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Comparison between Atmospheric Reanalysis Models ERA5 and ERA-Interim at the North Antarctic Peninsula Region

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The availability of accurate meteorological data is important for the modeling of atmospheric flows, enabling the understanding of climate change in a given environment over time. Therefore, this study aimed to evaluate the quality of the meteorological data of 2 m temperature (T) and mean sea level pressure (MSLP), obtained through the atmospheric reanalysis models ERA5 and ERA-Interim (ERA-i) in the northern region of the Antarctic Peninsula, covering the period from 1979 to 2018. To carry out the statistical process, local observations from nine weather stations installed in the study region were used, with data available from the Scientific Committee on Antarctic Research. Statistical analysis evaluated Pearson's linear correlation coefficient (R), standard deviation (σ), normalized bias, normalized mean absolute error, and normalized root mean square error. Regarding the difference in $\overline{T}$ between weather stations and reanalysis models, we found a better result for ERA5 ($\Delta\overline{T} = -0.34\,°C$) compared to ERA-i ($\Delta\overline{T} = 0.37\,°C$); however, for the difference in $\overline{MSLP}$ the ERA-i ($\Delta\overline{MSLP} = -0.04\,hPa$) presented a better response in relation to ERA5 ($\Delta\overline{MSLP} = 0.24\,hPa$). When verifying the local meteorological observations trend, an increase of T in $0.31\,°C$ decade^{-1} (Esperanza station) and a reduction of MSLP between -0.56 (Bellingshausen station) and $-0.80\,hPa$ decade^{-1} (Jubany station) were recorded. *Key Words: air temperature, Antarctic, atmospheric pressure, weather stations.*

The Antarctic Peninsula is one of the most sensitive regions to climate change on the Antarctic continent (Ress 2003). Weather stations installed in the region register a sharp increase in warming, with an average temperature (T) increase of $3.7 \pm 1.6\,°C$ century^{-1} (Vaughan et al. 2003). In addition, the Antarctic Peninsula is exposed to a strong influence of the Southern Hemisphere Annular Mode (SAM), which consists of a dominant mode of variability in atmospheric circulation in the Southern Hemisphere and is related to a change in atmospheric mass and therefore in mean sea level pressure (MSLP; Gong and Wang 1998). The increase in the SAM index induces a stronger flow of relatively warm oceanic air toward it from the west face, forcing it to cross the unbroken mountain chain and leading to marked warming in the eastern part of the peninsula (Marshall et al. 2006).

Given this, the availability of accurate meteorological observations is important for the study of climatological phenomena in that region. In regions of difficult access such as the Antarctic Peninsula, however, we find a limited number of these weather stations providing continuous information. A solution to this limitation is the use of the meteorological data set provided by atmospheric reanalysis models (Bracegirdle 2013). Atmospheric reanalysis consists of a global forecasting model with input observations and an assimilation scheme that are used together to produce better estimates (analyses) of past atmospheric states (temperature, wind fields, geopotential height, and humidity). The forecast model propagates information forward in time and space from

Annals of the American Association of Geographers, 0(0) 2020, pp. 1–13
Initial submission, November 2019; revised submissions, May and June 2020; final acceptance, June 2020
Published by Taylor & Francis, LLC.

previous analyses of the atmospheric state (Fujiwara et al. 2017).

With this objective in mind, an analysis of the data quality of atmospheric reanalysis models is important, quantifying the accuracy of the information provided in a given region. Bracegirdle and Marshall (2012) verified from the comparison of local observations found in weather stations with the main reanalysis models such as Climate Forecast System Reanalysis (CFSR), European Reanalysis Agency (ERA-40), European Reanalysis Agency-Interim (ERA-i), Japanese Meteorological Agency Reanalysis (JRA-25), and Modern Era Retrospective-Analysis for Research and Applications (MERRA), between 1979 to 2008, that ERA-i performed best for Antarctica, mainly for MSLP data and geopotential height at 500 hPa. Tastula et al. (2013) revealed errors related to the amplitude and shape of the diurnal cycle of variables such as T, humidity, and wind speed of these atmospheric reanalysis models, with the ERA-i showing the best results in the reproduction of these cycles.

In 2018, the European Center for Medium-Range Weather Forecasts (ECMWF) made available a new model of atmospheric reanalysis called ERA5, the successor to ERA-i since 31 August 2019, with some improvements like better spatial (regular $0.25° \times 0.25°$ grid) and temporal (time interval) data resolution, improved tropospheric modeling, representation of tropical cyclones, improved global precipitation and evaporation balance, and more consistent sea surface and sea ice temperature data (Hersbach et al. 2019).

Therefore, the objective of this study is to evaluate the accuracy of the MSLP and T data between the atmospheric reanalysis models ERA5 and ERA-i, based on local data provided by the weather stations located in the north region of the Antarctic Peninsula, from 1979 to 2018.

Study Site

The study site is located on the Antarctic Peninsula between latitudes 61.88° S and 64.52° S and longitudes 62.32° W and 55.33° W. In this place, there is a predominantly alpine topography with T in summer exceeding 0 °C at the average level of the sea (Vaughan et al. 2003). For this reason, the melting of ice is an important component, which allows the presence of melting water and seasonal rocky outcrops, thus enabling the existence of a more abundant terrestrial flora and fauna than in other regions of Antarctica. On the Antarctic Peninsula there is an uninterrupted mountain range with altitudes between 1,400 and 2,000 m, forming a climate barrier (Schwerdtfeger 1984). In the west and central regions, we find a maritime climate dominated by the Bellingshausen Sea, whereas the east coast has a continental climate dominated by the Weddell Sea (Martin and Peel 1978).

To the north of the Antarctic Peninsula we can find $\overline{T}$ in winter ranging from -5.6 ± 1.9 °C (Bellingshausen station) to -10.0 ± 2.2 °C (Esperanza station), and $\overline{T}$ in summer varies between 0.8 ± 0.6 °C (Vernadsky, located at 65.25° S, 64.26° W) to 1.3 ± 0.5 °C (Bellingshausen station) according to Turner et al. (2020). It is noteworthy in this region that the heating of the T is more accentuated during the winter (King 1994; Stark 1994), because Vaughan et al. (2003) found for the Vernadsky weather station, between 1950 to 2001, a trend of 11.0 ± 9 °C (century^{-1}) for winter and 2.4 ± 1.7 °C (century^{-1}) for summer.

