A Validation of the Antarctic Mesoscale Prediction System Using Self-Organizing Maps and High-Density Observations from SNOWWEB

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ABSTRACT

This study compares high-resolution output (1.1-km horizontal grid length) from twice-daily forecasts produced by the Antarctic Mesoscale Prediction System (AMPS) with a dense observational network east of Ross Island. Covering 10 000 km², 15 SNOWWEB stations significantly increased the number of observation stations in the area to 19 during the 2014–15 austral summer. Collocated “virtual stations” created from AMPS output are combined with observations, producing a single dataset of zonal and meridional wind components used to train a self-organizing map (SOM). The resulting SOM is used to individually classify the observational and AMPS datasets, producing a time series of classifications for each dataset directly comparable to the other. Analysis of class composites shows two dominant weather patterns: low but directionally variable winds and high but directionally constant winds linked to the Ross Ice Shelf airstream (RAS). During RAS events the AMPS and SNOWWEB data displayed good temporal class alignment with good surface wind correlation. SOM analysis shows that AMPS did not accurately forecast surface-level wind speed or direction during light wind conditions where synoptic forcing was weak; however, it was able to forecast the low wind period occurrence accurately. Coggins’s regimes provide synoptic-scale context and show a reduced synoptic pressure gradient during these classes, increasing reliance on the ability of Polar WRF to resolve mesoscale dynamics. Available initialization data have insufficient resolution for the region’s complex topography, which likely impacts performance. The SOM analysis methods used are shown to be effective for model validation and are widely applicable.

1. Introduction

The Ross Ice Shelf (RIS) is a largely flat expanse of permanent ice covering approximately 487 000 km². Straddling the date line, it is fed by both the West and East Antarctic Ice Sheets (WAIS and EAIS, respectively). The western edge of the roughly triangular-shaped shelf is bounded by the barrier of the Transantarctic Mountains, with the EAIS behind. Katabatic winds from the EAIS converge through multiple glacial valleys in the Transantarctic Mountains (Bromwich 1989), while corresponding drainage from the WAIS flows onto the eastern and southern edges of the RIS at the Siple Coast (Bromwich and Liu 1996; Bromwich et al. 1992). This katabatic drainage is known to move significant quantities of air onto the RIS from the interior of Antarctica (Parish and Bromwich 1987, 1997, 1998). In combination with meso- or synoptic-scale cyclones and the barrier presented by the
Transantarctic Mountains, the katabatic drainage helps to feed a southerly wind regime that dominates the climatology of the RIS. Known as the Ross Ice Shelf airstream (RAS) (Parish et al. 2006), the presence of this low-level stream of air can be seen in mean surface wind field plots from monthly to annual time scales.

The signature of the RAS is a corridor of high winds flowing north, parallel to the Transantarctic Mountains and out into the Ross Sea. There is no single consistent source of atmospheric forcing for a RAS (Parish et al. 2006; Seefeldt and Cassano 2012; Nigro and Cassano 2012); however, these events are often initiated by a low pressure system at the meso- or synoptic scale, either north of the RIS in the Ross Sea or over the ice shelf itself. These systems create barrier-parallel flows relative to the Transantarctic Mountains during a RAS either directly through their own horizontal pressure gradient force (PGF), or indirectly if conditions permit the formation of a “barrier wind.” These winds form when the horizontal PGF initially directs air toward the Transantarctic Mountains; if the boundary layer is stably stratified and the flow does not possess enough kinetic energy to overcome the barrier then mass convergence occurs, creating a PGF directed away from the Transantarctic Mountains. Under these conditions, winds will become approximately geostrophic and flow parallel to the mountains; in the case of the RIS this will always be to the north as the PGF is directed toward the east, away from the mountains. The size of the Transantarctic Mountains presents a significant barrier, rising to 2000 m above sea level, and the boundary layer in this area is usually stably stratified, therefore, barrier winds are extremely common (Parish et al. 2006; Seefeldt and Cassano 2012). Recent work by Nigro and Cassano (2014a) using output from the polar-modified Weather Research and Forecasting (WRF) Model in the Antarctic Mesoscale Prediction System (AMPS) showed that a PGF conducive to barrier-parallel flow is sometimes produced by the temperature gradient between cold air over the Antarctic plateau and relatively warm air over the RIS instead of cyclones in the Ross Sea or over the RIS.

Another feature that is commonly present during a RAS event is katabatic drainage from the surrounding ice sheets (Seefeldt and Cassano 2012; Coggins et al. 2014; Nigro and Cassano 2014a). These winds are formed when air over the ice sheets is cooled, typically radiatively or via sensible heat flux into the ice surface, and becomes negatively buoyant at the surface, generating a force directed along the fall line of the terrain. Accounting for the frictional and Coriolis forces, the air flows approximately down and to the left of the fall line of the terrain, with the exact direction influenced by the background PGF (Parish and Cassano 2003). The WAIS and EAIS are both extremely large and approximately dome shaped with high interior elevations dropping to sea level at the edges. Radiative cooling at the surface of the ice sheets resulting in katabatic drainage is extremely common, with the ensuing winds sometimes reaching very high speeds at the edges of the sheets—particularly when forced into confluence zones such as glacial valleys (Parish and Bromwich 1987, 1997, 1998). These winds are widespread, persistent, directionally constant, and capable of transporting extremely large volumes of air from the interior of Antarctica northward to the coast. Once a katabatic flow reaches a large expanse of level terrain, the katabatic (downslope buoyancy) force reduces and, in the absence of another source of forcing, the air will pool and begin to impede further drainage (van den Broeke and van Lipzig 2003; Renfrew 2004). A typical RAS event provides the ideal PGF to transport this air farther north, over the RIS and the Ross Sea. Because the RIS (and RAS) is positioned between the EAS and WAIS, a significant mass of air from the interior of both sheets is transported to the RIS and, therefore, available for further transport into the Ross Sea. A case study by Parish and Bromwich (1998), investigating a significant drop in surface pressure over the Antarctic continent, identified the RIS as the destination for katabatic drainage from approximately one-third of the entire Antarctic continent (by surface area) during the event.

