Variations in Precipitation across the Southern Ocean

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ABSTRACT: The Southern Ocean lies beneath a unique region of the global atmosphere with minimal effects of landmasses on the zonal flow. The absence of landmasses also means that in situ observations of precipitation are limited to a few ocean islands. Two reanalyses and two satellite-based gridded datasets are analyzed to estimate the character of the distribution of precipitation across the region. The latitudinal variation is computed across three longitudinal sectors, representing the Pacific, Atlantic, and Indian Oceans. The most recent ECMWF reanalysis (ERA5) is found to produce the most accurate estimate of the mean profile and seasonal cycle of precipitation. However, there is little consistency in the estimates of trends in monthly anomalies of precipitation. A more consistent description of precipitation trends is found by using linear regression of the precipitation anomaly with the local mean sea level pressure anomaly, the southern annular mode, and the Southern Oscillation index. In broad terms, precipitation is found to be decreasing at lower latitudes and increasing at higher latitudes, which is consistent with earlier climate model simulations on the impacts of anthropogenic climate change.

KEYWORDS: Atmosphere; Southern Ocean; Precipitation; Interannual variability; Trends

1. Introduction

Adams (2009) reported that precipitation at Macquarie Island (55°S, 159°E) increased from about 800 mm yr⁻¹ in the early 1970s to about 1080 mm yr⁻¹ in the 2000s. At the same time Berthier et al. (2009) reported that the precipitation on the Kerguelen Islands (49°S, 70°E) decreased in the 1960s and subsequently remained low, especially in the 1990s and 2000s. Given the large distance between these sites, it may not be surprising that their variations seem to be unrelated. On the other hand, they both lie in the midst of the Southern Ocean, which is the one region of the global atmosphere and ocean where the effects of landmasses are minimal. The region from 65° to 35°S is our best approximation to an aquaplanet (Fig. 1). However, the landmasses of South America, southern Africa, and Australasia (as well as the Antarctic Peninsula) are likely to introduce some longitudinal variations in climate. Latitudinal variations will be driven at least by the large-scale circulation of the Ferrel cell (e.g., Holton 2004), especially around 60°S at the junction of the Ferrel and polar cells.

The absence of landmasses ensures that the Southern Ocean is of scientific interest, but it also ensures that there are few direct observations of precipitation. There are only a small number of long-term observations of precipitation on ocean islands across the region (Fig. 1). On the other hand, there are several satellite-based precipitation datasets that have essentially global coverage, and these should provide homogeneous estimates over the last 40 years. Indeed, Adler et al. (2017) suggest that such datasets provide “mature estimates” of regional variations in precipitation. However, Behrangi et al. (2014, their Fig. 4) show very large differences in the mean zonal precipitation over the Southern Ocean estimated from different satellite-based datasets. They suggest that the best satellite estimate of precipitation can be derived from a combination of the CloudSat Cloud Profiling Radar (CPR) (Stephens et al. 2002), the TRMM Precipitation Radar (PR) (Simpson et al. 1996), and the Aqua Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) (Platnick et al. 2003). At high latitudes, the estimates of Behrangi et al. come from CloudSat rain and snow products, as well as the AMSR-E rain rate (Wilheit et al. 2003). However, there are uncertainties in the estimates of precipitation from these instruments, especially from boundary layer clouds below 1.5 km (Huang et al. 2012, 2015) and when ice is present (Hiley et al. 2011; Heymsfield 2016). Moreover, their records are generally too short to identify secular trends.

Simmons et al. (2010) demonstrate that reanalyses provide reasonable estimates of the variability of surface climate over land by comparing reanalysis variables with in situ observations of temperature, humidity, and precipitation. It follows that perhaps the most consistent estimates of precipitation and other climate variables across this region are provided by reanalysis datasets. However, the sparsity of direct observations may raise doubts about the accuracy of even reanalysis estimates across the Southern Ocean.

The purpose of this paper is to determine whether a consistent estimate and explanation of the broad spatial and temporal variability of precipitation across the Southern Ocean can be found from an analysis of all three available sources: reanalysis, satellite-based datasets, and island rain gauge sites.

2. Datasets

The present study considers the spatial and temporal variability of precipitation over the Southern Ocean, taken to be
the region between 65° and 35°S. Monthly precipitation has traditionally been an internationally shared climate dataset, providing reasonably robust estimates of the seasonal cycle and of long-term trends. We use data from two monthly precipitation datasets compiled by the U.S. National Centers for Environmental Information (NCEI): the Global Summary of the Month (GSOM) and Global Historical Climatology Network version 2 (GHCNv2). These data are limited to a few island sites where the observations may be influenced by local topographic features, and so we also consider gridded precipitation analyses, largely based on satellite measurements. Of the several global monthly analyses, we consider two: the Global Precipitation Climatology Project (GPCP) and the CPC Merged Analysis of Precipitation (CMAP). The gridded datasets and reanalyses are available for the period since 1979, and we consider the period from 1979 to 2016 inclusive. We also consider two reanalysis datasets, both from the European Centre for Medium-Range Weather Forecasts (ECMWF).

a. Reanalyses

Hersbach et al. (2018) describe the fifth-generation atmospheric reanalysis of the ECMWF, ERA5, which supersedes the well-established ERA-Interim reanalysis (herein ERAI; Dee et al. 2011). Bromwich et al. (2011) compare precipitation fields at high southern latitudes from a number of reanalyses and they suggest that ERAI is likely to provide the most useful estimates. Given the advances in the production of ERA5, we use both ERA5 (with a resolution of about 25 km) and ERAI (with a resolution of about 80 km) monthly datasets in the present study. Both the precipitation and mean sea level pressure (MSLP) datasets are used. Both ERAI and ERA5 data were downloaded from ECMWF.