Material and Methods

Atmospheric Reanalysis and Meteorological Observations Data

The evaluation of the accuracy between the atmospheric reanalysis models on the Antarctic Peninsula was made by comparing local meteorological information and data from the ERA models (ERA-i and ERA5) provided by ECMWF. These models are data assimilation systems that combine local observations and predictive models, providing information on the evolution of the atmosphere and the surface below it (Tetzner, Thomas, and Allen 2019). The study focused on meteorological parameters assessment of T and MSLP in two different aspects. The first refers to data availability from local weather stations, with only T, MSLP, wind speed, and wind direction observations being reported regularly. The second aspect is according that the relevance of meteorological parameters T and MSLP in climatological modeling of that region is strongly influenced by SAM (Gong and Wang 1998; Lefebvre and Goosse 2005; Marshall et al. 2006).

In the ERA-i model, monthly T and MSLP data were used in the digital format Network Common Data Form (NetCDF), with standard spatial grid

Table 1. Weather stations in Antarctic Peninsula with data available by MET-READER, geographical location, and time interval of analysis

Site	Latitude (°S)	Longitude (°W)	Elevation (m)	Data interval	Number of valid months
Bellingshausen	62.2	58.9	16	1979–2018	480
Esperanza	63.4	57.0	13	1979–2018	473
Ferraz	62.1	58.4	20	1993–2005	144
Great Wall	62.2	59.0	10	1985–2018	392
Jubany	62.2	58.6	4	1988–2018	342
King Sejong	62.2	58.7	11	1988–2014	266
Marambio	64.2	56.7	198	1979–2018	476
Marsh	62.2	58.9	10	1979–2018	454
O'Higgins	63.3	57.9	10	1979–2018	388

resolution of 0.75° × 0.75°. The monthly values are constituted by the arithmetic mean of all daily observations performed at times 0, 6, 12, and 18 Coordinated Universal Time (UTC) (Dee et al. 2011). To make these data compatible with the ERA5 model, the bilinear interpolator was used for continuous parameters available on the ECMWF Web site at the time of file acquisition, generating a final grid with a spatial resolution of 0.25° × 0.25°. In the ERA5 model the monthly values of T and MSLP are also constituted by the arithmetic mean of all daily observations performed but with an hourly interval. The file format used was also NetCDF with a standard grid resolution of 0.25° × 0.25°.

Starting from the geographic locations (latitude and longitude) of the nine weather stations used in this study, the extraction of T and MSLP values was performed in the corresponding NetCDF files considering the pixel information in the extraction over the surface (single level) for each weather station (WS). Table 1 presents a summary of the weather stations and the set of valid data used, and Figure 1 shows the geographic location of the referred weather stations located on the Antarctic Peninsula and the representation of the relief in the region through the Reference Elevation Model Antarctica (Howat et al. 2019). Meteorological observations are made available by the Scientific Committee on Antarctic Research's Reference Antarctic Data for Environmental Research (READER) project, which aims to create a set of data with long duration of meteorological measurements, from a system of stations installed in Antarctica (Turner and Pendlebury 2004), found on the Web site http://legacy.bas.ac.uk/met/READER (Turner and Pendlebury 2019). For the statistical analyses, only average monthly samples were considered that had in their metadata a percentage of daily observations greater than 90 percent for T and MSLP.

Among the information assimilated by the atmospheric reanalysis models to produce the forecasts are the data made available by the weather stations. The databases used by ECMWF for the assimilation of the ERA-i and ERA5 models are the Surface Synoptic Observations (SYNOP) and the Meteorological Airdrome Report (METAR; Dee et al. 2011). The Marsh station is part of the METAR database, and the Bellingshausen, Esperanza, Ferraz, Great Wall, Jubany, King Sejong, Marambio, and O'Higgins stations are part of SYNOP.

Statistical Analysis

To evaluate the accuracy of the reanalysis models, absolute mean monthly values of T and MSLP were used to apply the normalized bias (*NBIAS*), normalized mean absolute error (*NMAE*), and normalized root mean square error (*NRMSE*), as shown in Equations 1, 2, and 3 (Madsen et al. 2005; Rodrigo et al. 2013; Tetzner, Thomas, and Allen 2019).

$$NBIAS = \frac{1}{N}\sum\nolimits_{t=1}^{N} \frac{\bar{x}_{\text{reanalysis}}(t) - \bar{x}_{\text{WS}}(t)}{\bar{y}_{\text{WS}}} \tag{1}$$

$$NMAE = \frac{1}{N}\sum\nolimits_{t=1}^{N} \left| \frac{\bar{x}_{\text{reanalysis}}(t) - \bar{x}_{\text{WS}}(t)}{\bar{y}_{\text{WS}}} \right| \tag{2}$$

$$NRMSE = \sqrt{\left(\frac{1}{N}\sum\nolimits_{t=1}^{N} \left(\frac{\bar{x}_{\text{reanalysis}}(t) - \bar{x}_{\text{WS}}(t)}{\bar{y}_{WS}}\right)^2\right)}, \tag{3}$$

where $\bar{x}_{\text{reanalysis}}$ is the monthly average value obtained by atmospheric reanalysis, $\bar{x}_{\text{WS}}$ is the monthly average value obtained by observation at the weather stations, and $\bar{y}_{\text{WS}}$ is the annual