AMPS (Powers et al. 2012) generates forecasts twice daily for Antarctica and the Southern Ocean. Currently, it utilizes the WRF Model with polar modifications (Polar WRF) developed by the Polar Meteorology Group of the Byrd Polar Research Center at Ohio State University. While AMPS provides valuable forecast data for the flight and ground operations of many countries, its output is also used by researchers over longer time scales to supplement available observations from both staffed and automated weather stations. Multiple studies have validated, as either a primary or secondary objective, AMPS output for both the older MM5 model (Bromwich et al. 2005; Guo et al. 2003) and the newer Polar WRF Model (Powers 2007; Nigro et al. 2011, 2012a; Bromwich et al. 2012, 2013). AMPS forecasts compare very well with observations from the interior regions of Antarctica, where the terrain is rather uniform. Along the coast, AMPS forecasts still compare favorably with observations; however, it is clear that adequately resolving terrain is extremely important. This has a significant effect on winds in areas with complex topography, where higher-resolution nested grids provide better localized forecasts (Bromwich et al. 2005). Most recently, Nigro and Cassano (2014b)
calculated correlations between AMPS and 12 weather stations over the wider RIS area and showed considerably better results when using the 15-km model grid compared to the 30 km. While some of these studies have investigated the area around Ross Island, the spatial density of available observations is relatively sparse, thus detailed evaluations of the highest-resolution domains in AMPS have not been completed. This study refers to, and validates, forecasts produced by the AMPS system as a whole rather than the underlying Polar WRF Model specifically. The free availability and range of high-resolution nested grids make AMPS a viable data source for researchers and forecasters alike, so performing a holistic validation of the system will be of value to others in the community.

The air, sea, and land operations around Ross Island require accurate weather forecasts, which is why the highest-resolution AMPS nested grids are situated over this area. Fine grid spacings also assist in resolving some of the complex terrain in the region, where the effect of this terrain on wind patterns in the area is interesting in and of itself (e.g., O’Connor et al. 1994; Seefeldt et al. 2003; Monaghan et al. 2005; Powers 2007). The RAS commonly passes close to Ross Island (Parish et al. 2006; Coggins et al. 2014; Nigro and Cassano 2014a), where its impact on the nearby Ross Sea Polynya is the subject of ongoing research associated with this study. These factors, combined with easy physical access via the nearby research bases makes studying this area an attractive prospect. The SNOWWEB network of weather stations (Coggins et al. 2013; Jolly et al. 2013) has been designed and built by the Department of Physics and Astronomy at the University of Canterbury, New Zealand. The high-density observations from a SNOWWEB deployment in the vicinity of Ross and White Islands (see Fig. 1) provide a unique opportunity to assess Polar WRF output from AMPS at very high resolution.

Self-organizing maps (SOMs) are artificial neural networks commonly used to reduce the dimensionality of a dataset (Kohonen 1990). Training of the neural network is unsupervised, where the network adapts itself to the input dataset with no external indication of “correct” or “incorrect” results. While the user may specify the size and shape of the SOM as well as certain training parameters, the end result is an objective set of distinct patterns that is representative of the entire dataset. This makes SOMs very useful tools for cluster analysis of large, complex datasets, given the simplicity and computational efficiency of the algorithm. While SOMs have been used for a wide array of studies.
covering many disciplines, they are particularly effective at developing climatologies (Hewitson and Crane 2002; Reusch et al. 2005; Sheridan and Lee 2011) and investigating weather patterns and extremes (Seefeldt and Cassano 2012; Nigro and Cassano 2014a; Cassano et al. 2015). Clustering methods in general, and SOMs specifically, also have great potential for validating model output. Good examples are demonstrated by Nigro et al. (2011), who used SOM classifications to validate Polar WRF output from AMPS by a weather pattern, and Coggins et al. (2014), who used k-means clustering to classify ERA-Interim data over a similar area, which was then validated against observations from weather stations. Both highlighted the possibility that large model biases may be overlooked by more traditional methods such as monthly, seasonal, or annual statistics.

The work presented here builds upon the work of Nigro et al. (2011) by applying the SOM algorithm to both model output and SNOWWEB observations then comparing not only the classified data but also statistics from the classifications themselves. To compare the SNOWWEB observations with corresponding Polar WRF output from AMPS, “virtual stations” are generated from the model output by taking the nearest grid points. Surface wind data from both sources are then combined to create a single dataset, which is used to train a SOM. This combined SOM is used to classify wind data from SNOWWEB and AMPS separately and compare overall differences in wind and surface pressure by SOM class, as well as differences in SOM class frequency, transience, and temporal alignment to determine how well the highest-resolution AMPS output performs at this scale. In addition, the influence of synoptic-scale forcing is investigated by using climate regimes presented by Coggins and McDonald (2015) derived from 33 yr of ERA-Interim surface wind reanalysis data on a 0.75° × 0.75° grid. Throughout this study, observations from the University of Wisconsin–Madison Automatic Weather Station (AWS) network are incorporated to augment and extend the spatial coverage of SNOWWEB; however, these observations were not used during the SOM training process.

2. Data and methods

a. Observations

This analysis uses two sources of observational data: SNOWWEB Weather Stations (SWS) (Coggins et al. 2013; Jolly et al. 2013) from the University of Canterbury, New Zealand, and AWS run by the University of Wisconsin–Madison (UW) Antarctic Meteorological Research Center (AMRC) (Lazzara et al. 2012). SWS are smaller, temporary weather stations used on a campaign basis to boost the number of observations in an area during the summer months, whereas AWS are larger, permanent stations that are more widely spread over a far larger area. A total of 20 SWS stations were deployed at the end of November 2014 and retrieved in the middle of February 2015. The deployment area, approximately 120 km by 130 km, was to the east of Ross and White Islands as indicated in Fig. 1. The exact time span of this study follows the period when all SWS were deployed and runs from 1 December 2014 to 11 February 2015. The observations used in this analysis come from 15 of the 20 stations mentioned above, the remaining 5 experienced difficulties recording valid wind data throughout the period specified or were not equipped with wind sensors.

SWS commonly observe wind speed and direction, temperature, relative humidity, and pressure; however, exact sensor combinations vary with objectives from site to site. Measurements are recorded every minute to an onboard SD card for later quality control and post-processing to produce a 10-min dataset of mean values. These data are quality controlled by eliminating measurements greater than three standard deviations from the mean using a 3-h rolling window. This study focuses on wind and atmospheric pressure observations. While temperature 2 m above ground level was also recorded, there was a substantial positive bias caused by incoming solar radiation during low wind speeds. Filtering data to remove this bias, as per methods suggested by Genthon et al. (2011), removes a large proportion of the total temperature and relative humidity observations and thus reduces the usefulness of these measurements for this study.

AWS record similar observations to SWS but are designed to be permanently deployed with higher-grade, more expensive instrumentation and control systems. Most stations use satellite communications, or local wireless networks where possible, to upload data. Unfortunately the data collected over the local wireless network (freewave) is not yet integrated into the semi-automatic quality-controlled process carried out by the AMRC, so freewave data was processed by the authors using the same quality-controlled techniques as for SWS data. The final AWS dataset used is a combination of the “q10” manually quality-controlled 10-min (Lazzara et al. 2012) data product available from the AMRC and freewave data quality controlled by the authors.