All the gridded data for this study are masked by the ERA5 land–sea mask in order to remove the direct effects of the landmasses in the Southern Ocean. When this mask is applied to gridded datasets with different resolutions, points are simply matched to the nearest ERA5 grid point.

b. Satellite-based datasets

The well-established GPCP dataset (Adler et al. 2003) has a resolution of 2.5°, and version 2.3 of the Combined Precipitation Dataset is used. The dataset merges low-orbit microwave data, geosynchronous-orbit infrared data, and rain gauge data. We also use the enhanced version of CMAP (Xie and Arkin 1997), which blends satellite-based precipitation estimates from infrared and microwave radiances with rain gauge data and with precipitation from the NCEP–NCAR reanalysis. The monthly analyses are produced at a spatial resolution of 2.5°. Both GPCP and CMAP datasets were obtained from NOAA/OAR/ESRL at https://psl.noaa.gov/data/gridded/.

c. Island sites

Monthly quality-controlled data at observing sites around the world are compiled by NCEI as the GSOM dataset. The GHCNv2 data form a subset of GSOM, where precipitation data are corrected for bias. Both datasets were searched for sites in the Southern Ocean region but away from the landmasses of Australasia and South America. The GSOM has 11 Southern Ocean sites with at least 10 years of data between 1979 and 2016. However, one of these sites (Base Orcadas at 61°S, 45°W) has intermittent data with a very large mean (44.4 mm day$^{-1}$) and standard deviation (6.4 mm day$^{-1}$), and so it is ignored.

The GHCNv2 dataset [based on Menne et al. (2012)] has 10 sites with at least 10 years of data, with several sites overlapping those of GSOM. As the GHCNv2 data are better quality-controlled and generally contain more observations, we use all the GHCNv2 sites together with any additional sites from GSOM. The location of each site is shown in Fig. 1 and metadata for the precipitation data are given in Table 1. It is seen that five sites have data covering less than half the period of interest.

The site at Gough Island has data for almost all months over the period of interest. However, the data are modified by
dividing all recorded values by 2.54, under the assumption that the precipitation observations were measured in centimeters but treated as inches. This assumption was made because the raw values are much larger than those of other island sites (mean of 8.7 mm day$^{-1}$, standard deviation of 3.2 mm day$^{-1}$, and minimum of 1.8 mm day$^{-1}$). However, no metadata could be found to support the adjustment.

At high latitudes, some of the annual precipitation will be snow rather than liquid water. It is well known that measurement of solid precipitation is challenging especially at high wind speeds, and this difficulty may limit the accuracy of some of the site observations.

d. Climate indices

To understand any trends and variations in precipitation, it is useful to consider the correlations between monthly precipitation and key indicators of large-scale climate variability. For this study, we use the southern annular mode (SAM; Marshall 2003), the Southern Oscillation index (SOI; Allan et al. 1991), the dipole mode index (DMI; Saji and Yamagata 2003), the Interdecadal Pacific Oscillation (IPO; Henley et al. 2015), and the global surface temperature (GST; Smith et al. 2008). Monthly time series for these indices were obtained from the Climate Explorer site (http://climexp.knmi.nl).

3. Methodology

Because the Southern Ocean region has minimal effects from landmasses on the atmosphere, the focus of this study is on the latitudinal variations of precipitation. However, the landmasses are known to have some impact on climate and it is known that wavenumber-3 variations are common at high southern latitudes (e.g., Cai et al. 1999). Moreover, Huang et al. (2016) find differences in cloud properties at high latitudes between the Pacific, Atlantic, and Indian Oceans. We therefore consider longitudinal averages of precipitation over three ocean sectors, as shown in Fig. 1 and Table 2, to represent the Pacific, Atlantic, and Indian Ocean sectors. We also consider the average over the whole Southern Ocean (SO).

The breaks between the ocean sectors are chosen to provide distinct patterns in the mean monthly precipitation distribution (Fig. 1). Indeed, the precipitation pattern extending from lower to higher latitudes from the Pacific through the Atlantic to the Indian sector is similar to the mean tracks of fronts in the Southern Hemisphere found by Berry et al. (2011, their Fig. 2d). The sectors also capture the centers of the wavenumber-3 quasi-stationary MSLP pattern studied by Cai et al. (1999).