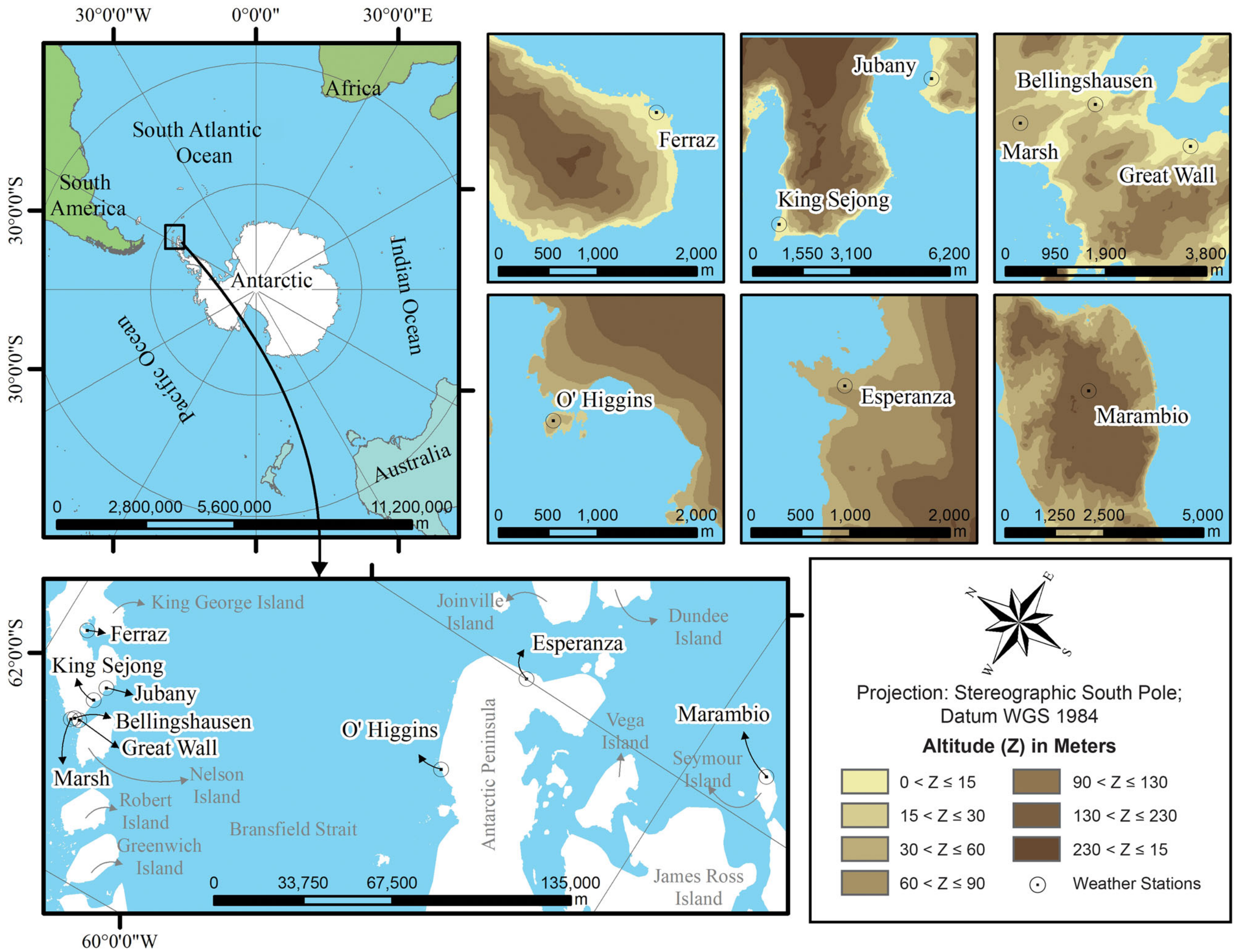

Figure 1. Map identifying the geographical location of weather stations and the relief of the Antarctic Peninsula.

average value obtained from observations at the weather stations.

The root mean square error (*RMSE*) is recommended for statistical analyses that combine errors with low correlation, high bias, and normal distribution (Bromwich and Fogt 2004), but this metric is sensitive to extreme values. In addition, other indicators such as *NBIAS* and *NMAE* were then applied to assess the performance of the models. *BIAS* makes it possible to obtain additional information related to the variance of errors in a given sample (Brassington 2017). The *MAE* indicates the average performance attributing the same weight to all errors and its tendency is to present values lower than that verified by the *RMSE* (Willmott and Matsuura 2005; Willmott, Matsuura, and Robeson 2009).

To assess the correlation between data from atmospheric reanalysis models and local observations, the normality of the data was checked previously using the Shapiro–Wilk test. This is a nonparametric test used to identify the adherence of the data to normal, allowing evaluation of different distributions and sample sizes (Shapiro and Wilk 1965). In this study, the decision rule adopted, at the 5 percent significance level, to identify whether the distribution is normal or not was (1) accept H_0 if $p > 0.05$; that is, the data set has normal distribution; and (2) reject H_0 if $p \leq 0.05$; that is, it cannot be assumed that the data set in question has a normal distribution. Given the assumption of parametric correlation, a sequence was given to calculate Pearson's linear correlation coefficient (R). This coefficient allows us to identify the degree of the correlation and the direction of that correlation (positive or negative) between two variables of metric scale, assuming a scale of values between -1 and 1 (Wilks 2011). The interpretation scale considers positive and negative values, presented as follows: Values greater than 0.90

Table 2. Presentation of the mean ($\overline{MSLP}$) and σ (hPa) of the data set of the months valid for each WS and the atmospheric reanalysis models

	WS		ERA-i		ERA5		Variation	
Site	$\overline{MSLP}$	σ	$\overline{MSLP}$	σ	$\overline{MSLP}$	σ	ERA-i −WS	ERA5 −WS
Bellingshausen	990.76	5.28	990.73	5.35	990.89	5.34	–0.03	0.13
Esperanza	989.73	5.71	989.76	5.52	990.16	5.50	0.03	0.43
Ferraz	991.70	5.29	991.12	5.29	991.70	5.29	–0.58	0.00
Great Wall	990.23	5.41	990.41	5.38	990.62	5.38	0.18	0.39
Jubany	991.08	5.46	990.50	5.44	990.70	5.44	–0.58	–0.38
King Sejong	989.56	5.46	990.82	5.50	991.00	5.50	1.26	1.44
Marambio	989.64	5.81	989.19	5.72	989.35	5.76	–0.45	–0.29
Marsh	990.94	5.37	990.73	5.33	990.90	5.32	–0.21	–0.04
O'Higgins	989.88	5.43	989.90	5.51	990.32	5.48	0.02	0.44
M	990.39	5.47	990.35	5.45	990.63	5.45	–0.04	0.24

Note: WS = weather station; MSLP = mean sea level pressure; ERA-i = ERA-Interim.

indicate a very strong correlation, 0.70 to 0.89 show a strong correlation, 0.50 to 0.69 represent a moderate correlation, 0.30 to 0.49 indicate weak correlation, and 0 to 0.29 show negligible correlation.

The linear trend of the behavior of MSLP and T over time was also calculated for local observations and for atmospheric reanalysis models, with the F test (Hair et al. 1998) being applied concomitantly to measure the fit of the linear model to the data set, considering the significance level of 5 percent. For the F test, the following hypotheses were considered: (1) accept H_0 if $p > 0.05$; that is, there is no statistically significant association between the response variable and the term; and (2) reject H_0 if $p \leq 0.05$; that is, it presents a statistically significant association between the response variable and the term. In this study, only the linear trends of T (°C decade^{-1}) and MSLP (hPa decade^{-1}) are presented for the equations that showed a statistically significant association between the variables.

Results

Mean Sea Level Pressure

For this analysis, MSLP means and standard deviation (σ) of local observations and ERA-i and ERA5 reanalysis models were first calculated within the monthly data set valid for each weather station (Table 2). In these results, average variation between the reanalysis models and local observations of nine weather stations found were an underestimation of −0.04 hPa by ERA-i and an overestimation of 0.24 hPa by ERA5. These responses show that the ERA-i presents an estimation of MSLP values closer to local observations.