Both (SWS and AWS) 10-min datasets were further down sampled to match the hourly resolution available from the domain 5 (1.1-km grid) output of AMPS, where
the closest possible measurement to the top of each hour was taken.

b. Model output—The Antarctic Mesoscale Prediction System

Using output from the Polar WRF Model within AMPS (Powers et al. 2012) as a proxy for observations over a medium to long time period usually requires the researcher to combine output from multiple forecasts into a single, cohesive dataset. Depending on the AMPS domain used, forecasts extend for 40–120 h, where higher-resolution (spatial and temporal) domains have shorter forecast lengths (Powers et al. 2012). As forecasts are run twice daily, the currently accepted method is to define a 12-h block of forecast hours then concatenate data from all forecasts for those hours only into a single dataset (e.g., Nicolas and Bromwich 2011; Nigro et al. 2011; Seefeldt and Cassano 2012; Nigro and Cassano 2014b). Most studies use forecast hours from the 12–24-h block, with exact hours varying with available model output intervals, to allow time for model spinup (Guo et al. 2003; Bromwich et al. 2005). A preliminary study reinvestigated this method and found that, for domain 5, earlier forecast hours could be used with a small increase in model skill. However, the benefit was not substantial and would reduce the relevance of this study for others in the research community, therefore, this study uses the accepted range of hours 12–23.

The AMPS physics options for Polar WRF include the following: the Rapid Radiative Transfer Model for GCMs (RRTMG) longwave radiation scheme, the Goddard shortwave radiation scheme, the Mellor–Yamada–Janjic (Eta) TKE boundary layer scheme, the Monin–Obukhov (Janjic Eta) surface layer scheme, and the WSM 5-class cloud microphysics scheme. The model top is set at 10 mb with vertical velocity damping applied in the top 7.5 km. Initial model conditions use the National Centers for Environmental Prediction (NCEP) Global Forecast System (GFS) with a horizontal resolution of 0.25° latitude/longitude and a temporal resolution of 6 h.

Several nested grids (‘‘domains’’) exist within AMPS. This study uses output from domain 5, a nested 613 km by 718 km grid centered near Minna Bluff south of Ross Island with a 1.1-km horizontal grid length and hourly temporal resolution. Zonal (u) and meridional (v) wind components are available at 10 m, temperature at 2 m, and pressure at the surface. To compare a gridded model output to a network of physical stations, ‘‘virtual’’ AMPS stations were generated by choosing model grid points that were close to physical station locations. As domain 5 uses a 1.1-km grid length, and the immediate area around each station is flat, interpolation was not required. However, vertical interpolation between 10 m above ground level (AGL) and 2 m AGL was required before the AMPS wind components could be compared to observations. A log wind profile was used with a surface roughness (z₀) parameter of 0.0001 m (Nigro and Cassano 2014b) and, as the distance was small (10–2 m), the atmosphere was assumed to be neutrally stable and there would be no discernible effect on wind direction. Wind components were also rotated from the model grid to true north using the parameters in the model output files. The time period chosen for the virtual stations matches that for the observations: 1 December 2014–11 February 2015.

c. Self-organizing maps

The purpose of SOMs in this study is to cluster time periods with similar wind conditions together into classes (where each class is a node within the SOM) that will be used to classify AMPS output and SWS observations. This allows for the creation of composites for each class as well as the comparison of class statistics between the input datasets. The size and shape of a SOM are important factors to consider before training: too many possible classes will result in low frequencies of occurrence for each class, while too few will result in classes that are ‘‘averages’’ of what may have been two similar but distinct classes in a larger SOM (Cassano et al. 2015). After some experimentation, a 4 × 3 rectangular SOM was selected as this shape showed sufficient intercluster variability while maintaining relatively high frequencies for each cluster, which allows robust analysis. Multiple randomly initialized SOMs were each trained in two stages: a brief run with aggressive training parameters to roughly shape the SOM, followed by a longer run with more conservative parameters. All returned similar patterns with similar quantization errors so the SOM with the lowest mean error was chosen. A Sammon map (Sammon 1969) was produced that showed approximately even separation between the SOM nodes with some minor distortion—a good indication that the SOM was well constructed and trained for the purpose of this study (Cassano et al. 2015).

The SOM was trained using a combined dataset of SWS 2-m zonal and meridional wind observations and output for corresponding AMPS virtual stations, with AWS observations reserved for independent validation. The integration of both model and observational data into a single training dataset for a SOM requires caution as the resulting classes will reflect the combined dataset, not the individual components. This is a problem when developing representative climatologies, but that is not the aim of this study as the duration of available observations is insufficient. The primary reason for training with the combined dataset is to produce a set of SOM nodes that can be used to classify either input dataset, with the goal being two classification time...
series (SWS and AMPS) that may be directly compared. Model bias will be reflected in differences in class frequencies between the time series, where observations will be less likely to receive a classification unduly influenced by model bias. The analysis approach presented is not possible if two separate SOMs (one for each dataset) are used as the classes will be slightly different and thus not exactly comparable. Additionally, a single SOM trained on one dataset would not produce valid classifications of another as the behavior of the SOM classifier on data outside the range (due to model bias/differences) of the training data is undefined.

Approximately two months of data were used for this analysis with just over 1700 hourly timestamps, so the number of periods from the combined SWS and AMPS datasets approaches 3400 timestamps, each with 30 data points (zonal and meridional components from 15 stations). Training the SOM with both SWS and AMPS data produced a common set of classes that could be used to compare the two, allowing the comparison of not only standard meteorological variables and associated correlations, but also SOM class frequency, duration, progression, and temporal alignment. The SOMPAK (v 3.1) software implementation of the SOM algorithm was used in this study (obtained from http://www.cis.hut.fi/research/som_pak/ on 5 March 2015).