For the gridded datasets, we compute the longitudinal average values of each variable across each sector. For these average values, the appropriate measure of uncertainty is the standard error. We compare the site-based data with the gridded averages by including the site-based values at the appropriate latitude and taking the standard deviation of the data as the measure of uncertainty for these individual values. The standard deviation of the gridded data provides a further estimate of potential uncertainty in the site data.

The monthly average of variables gives the seasonal cycle as a function of latitude in each sector. Anomalies from the seasonal cycle are used to compute decadal trends of variables and correlations between variables. The statistical significance of trends and correlations is estimated by the relevant $p$ value.

<table>
<thead>
<tr>
<th>Sector</th>
<th>Start longitude (°)</th>
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<tr>
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<td>Indian</td>
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TABLE 2. Extent of ocean sectors; SO denotes whole Southern Ocean region.
In addition to averages over all months, seasonal average results are also computed. Although these results provide an indication of seasonal variations in features of precipitation across the Southern Ocean, they have greater statistical uncertainty because the number of samples is reduced.

4. Mean profile and seasonal cycle of precipitation

The top row of Fig. 2 shows the latitudinal variation in mean monthly precipitation in each ocean sector for each of the gridded datasets, while the lower rows show the seasonal means in each sector. The reanalyses have the same shape, but ERA5 is systematically about 10% larger than ERAI. The mean monthly profile in each sector is distinct, reflecting the eastward and poleward paths of the storm tracks at middle latitudes apparent in Fig. 1. The Pacific sector has a maximum at somewhat lower latitudes than 35°S and smaller peak around 55°S. The Atlantic has a peak around 40°S and decreases rapidly beyond 55°S. The maximum precipitation in the Indian sector is around 50°S, but there is also a weak minimum between 60° and 65°S.

FIG. 2. Variability of mean precipitation (mm day⁻¹) with latitude across each ocean sector (columns) for the gridded datasets; the top row shows the mean over all months and the lower four rows show the mean for each season.
At lower latitudes, there is a distinct seasonal cycle with maximum precipitation in winter (JJA) and minimum in summer (DJF). The winter peak extends poleward from the Pacific through the Atlantic to the Indian sector, and the peak value decreases longitudinally across the sectors. Precipitation in MAM is significantly greater than in SON, except in the Indian sector where the former is only a little higher.

At higher latitudes (south of about 50°S), peak precipitation occurs in MAM with a minimum in DJF. In the Atlantic sector, there is a semiannual cycle with peaks in SON and MAM. Analysis of monthly data (not shown) also shows a semiannual cycle in the Pacific sector, with peaks in March and September. This result is consistent with Marshall (2009), who studied an earlier ECMWF reanalysis (ERA-40) to find that the semiannual cycle in the precipitation around the coast of Antarctica is greatest near 90°W and that the peak annual cycle is in the Indian Ocean sector. Van Loon (1967) shows that semiannual climate variations around Antarctica are due to differences in seasonal heating between middle and high latitudes, leading to increased cyclonic activity in the equinoctial months.

While the profiles of the reanalysis datasets are similar, the satellite-based datasets have some different features. The monthly estimates from the reanalyses have a standard error of less than about 0.1 mm day\(^{-1}\), while the standard error for the satellite datasets is less than about 0.2 mm day\(^{-1}\).

The GPCP dataset has a somewhat similar profile to that of the reanalyses. However, especially at higher latitudes, it has substantially larger values. The mean monthly value has a peak between 55° and 60°S in all sectors. Dee et al. (2011) find that ERAI has less precipitation than GPCP over much of the SO, especially in the Atlantic. They suggest that the precipitation over the midlatitude storm tracks is affected by spinup in the assimilation process. This defect is likely to have been addressed in ERA5, and so the larger peak values in GPCP may be overestimates.

The apparent overestimate of precipitation in GPCP occurs mainly in MAM in all sectors, and it is also seen in SON in the Atlantic sector. At lower latitudes, GPCP does not exhibit the well-defined peak values found in ERA5, especially in the Indian sector. There is an underestimate in GPCP at middle latitudes in JJA in the Pacific and Indian sectors. The GPCP dataset has a rather large semiannual cycle at high latitudes, with the peak occurring around 58°S rather than on Antarctica itself.

The CMAP dataset yields the well-defined peaks of ERA5, but with smaller maxima. It also gives the attenuated seasonal cycle around 55°S. However, it does not capture the semiannual cycle near Antarctica.

When comparing a number of reanalyses with GPCP and CMAP over 50°–60°S, Bromwich et al. (2011) find that all the reanalyses lie between CMAP and GPCP. Similar results are found by Behrangi et al. (2014, Fig. 4) when comparing CloudSat data with CMAP, GPCP, and reanalyses at high southern latitudes; in particular, they suggest that GPCP underestimates the mean precipitation around 40°S and overestimates it around 60°S.

It is interesting to note that the precipitation estimates tend to converge at the north and south boundaries of the SO; that is, where landmasses have a greater impact. Indeed, Dee et al. (2011) comment that estimates of precipitation tend to be better over the land than over the ocean, and that in situ observations can constrain factors that influence the model representation of precipitation.