Among the stations used in this analysis, King Sejong presented the greatest divergence in the comparison between the data provided by the models and that of the weather station (1.26 hPa for ERA-i and 1.44 hPa for ERA5). Only at Ferraz, Jubany, Marambio, and Marsh stations did we find that ERA5 showed superiority over ERA-i through the reduction in variation average between reanalysis data and local observations. For standard deviation average, both models showed the same value ($\overline{\sigma} = 5.45$ hPa), showing a higher degree of adherence between data than that obtained by weather stations ($\overline{\sigma} = 5.47$ hPa).

Pearson's linear correlation coefficients (Table 3) indicated very strong correlations for ERA-i ($\overline{R} = 0.96$) and ERA5 ($\overline{R} = 0.95$) in nine weather stations; however, only Esperanza was found to have a strong correlation for ERA-i ($R = 0.86$) and ERA5 ($R = 0.85$). In assessing the performance of the reanalysis models using *NBIAS*, *NMAE*, and *NRMSE*, both presented satisfactory performance for all weather stations, with values below 0.01 percent of these indicators.

Evaluating the statistical significance through the F test for the equations of the linear trends of MSLP in the weather stations, considering the local observations and the atmospheric reanalysis models ERA-i and ERA5, it was found that only the local

Table 3. Pearson's linear correlation between the annual mean sea level pressure averages of WS in relation to the ERA-i and ERA5 atmospheric reanalysis models

Site	ERA-i–WS	ERA5–WS
Bellingshausen	0.98	0.97
Esperanza	0.86	0.85
Ferraz	0.99	0.99
Great Wall	0.98	0.98
Jubany	0.97	0.95
King Sejong	0.93	0.91
Marambio	0.98	0.98
Marsh	0.94	0.93
O'Higgins	0.98	0.96
M	0.96	0.95

Note: WS = weather station.

observations of three stations are statistically significant, considering $\alpha = 0.05$. The stations Bellingshausen, Jubany, and Marsh presented the following values of significance (p value): 0.02, 0.04, and 0, respectively. Applying the equations, there is a negative linear trend in the behavior of MSLP over time (hPa decade^{-1}) with the following results: Bellingshausen (–0.56), Jubany (–0.80), and Marsh (–0.79). Figure 2 shows the average annual behavior of the MSLP of the local observations and of the ERA-i and ERA5 models in the weather stations of the study site.

Air Temperature

When assessing the difference in T between all weather stations and atmospheric reanalysis models, it can be seen in Table 4 that the largest differences in T in relation to the ERA-i model are concentrated in the months of March, April, and May ($\Delta\overline{T}$ = 0.57 °C) and June, July, and August ($\Delta\overline{T}$ = 0.78 °C). For ERA5, the biggest differences were concentrated in the months of December, January, and February ($\Delta\overline{T}$ = −0.68 °C) and September, October, and November ($\Delta\overline{T}$ = −0.37 °C).

Table 5 presents annual average temperature data and their respective standard deviations, confirming that ERA-i ($\overline{\sigma}$ = 3.33 °C) and ERA5 ($\overline{\sigma}$ = 3.44 °C) have a higher degree of adherence between their data in relation local observations ($\overline{\sigma}$ = 3.69 °C). Table 6 shows Pearson's linear correlation coefficients for T, highlighting that both atmospheric reanalysis models presented very strong correlations ($\overline{R}$ = 0.95) in the study region, a result similar to that found for MSLP. The Marambio station, located at a higher altitude (198 m) in relation to others stations, showed a strong correlation for ERA-i ($R = 0.85$) and ERA5 ($R = 0.89$) and the largest standard deviations for data analyzed from WS ($\sigma = 5.88$ °C), ERA-i ($\sigma = 4.82$ °C), and ERA5 ($\sigma = 4.89$ °C).

When calculating indicators $\overline{NBIAS}$, $\overline{NMAE}$, and $\overline{NRMSE}$, we identified that ERA-i (–0.12, 0.30, and 0.44, respectively) performed better compared to ERA5 (0.26, 0.40, and 0.58, respectively) in regional study; however, Bellingshausen, Great Wall, Marambio, and Marsh stations found $NBIAS$, $NMAE$, and $NRMSE$ values that highlight the superiority of ERA5 in relation to ERA-i according to results presented in Table 7.

Evaluating the statistical significance by means of the F test for the linear trend equations of T in the weather stations, considering the local observations and the atmospheric reanalysis models ERA-i and ERA5, it was found that only the local observations of the Esperanza station are statistically significant at the level $\alpha = 0.05$, presenting a p value = 0.04. Applying the equation, a positive linear trend in T at 0.31 °C decade^{-1} is found. Figure 3 presents the average annual T behavior of local observations and the ERA-i and ERA5 models at weather stations in the study region.

Discussion

Analyses comparing weather station observations and atmospheric reanalysis models have already been carried out in polar regions in other studies. Jones and Lister (2015), when evaluating T between 1979 and 2013 in Antarctica, found a strong correlation ($R = 0.88$) between ERA-i and local observations. Our work found for the north region of the Antarctic Peninsula very strong correlations between T observations from weather stations and ERA-i ($\overline{R}$ = 0.95) and ERA5 ($\overline{R}$ = 0.95) reanalysis models; however, Tetzner, Thomas, and Allen (2019) found that for automatic weather stations installed in the southern portion of the Antarctic Peninsula higher coefficients of R for T of ERA5 compared to ERA-i, accompanied by a reduction in $RMSE$. A similar performance evaluation of atmospheric reanalysis models ERA5, ERA-i, JRA-55, CFSRv2, and MERRA-2 for T was also performed in the Arctic using radiosondes, indicating superiority of ERA5, because it presented a very strong linear correlation ($R = 0.98$)