### 3. Results

#### a. SWS and AWS surface winds

After training the SOM using the combined SWS and AMPS dataset of hourly wind vectors, each dataset was classified individually and composites were created from the resulting SOM classes by taking the mean of all data points for each class by station. The objective of this study is to investigate the performance of AMPS (and therefore Polar WRF) and not to develop a new set of surface wind patterns, so the SOM classes themselves will be introduced and discussed briefly to establish confidence they are physically realistic before moving on to the question of validating AMPS forecasts. A subset of statistics for both the SWS and AMPS classifications is presented in Table 1, where the network mean wind speed for each class is most relevant to this section. Whenever observations (or model output from corresponding locations) are shown, observations from six AWS are included with those from the SWS network to form a combined set referred to as “SWS/AWS.” The six AWS—Laurie II, Lorne, Linda, Ferrell, Pegasus North, and Windless Bight—are included on all figures but are not specifically marked after Fig. 1 in order to increase readability of the already complex diagrams (refer to Fig. 1 for locations). Correlations with scalar wind speed and both zonal and meridional winds between AWS and SWS neighbors are consistent with equivalent stations within the SWS network alone.

Figure 2 shows the mean wind vectors for SWS/AWS observations for each class, with a “(col,row)” identifier (class name) and the class occurrence frequency displayed in each title. There is an obvious gradient in wind speed between class (0,0) at the top left and class (3,2) at the bottom right of Fig. 2, with mean wind speeds increasing toward (3,2). These two classes also have the highest frequencies, together accounting for

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Persistence (h)</th>
<th>Mean wind speed (m s$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SWS AMPS Diff</td>
<td>SWS AMPS Diff</td>
</tr>
<tr>
<td>(0,0)</td>
<td>24.77% 20.60% −4.17</td>
<td>8.0 8.5 −0.5</td>
</tr>
<tr>
<td>(0,1)</td>
<td>5.15% 5.50% 0.35</td>
<td>2.0 2.5 0.5</td>
</tr>
<tr>
<td>(0,2)</td>
<td>7.87% 7.35% −0.52</td>
<td>2.0 4.0 3.5</td>
</tr>
<tr>
<td>(1,0)</td>
<td>11.98% 8.04% −3.94</td>
<td>3.5 3.0 2.4</td>
</tr>
<tr>
<td>(1,1)</td>
<td>4.22% 3.65% −0.58</td>
<td>2.0 2.0 2.9</td>
</tr>
<tr>
<td>(1,2)</td>
<td>9.26% 5.67% −3.59</td>
<td>2.0 3.0 4.1</td>
</tr>
<tr>
<td>(2,0)</td>
<td>5.44% 11.69% 6.25</td>
<td>2.0 3.0 3.8</td>
</tr>
<tr>
<td>(2,1)</td>
<td>3.47% 3.41% 0.06</td>
<td>2.0 2.0 4.9</td>
</tr>
<tr>
<td>(2,2)</td>
<td>7.18% 3.88% −3.30</td>
<td>3.0 3.0 6.0</td>
</tr>
<tr>
<td>(3,0)</td>
<td>2.72% 9.32% 6.60</td>
<td>2.0 3.0 5.5</td>
</tr>
<tr>
<td>(3,1)</td>
<td>4.11% 7.23% 3.12</td>
<td>3.0 4.0 6.8</td>
</tr>
<tr>
<td>(3,2)</td>
<td>13.83% 13.60% −0.23</td>
<td>8.0 8.0 10.7</td>
</tr>
</tbody>
</table>
38.6% of all time periods. Class (0,0) is the only class to show mean northerly winds; however, the fact that it accounts for one-quarter of all periods suggests it simply represents a broad classification of light, northerly, winds. Classes (0,1) and (0,2) represent cases with significant westerly components; however, mean vector magnitudes are relatively low. Class (1,0) shows the most significant easterly components but with light overall winds again. All other classes show significant to solely southerly components with a wide range of mean wind speeds. Class (3,2) features the largest mean vector magnitudes and shows structure typical of a RAS event. Wind direction is predominantly southerly and there is a corridor of the highest wind speeds that closely follows the edge of White and Ross Islands, originating from the edge of Minna Bluff and stretching into the Ross Sea. The “Emilia” group of stations to the east (see Fig. 1) observe lower winds outside of this corridor. “Windless Bight” AWS station (named after its location—see Fig. 1) consistently stands out as an anomaly for most classes, displaying lower wind speeds and lower directional constancy.

Station elevations varied from 18 to 52 m above mean sea level. To aid in comparison, surface pressure observations were reduced to mean sea level by calculating a mean scale height every 12 h using temperature observations from four of the AWS stations: Linda, Lorne, Ferrel, and Pegasus North. These four were selected as they were widely spaced and had good data availability for the entire period. The sea level pressure (SLP) calculated for the easternmost station was then subtracted from the SLP of the other stations to create a relative SLP (RSLP) value for each, which is plotted in Fig. 6.
is a persistent positive westward pressure gradient in this region regardless of class; however, class (0,0)—the lowest wind speed class—displays the most homogeneity, which implies that, in the absence of a dominant pressure gradient, local forcing for winds is likely dominant and complex. In most other classes, there is a clear gradient from Windless Bight AWS along the Ferrell SWS group.

This is particularly pronounced in class (3,2), where Windless Bight shows an extremely high localized RSLP and the gradient is the strongest of all the classes. This is a good example of a high pressure stagnation zone caused by significant orographic blocking (O’Connor and Bromwich 1988; Seefeldt et al. 2003) and supports the low wind speed and directional constancy near Windless Bight.

This diagram illustrates the directional constancy of 2-m winds for SWS and AWS observations with composites chosen as per Fig. 2. A value of 1.0 indicates a perfectly constant wind direction, while lower values indicate higher variability.
Differences between AMPS and SWS are shown in Fig. 7 and are discussed in section 3b.

b. Comparison with AMPS

Comparing the AMPS vectors in Fig. 3 to the SWS/AWS in Fig. 2, where both composites use the SWS SOM classifications, there is general agreement between the two figures. The most notable network-wide differences occur in the left-hand column classes of (0,0), (0,1), and (0,2). Class (0,0) shows what are likely highly variable winds with vector magnitudes approaching 0, while (0,1) and (0,2) show larger southerly components (1.0 and 1.5 m s\(^{-1}\), respectively) and higher mean vector magnitudes (0.7 and 0.5 m s\(^{-1}\), respectively) than seen in the SWS/AWS vectors. There is also a large gradient in the mean vector magnitudes for these classes in AMPS than in SWS/AWS, an effect that is also seen in classes (1,1) and (1,2). For higher wind speed classes in the right-hand half of the SOM, the direction of the AMPS wind vectors appear more uniform than SWS and are not as visibly affected by surrounding topography. This is particularly pronounced in the final column [classes (3,0), (3,1), and (3,2)], where the northwestern section of the SWS network shows that the influence of Mt. Terror (Ross Island) on the wind field extends farther east than is reflected in the AMPS virtual stations.