On the assumption that ERA5 provides a reasonable estimate of the precipitation profiles, Fig. 3 compares the seasonal cycle at the island sites with that of ERA5. The standard deviation of the reanalysis profiles is around 1 mm day\(^{-1}\), which indicates the spatial variability within which the individual in situ data lie. The standard deviation of the monthly in situ data generally has a comparable magnitude.

At lower latitudes [Chatham Island (CH), Gough Island (GI), Martin de Vivicis (MV)], the seasonal cycle of the in situ data is consistent with that of the reanalyses, with a maximum in winter and minimum in summer.

Around 55°S, the seasonal cycle is attenuated, with peak precipitation in MAM, which is consistent with the in situ data from Macquarie Island (Wang et al. 2015). On the other hand, the detailed seasonal cycles for Enderby Island (EN), Campbell Island (CI), and Macquarie Island (MC) do not align with the reanalyses in this region where the seasonal cycle varies significantly with latitude. Figure 1 further indicates that there is significant spatial variability south of New Zealand.

The seasonal cycle at Mount Pleasant (MP) in the Atlantic sector does not align with that of the reanalyses. However, Fig. 1 indicates that MP may be affected by the “rain shadow” of South America.

While the magnitude of precipitation at Kerguelen (KG) is much smaller than the reanalysis estimates, the phase of the seasonal cycle is generally consistent. The magnitude of precipitation at Marion Island (MA) and Iles Crozet (CZ) is much larger than any of the gridded datasets, and their standard deviations (1.7 mm day\(^{-1}\) for MA and 2.0 mm day\(^{-1}\) for CZ) are much larger than at other sites. Nonetheless, the seasonal cycle at CZ is consistent with the reanalysis cycle at higher latitudes, with peak precipitation in MAM and minimum in DJF. Without detailed investigation of metadata, it is not possible to explain the large differences between the observations at Marion Island (47°S) and Iles Crozet (46°S) and at Kerguelen (49°S).

Three of the four sites at high latitude show a semiannual cycle in precipitation, with peaks in MAM and SON. The exception is B. A. Arturo Prat station (BA), which has an unusually large annual cycle as well as a relatively short record.

We note that surface precipitation data are not assimilated in ERAI or ERA5. While gauge data are included in both GPCP (Adler et al. 2003) and CMAP (Xie and Arkin 1997), it is unlikely that isolated island data would have a major impact on the merged products.

Bearing in mind the present results and the CloudSat comparisons of Behrangi et al. (2014), their Fig. 4, it is concluded that the reanalyses, especially the larger values of ERA5, provide a reasonable estimate of the mean precipitation across the region. These latitudinal profiles are consistent with the global maps of the frequency of storm tracks by Berry et al. (2011, their Fig. 2d), including the secondary peak in precipitation around 55°S in the Pacific sector. The enhanced storm track frequency along the coast of Antarctica in the Indian
sector would also account for the increasing precipitation south of 65°S in that sector. Further support for these regional differences is given by Hoskins and Hodges (2005), who analyze the Southern Hemisphere storm tracks in detail.

In summary, the annual cycle of precipitation across the Southern Ocean by the reanalyses is apparently consistent with much of the in situ data and with earlier studies. However, CMAP tends to have lower values than the reanalyses, and GPCP tends to have more extreme values especially in MAM and in the Indian sector.

5. Trends in precipitation

The top row of Fig. 4 shows the decadal trends in mean monthly precipitation anomalies across each ocean sector for the gridded datasets. The reanalyses have essentially the same shape, but the profile for ERAI is translated to more negative values. We consequently find that they may disagree on the sign of a trend, but their statistically significant values are consistent. The disagreement is most noticeable in the Atlantic sector, where ERAI has very large negative trends around 42°–52°S while ERA5 has essentially positive trends.

The lower rows of Fig. 4 show the seasonal variation in precipitation trends of the gridded datasets across ocean sectors. Most of the seasonal trends in the reanalysis datasets are not statistically significant. However, a negative trend at lower latitudes is consistent in DJF, except perhaps in the Atlantic sector. There is a positive trend at higher latitudes in MAM and JJA.

Especially at higher latitudes, the seasonal trends of GPCP are generally much larger than those of the reanalyses; they are
sometimes of different sign. However, there is broad agreement in the Pacific sector, with negative trends north of about 45°S and positive trends to the south. For the Atlantic sector, GPCP tends to have rather indeterminate trends at lower latitudes, and large negative trends at higher latitudes in JJA and SON. Apart from DJF, GPCP trends in the Indian sector tend to be of opposite sign to that the reanalyses and CMAP.

The precipitation trends from CMAP tend to be of the same sign as those from the reanalyses. The CMAP trends are similar across the ocean sectors, with negative values at lower latitudes and positive values at higher latitudes. Because CMAP is produced by a merging of the satellite-based data with a reanalysis, the similarity of its trends with ERA5 and ERAI may not be unexpected. The CMAP trends generally have a larger magnitude than those of the reanalyses.