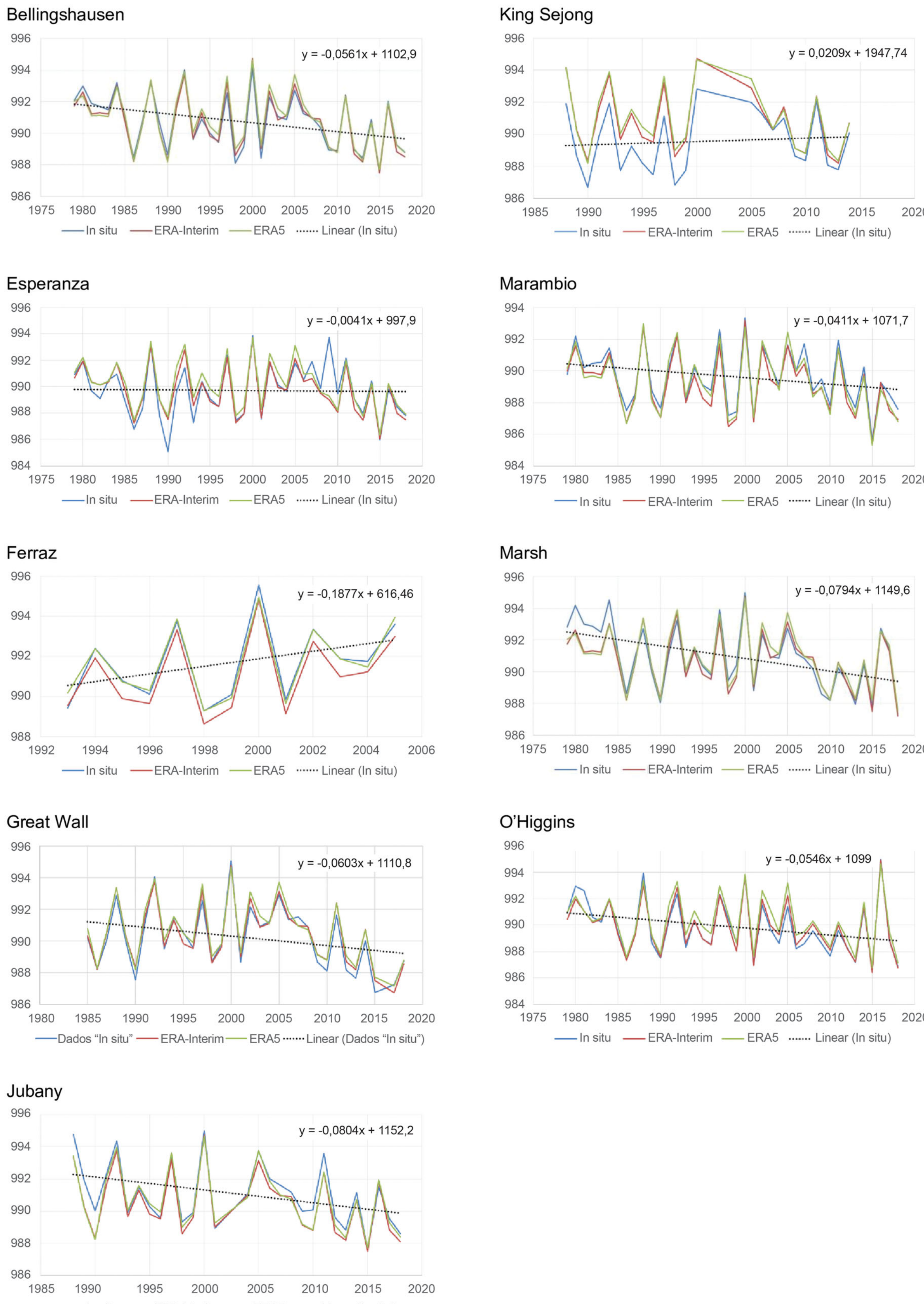

Figure 2. Variations in annual mean values of mean sea level pressure (in hPa) between local data collected from the weather stations in the Antarctic Peninsula and the atmospheric reanalysis models ERA-i and ERA5. ERA-i = ERA-Interim.

Table 4. Temperature (°C) differences between WS and atmospheric reanalysis models

Site	ERA-i–WS				ERA5–WS			
	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON
Bellingshausen	0.25	0.47	0.71	0.64	–0.41	0.10	0.50	0.20
Esperanza	–0.93	0.91	1.29	–0.18	–1.08	–0.43	–0.14	–0.75
Ferraz	–0.40	0.08	0.59	0.02	–1.40	–0.79	–0.33	–0.79
Great Wall	0.08	0.41	0.75	0.53	–0.58	0.09	0.54	0.11
Jubany	–0.34	0.20	0.53	–0.11	–1.24	–0.62	–0.35	–0.84
King Sejong	–0.06	0.24	0.40	0.08	–0.72	–0.16	0.11	–0.40
Marambio	1.22	3.10	3.02	1.39	0.33	1.55	2.00	0.30
Marsh	0.38	0.50	0.64	0.63	–0.11	–0.12	–0.12	0.18
O'Higgins	–0.31	–0.80	–0.87	–0.36	–0.94	–2.34	–2.35	–1.32
M	–0.01	0.57	0.78	0.29	–0.68	–0.30	–0.02	–0.37

Note: WS = weather station; DJF = December–January–February; MAM = March–April–May; JJA = June–July–August; SON = September–October– November.

Table 5. Presentation of the mean ($\bar{T}$) and σ (°C) of the data set for the months valid for each WS and the atmospheric reanalysis models

Site	WS		ERA-i		ERA5		Variation	
	$\bar{T}$	σ	$\bar{T}$	σ	$\bar{T}$	σ	ERA-i –WS	ERA5 –WS
Bellingshausen	–2.17	3.12	–1.66	2.94	–2.07	2.82	0.51	0.1
Esperanza	–4.72	4.94	–4.83	3.91	–5.31	4.45	–0.11	–0.59
Ferraz	–1.48	3.31	–1.40	2.88	–2.31	2.95	0.08	–0.83
Great Wall	–2.14	3.19	–1.69	2.94	–2.10	2.84	0.45	0.04
Jubany	–1.65	3.23	–1.58	2.86	–2.41	2.96	0.07	–0.76
King Sejong	–1.86	3.15	–1.69	2.96	–2.14	2.90	0.17	–0.28
Marambio	–8.18	5.88	–6.01	4.82	–7.14	4.89	2.17	1.04
Marsh	–2.20	3.02	–1.65	2.94	–2.22	3.12	0.55	–0.02
O'Higgins	–3.55	3.37	–4.13	3.71	–5.27	4.07	–0.58	–1.72
M	–3.11	3.69	–2.74	3.33	–3.44	3.44	0.37	–0.34

Note: WS = weather station; ERA-i = ERA-Interim.

and reduced *RMSE* compared to local weather observations (Graham, Hudson, and Maturilli 2019).

Statistical analyses comparing MSLP data between ERA-i and weather stations were carried out between 1979 and 2008 in Antarctica (Bracegirdle and Marshall 2012), showing a very strong correlation ($R > 0.98$). Our research also found in the study site a very strong correlation for ERA-i ($\overline{R} = 0.96$) and ERA5 ($\overline{R} = 0.95$) considering the period from 1979 to 2018.