Differences in directional constancy between AMPS and SWS/AWS observations (Fig. 5) are inversely proportional to the SWS constancies, where constancy is calculated as the ratio of the mean vector magnitude to the mean scalar speed. There are relatively large differences (both positive and negative) for the classes with lower constancy (see Fig. 4), decreasing as constancy increases alongside wind speed toward class (3,2). Class (0,0) shows a very large discrepancy, with the AMPS constancy less than half of the bulk of the SWS/AWS network. This suggests Polar WRF within AMPS does not resolve small-scale local forcing well, affecting winds to the east of White and Ross Islands and resulting in highly variable wind directions. The higher constancy of Windless Bight and Pegasus North (see Fig. 1) are unexpected but likely reflect the fact that WRF is correctly simulating the blocking effect of Hut Point Peninsula and the northeasterly winds that are so common to the area (Coggins et al. 2013)—a hypothesis supported by Figs. 2 and 3. The overestimation of constancy for the northern half of the network in class (0,1) can be linked to the higher wind speeds and a larger southerly component, with a similar though less pronounced effect seen in class (0,2).

Differences between the RSLP values in the SWS/AWS observations (Fig. 6) and those in AMPS are
shown in Fig. 7. For consistency, AMPS SLP was calculated from the surface pressure output using the same methods as SWS/AWS instead of simply using the SLP output that was also available. As this figure shows the difference in RSLP instead of SLP, it is not biased by any offset that may be present between AMPS output and observations. It shows general agreement between AMPS and SWS/AWS RSLP with a tendency for AMPS to very slightly underestimate the RSLP closer to topography for some classes. There are two outliers immediately apparent in the northernmost group of stations—one positive and one negative—yet closer
investigation of the SWS/AWS RSLPs in Fig. 6 does not reveal any obviously abnormal RSLP values. Inspection of the AMPS equivalent of Fig. 6 (not shown for brevity) reveals both locations to be consistent outliers in the AMPS RSLP values, one being lower while the other is higher (matching with the RSLP difference). As both station locations are very close to the edge of the ice shelf, we speculate that there may be a discrepancy between the actual edge and its representation within AMPS at these locations. While the ice shelf edge has recently been updated within AMPS, the stations are so close that the discrepancy need not be large. The largest differences are in two of the lowest wind speed classes, (0,0) and (1,0), with many stations showing a reduction in RSLP that indicates a weaker or non-existent gradient. The AMPS equivalent of Fig. 6 (not shown) confirms that the gradient in these classes is much smaller or nonexistent. This reduction carries through for the Linda/Lorne group into the higher wind speed classes (2,0), (3,0), and (3,1).

Least squares linear regression was used to determine if any significant linear relationship existed between SWS/AWS wind observations and corresponding AMPS output. Significance was determined using a t test for a 95% confidence interval (CI), where nonsignificant stations are omitted from all plots. To begin with, correlation coefficients ($r$ values) for the best fitting linear relationship between SWS/AWS observations and AMPS output were calculated over the entire deployment for 2-m scalar (Fig. 8a), zonal (Fig. 8b), and meridional (Fig. 8c) wind components. Speed is highly correlated for this period, while the zonal component is moderately correlated with coefficients between 0.5 and 0.7 for most stations with a distinctive negative east–west gradient as correlations decrease in proximity to topography. The meridional wind component is more highly correlated than the zonal wind, but also features higher variation between stations. Correlation coefficients decrease along the “Ferrell” string of stations toward Windless Bight AWS for both scalar wind speed and the meridional component, but the effect is not visibly obvious for the zonal wind, perhaps due to the fact that zonal correlations in this area are relatively poor. Windless Bight AWS is the poorest-performing location for all components, an important point which is addressed further in section 4.

Figure 9 shows the correlation coefficients for 2-m wind speed between AMPS and SWS/AWS for each SOM class. The unfilled markers denote stations with poor correlation coefficients ($-0.2 < r < 0.2$) that are still statistically significant (95% CI)—nonsignificant stations are not plotted. There is an obvious gradient present between the low wind speeds and correlations of class (0,0) and the higher wind speeds and correlations of class (3,2). The most consistently well performing locations are the “Emilia” stations to the east, which also happen to be the farthest from any topographical features.

Scalar wind speed bias is displayed in the final column of Table 1 and shows that Polar WRF within AMPS tends to overestimate wind speeds during lower wind speed classes (as classified by SWS observations). This overestimation is generally low and in the order of 0.1 m s$^{-1}$ averaged over the network, however it can reach as high as 0.7 m s$^{-1}$ [class (1,0)]. During the higher wind speed classes of the final column of the SOM, AMPS underestimated wind speeds by a similar amount. In general, the model estimates the network mean wind speed well.

The bias information is important context for Fig. 10, which displays the normalized root mean squared difference (NRMSD) between SWS/AWS observations and AMPS output. The NRMSD is simply the RMS difference between SWS/AWS observations and corresponding AMPS output, normalized by the standard deviation of the observations for each station (Bromwich et al. 2005). Low values (NRMSD < 1) indicate that the difference between the AMPS output...
and the observations is less than the variability within the observations alone. Figure 10 shows a similar gradient across the SOM to that of Fig. 9, except for class (0,0), which features the second lowest mean NRMSD—lower than all surrounding classes. Class (0,0) also has a very homogeneous spatial distribution of NRMSD values relative to the other SOM classes.

c. SOM statistics

The primary advantage of training a single SOM on the combined dataset is to allow the direct class-by-class comparison of SOM statistics between SWS and AMPS. Table 1 shows the frequencies (proportion of time during the entire study that a given class occurred) and persistence (median duration of class in hours) for each class for both SWS and AMPS classification sets. Differences in class frequency are also shown, where a negative difference indicates the AMPS frequency was lower than the SWS. Differences that are not in boldface are significantly equivalent within ±2.5% points, while those that are in boldface are significantly different. Both significance tests used variants of the \( z \) test with a 95% CI. Most of the differences are observed in the top row of the SOM, with AMPS output featuring a lower rate of occurrence of the lower wind speed classes (0,0) and (1,0) than SWS, and a higher rate of occurrence of the higher wind speed cases of (2,0) and (3,0). Other classes with substantial differences are (1,2) and (2,2) (under) and (3,1) (over), where it appears as though (3,1) is overpredicted at the expense of (2,2)—this is addressed later when discussing class alignment.

Persistence (or class duration) is calculated from contiguous blocks of timestamps with identical classifications; for example, 5 consecutive (3,2) classifications are interpreted as a single 5-h event. The distributions of persistence are nonnormal with uneven tails for most classes with occasional large outliers; therefore, class median values were calculated. Both SWS and AMPS show a median persistence of approximately 8 h for the most prevalent classes (0,0) and (3,2) with good agreement between the model and observations in this respect. While persistence values are largely similar for the majority of the other classes, with only one featuring a difference of more than one hour, the AMPS classes do tend to persist for longer than the SWS classes.