Figure 5 compares the seasonal trends at the in situ sites with those of ERA5. Most of the trends from the in situ observations are not statistically significant, and the seasonal variations in trends are sensitive to outlier values. Several of the sites have relatively short records (Table 1), reducing the significance of trend estimates. The largest mean trends (0.38 mm day\(^{-1}\) decade\(^{-1}\)) at BA

![Figure 4](image_url)

FIG. 4. Trends in precipitation (mm day\(^{-1}\) decade\(^{-1}\)) as a function of latitude for gridded datasets in each sector (columns). The top row shows trends in monthly precipitation anomalies and the lower four rows show trends in seasonal anomalies; large dots indicate statistically significant values.
and \(-0.40 \text{ mm day}^{-1} \text{ decade}^{-1}\) at MA) are at sites with questionable seasonal cycles. Nonetheless, the in situ observations are generally consistent in sign with the reanalyses. Dee et al. (2011) compare ERAI precipitation trends with those from land-based observations and find similar results for the southern parts of South America, Africa, and Australasia, providing further evidence of the accuracy of the reanalyses to the south of these continents.

The sensitivity to record-length and outliers is demonstrated by Macquarie Island. Adams (2009) finds a positive trend in precipitation between 1970 and 2008, mainly in winter (JJA). Figure 5 shows a very high trend in DJF, which is found to be at least partly due to high values in later years.

Around 60°S in the Atlantic sector, we see that, although the seasonal values are very variable, the lowest trends are in DJF and the highest in MAM. This observation is not inconsistent with the trends of both ERAI and ERA5 in Fig. 4.

While analyzing the water budget over Antarctica, Bromwich et al. (2011) compare precipitation fields from six reanalyses as well as GPCP, CMAP, and observations on the continent. They conclude that ERAI “likely offers the most realistic depiction of precipitation changes in high southern latitudes” (p. 4189) at least for the period 1989–2009. The present study may modify this conclusion to recommend a combination of the trends from ERA5 and ERAI. However, the detailed profile of the precipitation trend in each sector may be clarified by consideration of the likely factors that influence precipitation across the Southern Ocean.

6. Mean sea level pressure

Mean sea level pressure (MSLP) and relative humidity can be effective predictors of precipitation for short-term forecasting (e.g., Fraedrich and Leslie 1988). Given the availability
of water vapor over the ocean, it is likely that the main local control on precipitation across the Southern Ocean is MSLP. Reanalysis probably provides the best estimate of MSLP over the region. This suggestion is reinforced by the similarity of the MSLP fields from ERA5 and ERAI; the correlation between the monthly MSLP in each sector between ERA5 and ERAI is at least 0.995. In each ocean sector, MSLP decreases from nearly 1020 hPa at 35°S to about 985 hPa at 65°S (not shown). The profile in the Indian sector has a minimum around 63°S, indicating longitudinal variation in the boundary between the Ferrel and polar cells. The seasonal cycle in MSLP has a semiannual cycle south of about 60°S, with the largest amplitude of about 4 hPa and lowest values in March and September in the Indian sector. Indeed, Marshall (2009) states that the seasonal cycle of MSLP across Antarctica can be well described by the first two harmonics. The seasonal cycle of MSLP at high latitudes is consistent with the seasonal cycle of precipitation shown in Fig. 2.

The decadal trend in monthly MSLP from ERA5 (not shown) has a well-defined profile with a peak of 0.32 hPa decade⁻¹ at 44°S and negative values south of 56°S, but the details vary with sector. The peak trend is 0.39 hPa decade⁻¹ at 39°S in the Pacific, 0.38 hPa decade⁻¹ at 47°S in the Atlantic, and 0.30 hPa decade⁻¹ at 46°S in the Indian sector. The change in sign occurs at 52°S in the Pacific, 58°S in the Atlantic, and 57°S in the Indian sector.

The trends from ERAI are very similar to those of ERA5 at the lower latitudes, but they are more negative at the higher latitudes in the Pacific and Indian sectors. The MSLP trends at 65°S are −0.44 hPa decade⁻¹ in the Pacific, −0.26 hPa decade⁻¹ in the Atlantic, and −0.23 hPa decade⁻¹ in the Indian sector.

While the trend in mean monthly MSLP has a well-defined profile, the seasonal variations are more complex. In the Atlantic and Indian sectors, the trends in JJA and SON are positive at all latitudes. In DJF in the Pacific sector, the trend is positive, except at latitudes higher than about 60°S.

In a general sense, the trends in MSLP are in antiphase to those in precipitation. This relationship between MSLP and precipitation is further highlighted by the extremely high negative correlation between their monthly anomalies, shown in the top row of Fig. 6. The correlation profile varies with sector, but peak values are at least −0.7 in each sector for the reanalyses. The correlation falls at high latitudes in the Pacific and Indian sectors, with values of only −0.3 around 65°S in the Indian sector.

The lower rows of Fig. 6 show the seasonal variation of the correlation between MSLP and the gridded precipitation datasets. The correlations are most consistent in the Pacific sector, and most variable in the Indian sector where the correlations are weakest in SON and DJF around 60°S. The correlations also tend to be weak equatorward of about 40°S in DJF.