The differences in T and MSLP found between atmospheric reanalysis models and local observations can be influenced by several factors (Xie et al. 2014). Observational data refer to specific points, whereas reanalysis shows the average value over a

Table 6. Pearson's linear correlation between annual T averages of weather stations in relation to the ERA-i and ERA5 atmospheric reanalysis models

Site	ERA-i–WS	ERA5–WS
Bellingshausen	0.98	0.96
Esperanza	0.92	0.96
Ferraz	0.97	0.94
Great Wall	0.98	0.97
Jubany	0.97	0.97
King Sejong	0.97	0.94
Marambio	0.85	0.89
Marsh	0.96	0.93
O'Higgins	0.96	0.96
M	0.95	0.95

Note: ERA-i = ERA-Interim; WS = weather station.

Table 7. Normalized bias (*NBIAS*), normalized mean absolute error (*NMAE*), and normalized root mean square error (*NRMSE*) analyses between temperature parameters obtained from WS and atmospheric reanalysis models

Site	ERA-i–WS			ERA5–WS		
	NBIAS (%)	*NMAE* (%)	*NRMSE* (%)	*NBIAS* (%)	*NMAE* (%)	*NRMSE* (%)
Bellingshausen	–0.26	0.28	0.35	–0.04	0.23	0.29
Esperanza	–0.05	0.26	0.32	0.14	0.21	0.26
Ferraz	–0.04	0.53	1.08	0.89	0.96	1.59
Great Wall	–0.24	0.26	0.34	–0.01	0.25	0.34
Jubany	0.00	0.35	0.54	0.68	0.71	1.07
King Sejong	–0.10	0.21	0.33	0.25	0.37	0.52
Marambio	–0.26	0.28	0.35	–0.12	0.17	0.22
Marsh	–0.27	0.29	0.35	0.03	0.22	0.31
O'Higgins	0.17	0.20	0.26	0.51	0.51	0.59
M	–0.12	0.30	0.44	0.26	0.40	0.58

Note: WS = weather station; ERA-i = ERA-Interim.

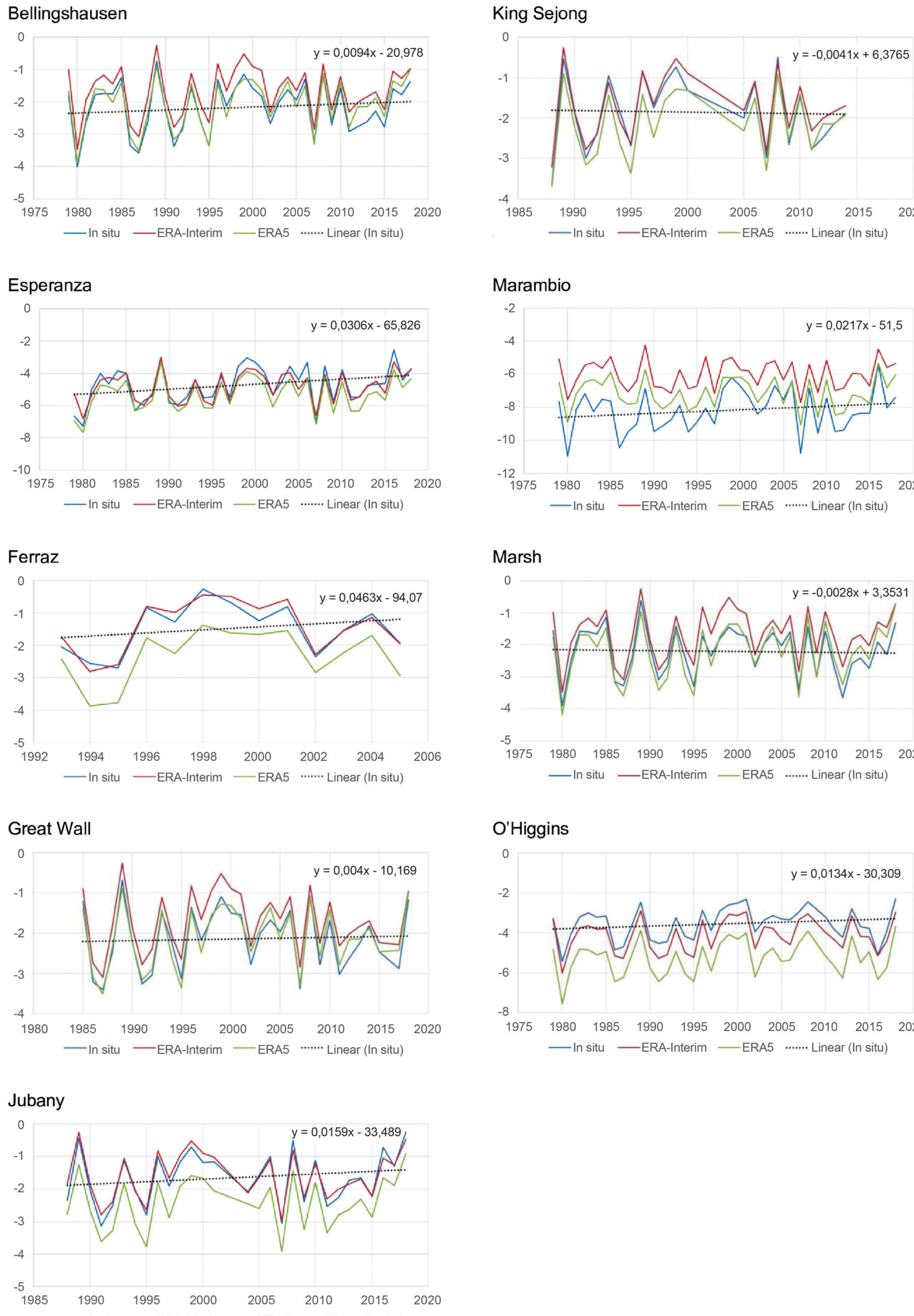

Figure 3. Variations of the annual averages of temperature (°C) between the local data collected from the weather stations located in the Antarctic Peninsula and the atmospheric reanalysis models ERA-i and ERA5. ERA-i = ERA-Interim.

grid cell. There are also significant differences in the temporal coverage of the data: Whereas ERA-i refers to the average of values every six hours, ERA5 refers to each hour. In addition, the orography of coastal regions where weather stations are installed can influence the accuracy of atmospheric reanalysis models. Tetzner, Thomas, and Allen (2019) reported the impact of orography on the performance of ERA5, finding better results in areas with higher altitude.

When analyzing the linear trend of T of the observations in the weather stations, for the period from 1979 to 2018, a warming of 0.31 °C decade^{-1} is observed for the Esperanza station. Between the years 1970 and 2000 a warming of 0.40 °C decade^{-1} was identified in the Antarctic Peninsula; however, when analyzing the interval between 2000 and 2016, a cooling of −0.67 °C decade^{-1} was detected (Gonzalez and Fortuny 2018). This recently observed signal change is highly sensitive when analyzed in a short period of time and therefore cannot be treated as a robust change in temperature evolution. The main variability is found in the autumn and winter months (Nicolas and Bromwich 2014; Gonzalez and Fortuny 2018).