Investigating how well SWS and AMPS classifications align in time provides much more information on the performance of AMPS than class frequencies alone. Figure 11 shows the probability (0 \( < P < 1 \)) of AMPS receiving the same classification as SWS by SOM class (values highlighted by green boxes). The other boxes show the probability (by class) that AMPS output will receive a different classification. For example, if a given snapshot of SWS observations receives a classification of (0,0), the probability of AMPS output for the same time slice also receiving the same classification is 0.6 (or 60%). Additionally, for the remaining 40% of occurrences, there is a roughly equal chance (approximately

![Fig. 9. Correlation between AMPS output and AWS/SWS observations for 2-m scalar wind speed, organized by class. All values displayed are significant (95% CI), nonsignificant values are not plotted. The mean correlation coefficient (r) is displayed in the title for each subplot. Again, SWS classifications were used when selecting data for each class.](image-url)
10%) of receiving a classification of (0,1), (0,2), (1,0), or (1,2). Figure 11 shows very poor alignment (less than 10% of the time) between AMPS and SWS for classes (1,1) and (2,1), yet the frequencies for these classes are equivalent (significant at 95% CI) between the datasets. This indicates that, while Polar WRF and AMPS may do a good job overall, there are substantial issues around timing.

Equally important is the very good alignment shown for class (3,2) within AMPS, with a probability of alignment with SWS classifications of 0.79. Additionally, the only other classification that AMPS received during SWS class (3,2) during this study was class (3,1), which is a lower wind speed variant of (3,2) with some minor associated differences in direction. Class (0,0) is also well represented in AMPS despite the fact it occurs at a lower rate than with SWS observations. While the alternative classifications for this class in AMPS (shown in Fig. 11) all feature very different mean vector patterns (Fig. 3), it is worth remembering that the directional constancies of these patterns are among the lowest of the SOM classes, which means conditions for some of these instances may overlap to a greater extent than displayed. Most other classes are poorly represented with respect to rate of occurrence (significant differences in Table 1) or alignment (low P values in Fig. 11) or both.

Figure 11 also provides insight into the differences in frequencies displayed in Table 1 for classes (2,2) and (3,1), where the differences in frequencies are −3.30% and +3.12% points, respectively. The preferred AMPS classification for SWS instances of (2,2) is (3,1), as shown by the dark cell shading, yet this is not reciprocated. Combined with the fact that class (3,1) is overpredicted by a similar amount that (2,2) is underpredicted, thus the majority of this difference is caused by AMPS output forecasting class (3,1) conditions at the expense of class (2,2). The main difference between these classes is the wind flow pattern (see Fig. 2), where class (3,1) displays a tendency for the predominantly southerly winds to curve to the west around the tip of White Island, resulting in easterly winds at Windless Bight and Pegasus North. Class (2,2) shows the southerly being deflected in the opposite direction, toward the east, with very light winds at Windless Bight and a stronger southerly component at Pegasus North. Both these AWS locations show higher variability in direction in class (2,2) (Fig. 4) along with increased RSLP (Fig. 6) in the observations.

In the same way that results shown in Table 1 need to be considered in the context of Fig. 11, the opposite is also true. While class (3,0) has a relatively acceptable alignment between AMPS and SWS at 45%, AMPS
receives that classification at 3.4 times the rate of SWS. This effectively means that AMPS is forecasting those conditions so often that the good alignment is not necessarily a reflection of model skill; classes (2,0) and (3,1) also show similar tendencies. While the reverse may be said of (0,0), (1,0), (1,2), and (2,2), the alignment probabilities of all bar (0,0) are low enough that the effect would likely be minimal.

SOM class progression for both SWS (Fig. 12a) and AMPS (Fig. 12b) is shown in Fig. 12, where the probability that an instance of a given SOM classification (x axis) will progress to another classification (y axis) that is not itself (class is not persisting) is indicated by the color. For example, Fig. 12a shows that class (0,0) tends to progress toward class (1,0) most frequently (approximately 60%), followed by (0,1) (approximately 40%), then (0,2). The overall pattern (roughly symmetrical about the diagonal) in this figure shows that, for SWS observations, classes tend to progress toward adjacent neighbors. This behavior is expected as the SOM algorithm groups similar classes together in SOM space, so a large number of transitions that were not to an adjacent neighbor would indicate a very unstable or nonlinear underlying system, or a poorly designed SOM.

Figure 12b shows class progression through AMPS output. Immediately visible is the tendency for AMPS classes to occasionally jump adjacent neighbors and progress to very different classes. Upon further investigation, it was found that most of these jumps coincide with boundaries between the different blocks of forecast hours used to construct the AMPS dataset, where blocks change at 0000 and 1200 UTC every day. Class progressions that occur predominantly (at least 75%) during these hours are indicated by black-and-white markers in Fig. 12, where all obviously abnormal transitions in (Fig. 12b) fall into this category. The markers in Fig. 12a (SWS) are provided for context only and show that transitions during this time occur randomly and are not common. There is evidently a deviation from the observations as the forecast progresses, which results in a step change as the output from the subsequent forecast—12 h younger with a new set of initialization inputs—is introduced into the dataset. It can be seen that AMPS has a higher tendency to deviate from the observations under lower wind conditions as none of the highest wind speed classes are affected.

d. Synoptic-scale context

While this study focuses on the mesoscale, it is important to also understand larger-scale processes that are forcing the conditions seen in the target area and their potential contribution to differences between SWS and AMPS. The synoptic climatology developed by Coggins et al. (2014), using k-means clustering to classify 33 yr of 10-m wind output from the ERA-Interim reanalysis, is a useful tool for providing wider-scale context for the SOM presented here. Of particular interest are the broader “regimes” as outlined by Coggins and McDonald (2015) and shown in Fig. 2 of their study, which are referred to hereafter as “Coggins’s regimes.” Five regimes were identified in
total: weak northern cyclonic (WNC), strong northern cyclonic (SNC), Ross Ice Shelf airstream (RAS), weak southern cyclonic (WSC), and weak synoptic (WS). The WNC and SNC regimes feature a cyclone in the Ross Sea to the north of the RIS with varied degrees of intensity, alongside light to moderate winds over the RIS. The WSC regime features a cyclone over the RIS itself with light winds, while WS has a very small pressure gradient over the RIS with widespread calm conditions. The RAS regime features a strong pressure gradient over the RIS with strong southerly winds transporting air from the Siple Coast and the interior of Antarctica out into the Ross Sea, often past the edge of Ross Island. Updated classifications of 6-hourly ERA-Interim reanalysis output for the relevant time period were created to directly compare with the SOM from this study. SOM classifications were down-sampled to match the 6-hourly resolution of the ERA-Interim output.