It is interesting to note that the profile shapes for the correlations of MSLP with GPCP and CMAP are very similar to those of the reanalyses, but with attenuated amplitude. In the Indian sector, CMAP and especially GPCP have positive correlations around 50°S in SON and DJF.

The monthly in situ data also have consistently negative correlations with MSLP, with most of the correlations being statistically significant. The correlations with the in situ data are relatively weak because the MSLP values are longitudinally averaged, rather than local. Thus, most of the seasonal correlations are not statistically significant.

It is clear that there tends to be strong linear relationships between precipitation and local MSLP in terms of both decadal trends and variability on monthly and seasonal time scales (indicated through correlations).

7. Relationship between precipitation and climate indices

Precipitation is controlled not just by local variables like MSLP, but also by large-scale climate factors, characterized by indices such as SOI, SAM, DMI, IPO, and GST. To estimate the relative importance of each factor across the Southern Ocean, we first compute the latitudinal profiles of the correlations of indices with precipitation anomalies in each sector. The correlation profiles for most climate indices are found to be inconsistent, especially at higher latitudes where GPCP and CMAP may have opposite but statistically significant signs. Moreover, even the reanalyses may not have consistent profiles.

The only two climate indices that have consistent profiles across the different datasets are SOI and SAM. The profile of the correlation between precipitation anomalies and SAM (Fig. 7) is common across the sectors and seasons, with a minimum of at least −0.4 near 45°S and a maximum of at least 0.5 near 60°S. The correlations are lowest near the 35°S boundary. The profiles for GPCP and CMAP are similar to those for the reanalyses, which in turn are almost identical. Even the site data tend to have signs consistent with the profiles. These results are consistent with Hendon et al. (2014), who show that high SAM, associated with a shift of the polar jet to higher latitudes, leads to reduced precipitation at midlatitudes (centered around 45°S) and increased precipitation at high latitudes (centered south of 60°S).

The change in the sign of the correlation between precipitation and SAM arises because SAM is essentially the difference between the mean MSLP at 40°S and at 60°S (Marshall 2003). Because local MSLP and precipitation are negatively correlated, the correlation between SAM and precipitation at lower latitudes tends to be between MSLP at 40°S and local precipitation (i.e., negative). At higher latitudes, the correlation is largely between the negative of MSLP at 60°S and local precipitation (i.e., positive).

The correlation profiles for monthly precipitation anomalies with SOI (Fig. 8) are consistent, but less consistent than for SAM. Moreover the profiles are different in each sector. The all-months correlation in the Pacific sector is generally positive at around 0.2, but it falls away at low and high latitudes. In the Atlantic, the profile increases almost monotonically from about −0.2 at 35°S to about 0.2 at 65°S. The profile in the Indian sector has a maximum of about 0.15 near 40°S and a minimum of about −0.15 near 50°S; at higher latitudes the correlation becomes positive with a value of about 0.1 at 65°S.

As with the SAM, the changes in sign of the correlation between precipitation and SOI are at least in part due to it being the normalized difference in MSLP between Tahiti and Darwin. Thus when Tahiti MSLP is dominant we expect the correlation to be negative, whereas the correlation will be positive when Darwin MSLP is the main influence on the local
precipitation. The relationship is more complex than with SAM, because the geographical separation is longitudinal rather than latitudinal. Thus in SON the correlations at lower latitudes are positive in the Pacific and Indian sector, but negative in the Atlantic sector.

There are substantial seasonal variations in the correlation between precipitation and SOI. In the Pacific sector at lower latitudes, the correlation tends to be negative in DJF and MAM. In the Atlantic sector, the correlation at higher latitudes becomes negative in SON. In the Indian sector, the peak correlations are in JJA.

Using reanalysis data, Cullather et al. (1996) show that there is a relationship between SOI and precipitation in Antarctica in the Pacific sector. However, they find that the relationship varies with the large-scale MSLP pattern around the coast. That finding is consistent with the present correlation profile, which falls markedly toward 65°S in the Pacific sector for all seasons.

8. Prediction of precipitation

Although we have been able to deduce that the latitudinal profile of mean monthly precipitation in the Southern Ocean is
represented reasonably well by reanalysis, especially ERA5, the variations in Fig. 4 make it difficult to decide on the actual profile of trends in precipitation across the Southern Ocean. The seasonal trends are even less certain. However, the results from sections 6 and 7 show that variability in precipitation on monthly and even seasonal scales is correlated with the local MSLP, SAM, and SOI. Assuming that the processes acting on these time scales are also reflected on longer times, we may use these variables to predict the precipitation over the period of interest. The predicted trend profiles can then be compared with Fig. 4.

Although we have three potential predictors (local MSLP, SAM, and SOI) of precipitation, those predictors are not statistically independent, and so there is a danger of overfitting when applying multivariate regression. To test the validity of using the three predictors, we carry out model selection using forward stepwise linear regression (e.g., Burnham and Anderson 2002), with the Bayesian information criterion (BIC) as the indicator of the optimal balance of model complexity and goodness of fit. The model selection is applied to each dataset. The results of stepwise regression for ERA5
precipitation are summarized in Fig. 9, which shows the selected predictors for each latitude band in each ocean sector and each season. Clearly the MSLP is the leading predictor for most cases, and it is the only predictor over much of the Atlantic sector. On the other hand, the SAM is the leading predictor at high latitudes in the Indian Ocean sector, where the correlation between local MSLP and precipitation tends to be low (Fig. 6). The SOI makes a significant contribution to prediction at lower latitudes in the Pacific and at higher latitudes in the Atlantic sector in MAM. Rarely are all three predictors optimal, and so only the optimal predictors are used for each regression.