Our research also analyzed the MSLP trend from 1979 to 2018 in local observations of weather stations, noting a reduction in MSLP between −0.56 (Bellingshausen station) and −0.80 hPa decade^{-1} (Jubany station). Reductions in MSLP were also observed at the Arctowski weather station (62.16° S, 58.47° W), where average annual values of 991.5 hPa were found during 1977 to 1998 and declined to 989.9 hPa between 2013 and 2017 (Plenzler et al. 2019). At the Bellingshausen weather station, Kejna, Araźny, and Sobota (2013) reported a decrease in MSLP by −0.36 hPa decade^{-1} in the period from 1948 to 2011. This reduction induces a greater occurrence and intensity of the winds from the west, raising the T in the region, consequently affecting the Antarctic environment with the acceleration of the melting processes of the sea and continental ice masses, combined with the change in the frequency of rainfall precipitation in the study region (Turner and Colwell 1995; Cook et al. 2005).

The trends observed for T and MSLP might be related to predominantly positive phases of SAM in the analyzed period (Turner et al. 2020). In addition, a pressure center at sea level located between latitudes 60° and 70° S, called Amundsen Sea Low, causes anomalies in the meridional component of the wind, which in turn alters the concentration of sea ice and the heat flow from the ocean (Fogt et al. 2012; Hosking et al. 2013; Turner et al. 2016).

Conclusions

The statistical results obtained by comparing meteorological variables T and MSLP of local observations in relation to atmospheric reanalysis models ERA5 and ERA-i indicated that both models present satisfactory results for the northern region of the Antarctic Peninsula. Checking the difference in $\overline{T}$ between weather stations and reanalysis models, we found a better result for ERA5 ($\Delta\overline{T} = -0.34\,°C$) compared to ERA-i ($\Delta\overline{T} = 0.37\,°C$); however, for the difference in $\overline{MSLP}$ the ERA-i ($\Delta\overline{MSLP} = -0.04\,hPa$) presented a better response in relation to ERA5 ($\Delta\overline{MSLP} = 0.24\,hPa$).

For T, ERA-i resulted in indicators $\overline{NBIAS}$, $\overline{NMAE}$, and $\overline{NRMSE}$ superior in relation to ERA5, but $\overline{R}$ presented very strong correlations for both models. When evaluating the MSLP, both atmospheric reanalysis models showed satisfactory results in the indicators $\overline{NBIAS}$, $\overline{NMAE}$, and $\overline{NRMSE}$, with values below 0.01 percent, accompanied by a very strong correlation of data from the reanalysis models with local observations.

Analyzing the trend of T and MSLP from the statistically significant local observations, an increase in T of 0.31 °C decade^{-1} (Esperanza station) and a reduction of MSLP between −0.56 (Bellingshausen station) to −0.80 hPa decade^{-1} (Jubany station) were found.

Acknowledgments

Thanks go to the Federal Institute of Education, Science and Technology of Rio Grande do Sul (Instituto Federal de Educação, Ciência e Tecnologia do Rio Grande do Sul, IFRS), which allowed doctoral studies for Fernando Luis Hillebrand. We also thank the Coordination for the Improvement of Higher Education Personnel (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior, CAPES).

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References

Bracegirdle, T. J. 2013. Climatology and recent increase of westerly winds over the Amundsen Sea derived from six reanalyses. *International Journal of Climatology* 33 (4):843–51. doi: 10.1002/joc.3473.

Bracegirdle, T. J., and G. J. Marshall. 2012. The reliability of Antarctic tropospheric pressure and temperature in the latest global reanalyses. *Journal of Climate* 25 (20):7138–46. doi: 10.1175/JCLI-D-11-00685.1.

Brassington, G. 2017. Mean absolute error and root mean square error: Which is the better metric for assessing model performance? Paper presented at EGU General Assembly Conference: 19th EGU General Assembly, Vienna, April 23–28.

Bromwich, D. H., and R. L. Fogt. 2004. Strong trends in the skill of the ERA-40 and NCEP–NCAR reanalyses in the high and midlatitudes of the Southern Hemisphere, 1958–2001. *Journal of Climate* 17 (23):4603–19. doi: 10.1175/3241.1.

Cook, A. J., A. J. Fox, D. G. Vaughan, and J. G. Ferrigno. 2005. Retreating glacier fronts on the Antarctic Peninsula over the past half-century. *Science* 308 (5721):541–44. doi: 10.1126/science.1104235.

Dee, D. P., S. M. Uppala, A. J. Simmons, P. Berrisford, P. Poli, S. Kobayashi, U. Andrae, et al. 2011. The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society* 137 (656):553–97. doi: 10.1002/qj.828.

Fogt, R. L., A. J. Wovrosh, R. A. Langen, and I. Simmonds. 2012. The characteristic variability and connection to the underlying synoptic activity of the Amundsen-Bellingshausen Seas Low. *Journal of Geophysical Research: Atmospheres* 117 (D7):22. doi: 10.1029/2011JD017337.

Fujiwara, M., J. S. Wright, G. L. Manney, L. J. Gray, J. Anstey, T. Birner, S. Davis, et al. 2017. Introduction to the SPARC Reanalysis Intercomparison Project (S-RIP) and overview of the reanalysis systems. *Atmospheric Chemistry and Physics* 17 (2):1417–52. doi: 10.5194/acp-17-1417-2017.

Gong, D., and S. Wang. 1998. Antarctic oscillation: Concept and applications. *Chinese Science Bulletin* 43 (9):734–38. doi: 10.1007/BF02898949.

Gonzalez, S., and D. Fortuny. 2018. How robust are the temperature trends on the Antartic Peninsula? *Antarctic Science* 30 (5):322–28. doi: 10.1017/S0954102018000251.

Graham, R. M., S. R. Hudson, and M. Maturilli. 2019. Improved performance of ERA5 in Arctic gateway relative to four global atmospheric reanalyses. *Geophysical Research Letters* 46 (11):6138–47. doi: 10.1029/2019GL082781.

Hair, J. R., R. E. Anderson, R. L. Tatham, and W. C. Black. 1998. *Multivariate data analysis*. Englewood Cliffs, NJ: Prentice-Hall.

Hersbach, H., B. Bell, P. Berrisford, A. Horányi, J. M. Sabater, J. Nicolas, R. Radu, et al. 2019. Global reanalysis: Goodbye ERA-i, hello ERA5. *ECMWF Newsletter* 159:17–24. doi: 10.21957/vf291hehd7.