Figure 13a shows $P(\text{Coggins} | \text{SOM}_{\text{SW}})$, the probability of finding each Coggins’s regime for each SOM classification of SWS observational data. Because two different classification schemes on very different spatial and temporal scales are being compared, and the ERA-Interim dataset is not perfect, SOM classes will not always align with their ideal Coggins’s regime counterparts. However, there is good agreement between the two, with synoptic regimes likely to have a weaker forcing effect on the SOM target area (WNC, WS, and WNC) being more prevalent in the upper half of the SOM, corresponding to the first two columns of the SOM space in other figures, where weaker and more variable winds are observed. Conversely, SNC has a higher prevalence in the lower half where winds are higher and more directionally constant. The RAS regime is dominant for SOM class (3,2), which has already been identified. In rare cases, the RAS regime is also present in (1,0) or (2,2), which is likely caused by the exact location of the airstream shifting away from Ross Island toward the middle of the RIS with the SWS/AWS network observing reduced wind speeds. If alignment is investigated in reverse by calculating SOM class occurrence for each Coggins’s regime (not shown for brevity), SWS class (3,2) is present for 83% of all Coggins’s “RAS” regime occurrences.

Figure 13b shows the alignment of Coggins’s regimes with the AMPS SOM classifications, with Fig. 13c displaying the differences between the AMPS and SWS classifications. A recurring theme is the switching of prevalence of the WNC and SNC regimes between SWS and AMPS SOM classifications, the most notable classes being (2,1) and (2,2). These two AMPS classes also have poor alignment with SWS (as shown in Fig. 11), so the fact they relate to different synoptic situations suggests the large-scale forcing is important for the differences in these classes. While AMPS has slightly more spread during the RAS regime than SWS, it is promising that it still aligns well with class (3,2). Additionally, there is very little difference between the regimes present for SWS and AMPS during classes (0,0), (0,2), and (1,0) which, when combined with (3,2), account for almost 60% of the study period (by SWS classifications). As with SWS classes in Fig. 13a, if the reverse of Fig. 13b is calculated then SWS class (3,2) is predominantly present.
(in this case 75% of the total) during Coggins’s RAS regime occurrences.

4. Discussion

The use of SOMs for analyzing Antarctic atmospheric data over the RIS, in particular output from the AMPS forecast system, is not a new idea (e.g., Seefeldt and Cassano 2008; Nigro et al. 2011, 2012a,b; Seefeldt and Cassano 2012; Nigro and Cassano 2014a,b). However, previous studies have operated at far larger spatial and temporal scales, predominantly seeking to develop climatologies or insights into physical processes at the synoptic scale. Only a single summer season of observations from the SWS network are available for the target location of this study, so attempting to define a climatology is unrealistic. However, this does not preclude the use of a SOM for model validation and the classes produced (Fig. 2) appear to represent a wide variety of wind patterns that may be expected over the summer months in the target area. Large periods of calm or light winds are often encountered during this time, with occasional southerly storms of varying intensity and duration (Savage and Stearns 1985; O’Connor and Bromwich 1988; Seefeldt et al. 2003). This is reflected in the frequency and persistence information presented in Table 1, with calm or light wind conditions accounting for around 50% of the study period, gentle to moderate winds for 32%, and strong winds for almost 14% [class (3,2)]. Additionally, classes (0,0) and (3,2) were both very persistent with median durations of 8 h each. The intraclass spatial patterns observed in Figs. 2, 4, and 6 are coherent between variables, with lighter and more variable winds closer to orographic features and the high pressure stagnation zone observable in Windless Bight. Class (0,0) of the SOM in this study is the most prevalent, with a class frequency of almost 25% in the observations, and represents light winds with a mean northerly, yet highly variable, direction. This is likely the result of a bias in granularity in the SOM algorithm toward higher wind speeds that have a greater effect on the Euclidean distance metric (root-mean-squared difference between training data and SOM class weights) used. The SOM was repeated as a separate study using normalized wind components, effectively removing any bias due to vector magnitude. The patterns produced

![Fig. 13. Alignment of Coggins’s regimes for each SOM type as classified by (a) SWS observations and (b) AMPS output, with (c) the difference.](image-url)
were similar to those presented in this study, though greater granularity was observed at lower wind speeds. While this behavior is desirable, wind speed information is still vital for fair comparisons with AMPS so the study was not pursued further. An improvement to the current study would be to create a second SOM using data from class (0,0), and possibly the surrounding low wind speed classes, to gain further clarity about what happens under lower wind speed conditions. Whether or not this would improve the correlations, bias, NRMSD, and alignment between AMPS and the observations is unknown as it is likely that some detrimental attributes are being masked by the high variability and large number of occurrences.

Class (3,2) is the next most prevalent and is representative of those periods with the largest mean wind vectors (Fig. 2), highest constancy (Fig. 4) and largest representative of those periods with the largest mean wind speed conditions. Whether or not this would improve the correlations, bias, NRMSD, and alignment between AMPS and the observations is unknown as it is likely that some detrimental attributes are being masked by the high variability and large number of occurrences.

Class (3,2) is the next most prevalent and is representative of those periods with the largest mean wind vectors (Fig. 2), highest constancy (Fig. 4) and largest pressure gradient (Fig. 6). Coggins’s regimes (Coggins et al. 2014; Coggins and McDonald 2015) add context with wider synoptic conditions and show that (3,2) is associated with the RAS regime 50% of the time, with RAS or the strong synoptic forcing of SNC present for almost 70% for all instances of (3,2). AMPS represents conditions during class (3,2) very well, with the highest correlations (Fig. 9), smallest NRMSD (Fig. 10), smallest differences (Figs. 5 and 7), best class alignment (Fig. 11), and good agreement for class frequency and persistence (Table 1), and transitions (Fig. 12). The exception is the magnitude of the pressure gradient from Windless Bight toward the RIS and the corresponding low correlations, large difference in constancy, and obvious difference in mean vectors for Windless Bight AWS. Thus, while Polar WRF within AMPS does well at representing RAS conditions in general, it appears to underestimate the magnitude of the orographic blocking provided by Mt. Erebus and Mt. Terror on Ross Island. This blocking manifests as the Windless Bight high pressure stagnation zone, which has a large impact on wind flow in the area (O’Connor and Bromwich 1988; Seefeldt et al. 2003). The effect of this underestimation is visible in the wind vectors of Fig. 3 relative to the SWS/AWS observations in Fig. 2, where the AMPS vectors are more uniform with reduced components for all high wind speed classes. The cause of the underestimate is likely influenced by terrain smoothing due to the relative (to the terrain features) coarseness of the model grid; Mt. Erebus and Mt. Terror are approximately 250 m too short and the high points of Hut Point Peninsula are 100 m too short with more gentle slopes in the model than reality.