The model selection process demonstrates that it is appropriate to use the three potential predictors of precipitation, and so we apply linear regression at each latitude and sector to predict the precipitation anomaly across all months and seasons. Linear regression inevitably underestimates the variability of the dependent variable, and one measure of the fit of the model is to compare the standard deviation of the predicted precipitation with that of the actual precipitation. Figure 10
shows latitudinal profiles of this ratio for each dataset. Over the Pacific and Atlantic sectors, the standard deviation ratio is around 0.6 for the reanalyses for all seasons. In the Indian Ocean sector, the all-months ratio falls from about 0.8 around 45°S to about 0.35 at 65°S, largely due to low values in DJF. In the Indian sector, the ratio is particularly low around 55°S in SON. The ratios for GPCP and CMAP have the same shape as for the reanalyses, but their values are attenuated. The ratios for the site data are even lower. The magnitude and consistency of the ratio profiles in each sector suggest that the simple regression model provides a reasonable estimate of the variability of precipitation on monthly and seasonal time scales.

With some confidence in the regression model, we can use it to estimate the trend in precipitation anomaly in each sector. Figure 11 shows substantial consistency in the predicted trend profiles from both the reanalyses and gridded datasets on the monthly time scale. Even several of the site data have appropriate values. Comparing Figs. 4 and 11, it appears that ERAI (which has a similar shape to CMAP) provides the best direct estimate of the variations in trends across the region. In comparing these figures, we note the difference in scales: the
observed trends in the reanalysis datasets have magnitudes less
than about 0.05 mm day\(^{-1}\) decade\(^{-1}\).

In the Pacific sector, the trend across all months is negative at
lower latitudes with values around \(-0.02 \text{ mm day}^{-1} \text{ decade}^{-1}\),
but it changes sign around 50\(^\circ\)S with values of up to
0.03 mm day\(^{-1}\) decade\(^{-1}\) around 60\(^\circ\)S. In the Atlantic sector,
the precipitation trend is negative at lower latitudes with values
of around \(-0.05 \text{ mm day}^{-1} \text{ decade}^{-1}\). It changes sign around
55\(^\circ\)S and has values around 0.02 mm day\(^{-1}\) decade\(^{-1}\) at higher
latitudes. The trend in the Indian sector appears to have a well-
defined minimum of around \(-0.04 \text{ mm day}^{-1} \text{ decade}^{-1}\) near
45\(^\circ\)S, changes sign around 55\(^\circ\)S, and has a maximum of about
0.02 mm day\(^{-1}\) decade\(^{-1}\) near 60\(^\circ\)S.

There is substantial seasonal variation in estimated precip-
itation trend. In the Pacific sector, the trend approaches zero
near 35\(^\circ\)S in DJF, and the trends are small near 65\(^\circ\)S in JJA
and SON. In the Atlantic sector, there is a peak trend of
around \(-0.10 \text{ mm day}^{-1} \text{ decade}^{-1}\) in MAM around 45\(^\circ\)S, while

FIG. 10. Ratio of standard deviation of precipitation from regression model to that of precipitation anomaly for each dataset for each
sector (columns). The top row shows values across all months; lower rows show seasonal values. Profiles are for gridded datasets with large
dots for statistically significant values; red dots for values at island sites; large red asterisks denote statistically significant values as
island sites.
the peak trend at high latitudes is in DJF of around 0.05 mm day$^{-1}$ decade$^{-1}$. In JJA and SON, the trend tends to be negative across the Atlantic sector. In the Indian sector, there is a persistent peak trend of up to $-0.05$ mm day$^{-1}$ decade$^{-1}$ around 45°S, but the positive trend at high latitudes occurs mainly in DJF and MAM.

Overall there is a consistent pattern of negative precipitation trend at lower latitudes and positive at higher. This pattern is associated with increasing MSLP at lower latitudes and decreasing at higher latitudes. Gillett et al. (2013) confirm that these trends in MSLP are associated with the upward trend in SAM, which is in turn related to depletion of polar stratospheric ozone. Kang et al. (2011) use model experiments to clearly demonstrate the link between ozone depletion and this latitudinal response in precipitation. Although the increase in SAM is linked with polar ozone depletion, Lim et al. (2016) analyze climate model projections to show that greenhouse gas forcing also is associated with a positive trend in SAM, leading
to the signal of increasing precipitation at high latitudes and decreasing at midlatitudes.