Hosking, J. S., A. Orr, G. J. Marshall, J. Turner, and T. Phillips. 2013. The influence of the Amundsen–Bellingshausen Seas Low on the climate of West Antarctica and its representation in coupled climate model simulations. *Journal of Climate* 26 (17):6633–48. doi: 10.1175/JCLI-D-12-00813.1.

Howat, I. M., C. Porter, B. E. Smith, M. J. Noh, and P. Morin. 2019. The reference elevation model of Antarctica. *The Cryosphere* 13 (2):665–74. doi: 10.5194/tc-13-665-2019.

Jones, P. D., and D. H. Lister. 2015. Antarctic near-surface air temperatures compared with ERA-Interim values since 1979. *International Journal of Climatology* 35 (7):1354–66. doi: 10.1002/joc.4061.

Kejna, M., A. Araźny, and I. Sobota. 2013. Climatic change on King George Island in the years 1948–2011. *Polish Polar Research* 34 (2):213–35. doi: 10.2478/popore-2013-0004.

King, J. C. 1994. Recent climate variability in the vicinity of the Antarctic Peninsula. *International Journal of Climatology* 14 (4):357–69. doi: 10.1002/joc.3370140402.

Lefebvre, W., and H. Goosse. 2005. Influence of the Southern Annular Mode on the sea ice–ocean system: The role of the thermal and mechanical forcing. *Ocean Science* 1 (3):145–57. doi: 10.5194/os-1-145-2005.

Madsen, H., P. Pinson, G. Kariniotakis, H. A. Nielsen, and T. S. Nielsen. 2005. Standardizing the performance evaluation of short-term wind power prediction models. *Wind Engineering* 29 (6):475–89. doi: 10.1260/030952405776234599.

Marshall, G. J., A. Orr, N. P. Van Lipzig, and J. C. King. 2006. The impact of a changing Southern Hemisphere Annular Mode on Antarctic Peninsula summer temperatures. *Journal of Climate* 19 (20):5388–404. doi: 10.1175/JCLI3844.1.

Martin, P. J., and D. A. Peel. 1978. The spatial distribution of 10 m temperatures in the Antarctic Peninsula. *Journal of Glaciology* 20 (83):311–17. doi: 10.3189/S0022143000013861.

Nicolas, J. P., and D. H. Bromwich. 2014. New reconstruction of Antarctic near-surface temperatures: Multidecadal trends and reliability of global

reanalyses. *Journal of Climate* 27 (21):8070–93. doi: 10.1175/JCLI-D-13-00733.1.
Plenzler, J., T. Budzik, D. Puczko, and R. J. Bialik. 2019. Climatic conditions at Arctowski Station (King George Island, West Antarctica) in 2013–2017 against the background of regional changes. *Polish Polar Research* 40 (1):1–27. doi: 10.24425/ppr.2019.126345.
Ress, G. W. 2003. *Remote sensing of snow and ice*. London and New York: Taylor and Francis.
Rodrigo, J. S., J. M. Buchlin, J. van Beeck, J. T. Lenaerts, and M. R. van den Broeke. 2013. Evaluation of the Antarctic surface wind climate from ERA reanalyses and RACMO2/ANT simulations based on automatic weather stations. *Climate Dynamics* 40 (1–2):353–76. doi: 10.1007/s00382-012-1396-y.
Schwerdtfeger, W. 1984. *Weather and climate of the Antarctic*. Amsterdam: Elsevier.
Shapiro, S. S., and M. B. Wilk. 1965. An analysis of variance test for normality (complete samples). *Biometrika Trust* 52 (3–4):591–609. doi: 10.2307/2333709.
Stark, P. 1994. Climatic warming in the central Antarctic Peninsula area. *Weather* 49 (6):215–20. doi: 10.1002/j.1477-8696.1994.tb06016.x.
Tastula, E. M., T. Vihma, E. L. Andreas, and B. Galperin. 2013. Validation of the diurnal cycles in atmospheric reanalyses over Antarctic sea ice. *Journal of Geophysical Research: Atmospheres* 118 (10):4194–204. doi: 10.1002/jgrd.50336.
Tetzner, D., E. Thomas, and C. Allen. 2019. A validation of ERA5 reanalysis data in the southern Antarctic Peninsula–Ellsworth land region, and its implications for ice core studies. *Geosciences* 9 (7):289–306. doi: 10.3390/geosciences9070289.
Turner, J., and S. R. Colwell. 1995. Temporal variability of precipitation over the western Antarctic Peninsula. Paper presented at Fourth Conference on Polar Meteorology and Oceanography, Dallas, TX, January 15–20.
Turner, J., J. S. Hosking, G. J. Marshall, T. Phillips, and T. J. Bracegirdle. 2016. Antarctic sea ice increase consistent with intrinsic variability of the Amundsen Sea Low. *Climate Dynamics* 46 (7–8):2391–402. doi: 10.1007/s00382-015-2708-9.
Turner, J., G. J. Marshall, K. Clem, S. Colwell, T. Phillips, and H. Lu. 2020. Antarctic temperature variability and change from station data. *International Journal of Climatology* 40 (6):2986–3007. doi: 10.1002/joc.6378.
Turner, J., and S. Pendlebury. 2004. *The international Antarctic weather forecasting handbook*. Cambridge, UK: British Antarctic Survey.
Turner, J., and S. Pendlebury. 2019. Antarctic Climate Data: Results From The SCAR READER Project. Accessed August 22, 2019. http://legacy.bas.ac.uk/met/READER.
Vaughan, D. G., G. J. Marshall, W. M. Connolley, C. Parkinson, R. Mulvaney, D. A. Hodgson, C. K. John, C. J. Pudsey, and J. Turner. 2003. Recent rapid regional climate warming on the Antarctic Peninsula. *Climatic Change* 60 (3):243–74. doi: 10.1023/A:1026021217991.
Wilks, D. S. 2011. *Statistical methods in the atmospheric sciences*. Oxford, UK: Academic Press.
Willmott, C. J., and K. Matsuura. 2005. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate Research* 30 (1):79–82. doi: 10.3354/cr030079.
Willmott, C. J., K. Matsuura, and S. M. Robeson. 2009. Ambiguities inherent in sums-of-squares-based error statistics. *Atmospheric Environment* 43 (3):749–52. doi: 10.1016/j.atmosenv.2008.10.005.
Xie, A., I. Allison, C. Xiao, S. Wang, J. Ren, and D. Qin. 2014. Assessment of surface pressure between Zhongshan and Dome A in East Antarctica from different meteorological reanalyses. *Arctic, Antarctic, and Alpine Research* 46 (3):669–81. doi: 10.1657/1938-4246-46.3.669.

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