In this study, the Polar WRF Model in AMPS clearly performed poorly under the low wind conditions of class (0,0). While the frequency and alignment of this class (Table 1 and Fig. 11), along with the Coggins’s regimes presented (Fig. 13), compared relatively well with observations, the actual conditions forecast did not correlate well (Fig. 9) and contained some large differences (Figs. 3 and 5). The observed pressure gradient for class (0,0) is smaller than all other classes (Fig. 6) and there is a high prevalence of weak synoptic or weak northern cyclonic regimes (Fig. 13) developed by Coggins and McDonald (2015). This shows the synoptic-scale sources of forcing are weak for this class, which is expected in conjunction with the lower wind speeds. Other classes surrounding (0,0) also feature small pressure gradients, high probability of the weak synoptic Coggins’s regime, low wind speeds, and poor correlation, high NRMSD, and larger biases in directional constancy. While Polar WRF within AMPS may predict the occurrence of low wind conditions well (class alignment in Fig. 11), the actual wind conditions forecast do not often match the observations (intraclass correlation in Fig. 9 and comparison of vectors in Figs. 2 and 3). In a practical sense, this may not have a large impact on the logistical (predominantly flight) operational planning that utilizes AMPS forecasts; however, wind flow patterns at low wind speeds will impact the formation and trajectory of fog in the region, which often interferes with human activity and impacts on the radiation balance.

During periods of reduced synoptic-scale pressure gradients, such as those highlighted above, mesoscale atmospheric dynamics play a larger role in dictating the surface wind field. Two important factors that need to be well resolved are incoming and outgoing radiation and their interaction with the local terrain (Pielke 2013), which influence mesoscale pressure gradients and thereby wind fields. The correct simulation of cloud, particularly cloud microphysics, is extremely important in this context—a difficult task especially at such a small scale (Bromwich et al. 2013). Mixed-phase and supercooled clouds are common (Lawson and Gettelman 2014; Scott and Lubin 2014) and the ratio of liquid water to ice within clouds will affect the incoming and outgoing radiation balance (Wilson et al. 2012). To assist, appropriately fine model grids are required that, in turn, require high-resolution datasets (including sea and land ice cover) for initial parameterization. Data sources used for initialization are also likely insufficient given the complex, small-scale, topography near Ross Island. The GFS output assimilated by AMPS provides 0.25° horizontal resolution, which equates to 27.9 km × 5.8 km (latitude–longitude, respectively) over Ross Island. This is insufficient for GFS to resolve the complex topography of the region and, therefore, its interaction with the atmosphere, which will result in differences between the GFS output
and reality. It is worth noting that a previous study by Bromwich et al. (2013) identified that Polar WRF is very sensitive to initial conditions.

Using the Coggins’s regimes as a method to gain synoptic-scale perspective for a mesoscale SOM works very well and helps to highlight classes where AMPS does not characterize available observations. Some classes with high disagreement between AMPS and SWS also tend to show very different regimes, with AMPS tending to be more spread between the five possible options. Class (3,0) is a good example, where the synoptic forcing appears to be either a low pressure system to the north (SNC/WNC), or weak overall pressure gradients (WS) in the observations, yet an almost even spread for AMPS. Class (2,2) shows poor correlation, alignment, and frequency difference features a swap in the dominant regime from SNC (SWS) to WNC (AMPS), and a reduction in the probability of seeing RAS and WSC regimes for AMPS. This switching between SNC and WNC between AMPS and SWS is also very visible in class (2,1), and less obvious but still present in many other classes, which suggests that AMPS may not be reflecting the magnitude or position of low pressure systems seen over the Ross Sea in ERA-Interim output. This is consistent with previous work by Nigro et al. (2012a), who found problems with the representation of cyclones within AMPS over the Ross Sea.

The discontinuities within the dataset of concatenated AMPS forecast blocks highlighted in Fig. 12b could prove to be an interesting measure in the future for the analyses of larger datasets. Unfortunately, the period of available observations for this study was not large enough to allow further study of the discontinuities with a high level of confidence; however, future studies employing SOMs to analyze concatenated output from multiple model runs over longer periods of time could use the SOM class progression as a proxy to identify radical discontinuities in their dataset.

5. Conclusions

This study used wind observations during the 2014–15 austral summer from 15 SWS (weather stations). Combined with output from corresponding nearby AMPS grid points (“virtual stations”), the resulting dataset was used to train a single SOM, which in turn, classified the original datasets individually. This allowed a comparison of both the datasets and their corresponding SOM statistics in order to gain further insight into the quality of simulations over part of AMPS domain 5, a nested grid with a spacing of 1.1 km not previously studied in detail. Both wind and pressure SWS and AWS observations were compared with output from nearby AMPS grid points for each SOM class. Within AMPS, Polar WRF did not accurately model surface-level winds during light wind conditions when synoptic-scale forcing was weak; however, it was able to forecast the low wind periods themselves well and there was good alignment with synoptic-scale regimes identified. This suggests that Polar WRF within AMPS may struggle to resolve localized (mesoscale) forcing during periods of low winds and weak synoptic forcing. Insufficient resolution of available model initialization data, along with model grid length are possible contributors, given the complex nature of the topography in this region.

Surface wind correlation generally increased with wind speed; however, problems arose around the timing of certain SOM classes (wind patterns) for classes with lower persistence and/or frequencies. Polar WRF performed extremely well during the high wind speed RAS events in the study, with good temporal class alignment, good correlation of surface winds, and a low (good) NRMSD. Synoptic-scale context for the SOM region was provided by Coggins’s regimes and demonstrated that combining classification sets from different studies that cover overlapping areas, but different scales, is useful in differentiating between large- and small-scale drivers. In particular, analyzing the SOM classes within the context of these regimes suggested that Polar WRF within AMPS did not accurately resolve the strength and location of cyclones in the Ross Sea. The use of SOMs to increase the temporal granularity of this validation study, particularly the ability to directly compare time series of classifications of model output and observations, proved to be effective and is widely applicable.

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