schneider et al. 2012; Yu et al. 2012), extending the regional picture to highlight equally strong temperature anomalies (of opposite sign) over West Antarctica. Large precipitation anomalies were also identified along the coast of West Antarctica and the Antarctic Peninsula, as well as over South America. These South American anomalies show a more complex spatial pattern than previous analyses (perhaps due to the higher-resolution data), but are otherwise broadly consistent with the results of Mo and Paegle (2001), who found the positive phase of the PSA pattern to be associated with anomalously wet conditions over southern South America.
and anomalously dry conditions farther north. Previous studies also indicate that the PSA pattern plays an important role in sea ice variability in the Amundsen and Bellingshausen Seas (Raphael and Hobbs 2014). Our results suggest that this role is not uniform across that region, with composites of the positive phase of the PSA pattern simultaneously displaying positive sea ice anomalies in the Bellingshausen Sea and negative in the Amundsen Sea.

With respect to trends in the PSA pattern over the period 1979–2014, a trend toward the negative phase was identified on an annual basis and also during summer, autumn and winter. This autumn trend (and the high-latitude temperature and sea ice anomalies associated with the negative phase of the PSA pattern) is consistent with the work of Ding and Steig (2013), who found that autumn warming over the Antarctic Peninsula and associated sea ice declines over the Bellingshausen Sea are associated with an atmospheric circulation resembling the negative phase of the PSA pattern. While this explanation makes sense on the eastern flank of the

Fig. 8. Variability and trends in the negative phase of the PSA pattern. (a) The total PSA-negative data times for each individual season are shown in panel, and (c) corresponding seasonal linear trends (black represents the annual trend); (b) monthly totals for the entire study period (1979–2014). To account for the fact that not all months have an equal number of days, the counts for each month are presented as a percentage of the total number of days for that month. Years in (a) are defined from December to November (e.g., the “year” 1980 spans December 1979 to November 1980) and trends that are statistically significant at the $p < 0.10$ and $p < 0.05$ level are indicated with a circle and star respectively.
central circulation anomaly associated with that pattern, the negative phase of the PSA pattern is also associated with strong cooling over West Antarctica. Autumn temperature declines have not been observed in that region, and thus our results suggest that the PSA-related cooling must have been offset by other factors.

In contrast to the autumn warming over the Antarctic Peninsula, winter warming over West Antarctica has been associated with an atmospheric circulation resembling the positive phase of the PSA pattern (Ding et al. 2011). Our climatology revealed a (albeit non-significant) trend toward the negative phase of the PSA pattern during winter, which raises this question: How is it that winter temperature trends over West Antarctica are associated with an atmospheric circulation resembling the positive phase of the PSA pattern, but a climatology of PSA pattern activity reveals a trend that directly opposes that finding? One possible answer to this question comes from X. Li et al. (2015). They analyzed Rossby wave trains associated with observed SST trends in the tropical Atlantic, tropical Indian, west Pacific, and east Pacific regions and found that all four have a center of action over the Amundsen Sea. While none of these individual wave trains resembled the PSA pattern, a linear combination of the four of them did (with the tropical Atlantic and west Pacific identified as most influential). In other words, the integrated influence of tropical SST trends on the atmospheric circulation resembles the positive phase of the PSA pattern, but the waves underpinning that teleconnection do not. This result is consistent with an earlier study that identified the
tropical Atlantic as a driver of recent winter trends in West Antarctica (Li et al. 2014). Another possible answer comes from Fogt and Wovrosh (2015), who suggest that radiative forcing has played a role in Amundsen Sea low trends that are consistent with winter warming in West Antarctica. The absence of any springtime trend in the PSA pattern suggests that it has also not played a role in high-latitude warming during that season. Similar to winter, the Atlantic has been linked to warming in West Antarctica during spring (Simpkins et al. 2014), while others point to a more meridionally oriented wave train associated with the Pacific decadal oscillation (PDO; Clem and Fogt 2015; Clem and Renwick 2015).