While there is a well-defined signature in the precipitation trend across the Southern Ocean, there are noticeable regional differences. These differences would reflect the spatial variability of the large-scale meridional circulation, which has been identified in studies of the Hadley cell. Lucas and Nguyen (2015) find that the expansion of the Hadley cell is greater over the Australia–New Zealand region than over Africa and South America. Such regional differences are further analyzed by Nguyen et al. (2018), who find that expansion of the Southern Hemisphere Hadley cell is associated with low MSLP south of 60°S and high MSLP north of 60°S in the Pacific sector. Indeed, Lucas and Nguyen (2015) and Nguyen et al. (2018) find that variations in the Hadley cell are associated with both SAM and SOI. It is expected that such large-scale factors will impact on the overall meridional circulation, linking variations in the Hadley and Ferrel cells.

The observation that precipitation is increasing at high latitudes is consistent with the analysis of Medley and Thomas (2019) of accumulated snowfall on Antarctica, where they find an increasing trend associated in part with changes in SAM. They further find considerable spatial and temporal variability in the snowfall record.

### 9. Conclusions

The atmosphere above the Southern Ocean (SO) is of great interest because it is relatively free of landmasses and it includes the boundary between the Ferrel and polar cells of the large-scale meridional circulation. The main character of longitudinal variations in precipitation across the region is captured by dividing the full annulus into sectors covering the Pacific, Atlantic, and Indian Oceans. Comparing the present results with those from Bromwich et al. (2011) and Behrangi et al. (2016), it is apparent that ERA5 provides the best estimate of the mean latitudinal variation in precipitation across the SO. The variation is different in each sector, with the differences associated with the propagation of storm tracks across the region (Hoskins and Hodges 2005; Berry et al. 2011).

CMAP consistently has lower values of the mean precipitation than the reanalyses, while GPCP tends to have larger values at high latitudes. The ERA5 estimate is consistently about 10% larger than that of ERAI.

The seasonal cycle of precipitation across the SO is also captured well by ERA5. North of about 50°S there is a strong winter (June) maximum in precipitation. The latitude of the maximum moves poleward from the Pacific through the Atlantic to the Indian sector. Around 55°S the seasonal cycle is greatly attenuated. Close to the Antarctic coast, the seasonal cycle has a semiannual mode with maxima in March and September, consistent with van Loon (1967) and Marshall (2009).

The seasonal cycle of precipitation in ERAI is similar to that of ERA5, but both of the gridded datasets have differences from the reanalyses. The CMAP captures the general structure of the reanalyses, except for the semiannual variation near Antarctica. However, GPCP does not well represent the structure of the reanalyses at any latitude.

Given the documented effects of increasing greenhouse gases and stratospheric ozone depletion on the Southern Hemisphere climate, there are likely to be discernible trends in precipitation across the SO. Each of the reanalyses and gridded datasets, as well as some of the in situ observations, has statistically significant trends. However, there is little consistency in the latitudinal profiles of the trends in the monthly anomalies of precipitation. Even the reanalyses can have trends of opposite sign at some latitudes.

A consistent profile for the precipitation trends can be deduced by consideration of factors that are known to influence precipitation across the region. In particular, it is found that there are consistent profiles of correlations between precipitation anomalies and local MSLP, SAM, and SOI. Linear regression with these potential predictors is able to generate a reasonable fraction of the monthly variability in precipitation anomaly. Given the ability of the regression model to reproduce the precipitation variability, it is reasonable to apply it to estimate the trend in precipitation across the SO. The model is found to generate profiles of the trends that are consistent across the reanalyses and the gridded datasets.

Comparing the model trends with the variable results from the direct estimates of trends from the datasets, it appears that ERAI provides the most accurate estimate of trends in precipitation across the region. There is a negative trend in monthly precipitation north of 50°–55°S, and positive trends at higher latitudes. The trend profiles vary with sector, with negative trends of up to −0.05 mm day$^{-1}$ decade$^{-1}$ in the Indian sector and positive trends of up to 0.04 mm day$^{-1}$ decade$^{-1}$ in the Pacific sector. The seasonal trends are more variable than those over all months, especially in the Atlantic and Indian sectors at high latitudes where the trends are weak or even negative in JJA and SON.

The overall precipitation trends are consistent with analyses of the meridional circulation by Nguyen et al. (2018), who find that variations in the Hadley cell are associated with SAM and SOI and that expansion of the Hadley cell is associated with MSLP variations at middle and high latitudes.

Although the present analysis provides some further understanding of the climate of the SO, one conclusion is confirmation of the observation of Bromwich et al. (2011) that “The high southern latitudes remain a challenging place for retrospective analysis experiments” (p. 4206). This challenge would be attenuated in the future if the quantity and quality of meteorological observations from the sparse island sites of the Southern Ocean were enhanced.

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### Data availability statement

Reanalysis data can be accessed from ECMWF (https://www.ecmwf.int/en/forecasts/datasets/browse-reanalysis-datasets), the monthly climate indices can be accessed from the Climate Explorer site (http://climexp.knmi.nl), the gridded satellite data can be accessed from NOAA/OAR/ESRL (https://pdl.noaa.gov/data/gridded/), and the island precipitation data can be accessed from NCEI (https://www.ncei.noaa.gov/data).
REFERENCES