This idea that radiatively forced Amundsen Sea low variability and/or wave trains associated with the Atlantic or PDO might be responsible for a teleconnection resembling the PSA pattern (i.e., as opposed to changes in actual PSA pattern activity) goes to the heart of the reversibility argument made at the beginning of this paper. For a proposed teleconnection to be robust, it must be evident when looking through the lens of both the variable and mechanism of interest. However, even if these alternative explanations do reconcile the discrepancy between our climatology and winter warming over West Antarctica, the associated circulation anomaly would bring cooler conditions and wind-driven increases in sea ice along the western Antarctic Peninsula, contrary to the observed warming and sea ice declines (Clem and Fogt 2015). One possible explanation is that the negative autumn sea ice anomalies persist into winter (Ding and Steig 2013); however, it is clear that there is still work to be done to fully understand recent winter temperature and sea ice changes in the region.

One topic not addressed here is variability in the east/west location of the PSA pattern. In response to the emergence of central Pacific ENSO events in recent
years (e.g., Ashok et al. 2007), some authors have suggested that the PSA pattern moves east or west depending on the precise location of the associated tropical SST anomalies (e.g., Sun et al. 2013; Wilson et al. 2014; Ciasto et al. 2015). Others suggest that the pattern is relatively stationary (e.g., Liu and Alexander 2007; Ding et al. 2012), but either way the broad region (10°N to 10°S in the rotated coordinate system) used by our identification algorithm renders it insensitive to subtle east–west movements. Given that the PSA pattern did not show a strong association with the Niño-3.4 index (an index that is sensitive to both central and eastern Pacific ENSO events), it would be fair to say that even if the location of tropical SSTs does cause the pattern to move slightly, this would represent only a small fraction of all PSA pattern activity.

This weak association with ENSO challenges our fundamental understanding of the PSA pattern. The most commonly held view to date is that the pattern is primarily a response to ENSO forcing (e.g., Mo and Paegle 2001), whereby anomalous ENSO-related SST anomalies modify tropical convection, leading to atmospheric vorticity gradients conducive to Rossby wave generation (Sardeshmukh and Hoskins 1988). A more comprehensive analysis of the relationship between the pattern and tropical convection would be required to confirm this (e.g., lagged correlations with SSTs and other indicators of tropical convection like the outgoing longwave radiation), but our results suggest that the PSA pattern might actually be better conceptualized as a preferred regional atmospheric response to various

**Fig. 11.** Composite mean surface air temperature anomaly, precipitation anomaly, and sea ice fraction anomaly for all data times corresponding to the (top) positive (phase grouping 4.5°–19.5°E) or (bottom) negative (37.5°–52.5°E) phase of the PSA pattern. Black contours show the composite mean 500-hPa streamfunction anomaly (dashed contours indicate negative values, and the contour interval is \(1.5 \times 10^6 \text{ m}^2 \text{ s}^{-1}\)), while the hatching shows regions where the difference between the composite mean and climatological mean is significant at the \(p < 0.01\) level.
internal and external forcings (i.e., with ENSO being just one of many players). Tropical convection is almost certainly an important factor, but its role is likely more complicated than can be captured by a broad-scale ENSO index like the Niño-3.4. This complex relationship between tropical SSTs, convection and the PSA pattern has been the focus of a small number of studies (e.g., Harangozo 2004; Lachlan-Cope and Connolley 2006) and is a topic that warrants much more attention. The relationship between the PSA pattern and ENSO has also traditionally been thought to be moderated by the state of the “atmospheric bridge” (Liu and Alexander 2007). In particular, the pattern is thought to be most active when ENSO and the SAM are in phase (Fogt and Bromwich 2006). Rather than casting the SAM in a facilitating or bridging role, the strong association identified here is more consistent with the idea that the PSA pattern is an integral part of the zonally asymmetric structure of the SAM (e.g., Ding et al. 2012; Fogt et al. 2012).

In addition to a more detailed analysis of the relationship between the PSA pattern, tropical convection, and the SAM, our new methodology could also be adapted for use in future studies of other quasi-stationary waveforms. The most obvious candidate is the Pacific–North American (PNA) pattern (Wallace and Gutzler 1981), which plays an important role in winter climate variability over the North Pacific and North America (e.g., Notaro et al. 2006). Like its SH counterpart, the PNA pattern follows an approximate great circle path, has been analyzed via EO5 analysis, and has been implicated in recent mid-to-high latitude trends (e.g., Ding et al. 2014; Liu et al. 2015). Other nonzonal waveforms that do not follow an approximate great circle path would be more challenging; however, methods have been developed for applying Fourier analysis to synoptic-scale, nonzonal waveforms (Zimin et al. 2006; Souders et al. 2014) and may represent a starting point for future research.

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