A Comparison of Automated Methods of Front Recognition for Climate Studies: A Case Study in Southwest Western Australia

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ABSTRACT

The identification of extratropical fronts in reanalyses and climate models is an important climate diagnostic that aids dynamical understanding and model verification. This study compares six frontal identification methods that are applied to June and July reanalysis data over the Central Wheatbelt of southwest Western Australia for 1979–2006. Much of the winter rainfall over this region originates from frontal systems. Five of the methods use automated algorithms. These make use of different approaches, based on shifts in 850-hPa winds (WND), gradients of temperature (TGR) and wet-bulb potential temperature (WPT), pattern matching (PMM), and a self-organizing map (SOM). The sixth method was a manual synoptic technique (MAN). On average, about 50% of rain days were associated with fronts in most schemes (although methods PMM and SOM exhibited a lower percentage). On a daily basis, most methods identify the same systems more than 50% of the time, and over the 28-yr period the seasonal time series correlate strongly. The association with rainfall is less clear. The WND time series of seasonal frontal counts correlate significantly with Central Wheatbelt rainfall. All automated methods identify fronts on some days that are classified as cutoff lows in the manual analysis, which will impact rainfall correlations. The front numbers identified on all days by the automated methods decline from 1979 to 2006 (but only the TGR and WPT trends were significant at the 10% level). The results here highlight that automated techniques have value in understanding frontal behavior and can be used to identify the changes in the frequency of frontal systems through time.

1. Introduction

Midlatitude fronts have significant day-to-day impacts on the southern reaches of the Southern Hemisphere continents, bringing rainfall and, in extreme cases, hail, broadscale wildfires, and large-scale soil erosion associated with dust storms (e.g., Trewin 2002). It is therefore of value to recognize, count, and characterize fronts impacting population centers and regions of important agricultural activity in the Southern Hemisphere both in the current climate and in future projections.

To recognize a front on any given day takes a synoptician some time, and to create a climatology using a manual identification technique would be a major undertaking. Thus, it is desirable to use an automated method to create such climatologies in observed data, reanalyses, and climate model output. Early efforts to develop automated methods to identify fronts were generally used to assist in weather forecasting (Renard and Clarke 1965; Clarke and Renard 1966; Hewson 1998, and references therein; Simmonds et al. 2012), and specific methods are used routinely for this purpose today (Hewson 2009). Some methods have been developed to understand extreme events, such as widespread fire (Mills 2005). A number of automated algorithms have now been applied to large-scale fields available from reanalyses in order to generate climatologies of fronts [McIntosh et al. (2008) for southwest Western Australia, Berry et al. (2011a) for the globe, and Simmonds et al. (2012) for the Southern Hemisphere]. The ability of these methods to identify fronts from relatively low-resolution data suggests that
they can also be applied to climate model output, and this has recently been demonstrated by Catto et al. (2013). The focus of the Berry et al. and Simmonds et al. studies was on the climatologies, whereas here our interest centers on the synoptics of the fronts and their consequences.

While global, long-term sets of manually identified fronts have not been compiled, a number of regional climatologies have been assembled. For the southwest of Western Australia (SWWA), Pook et al. (2012) performed a manual frontal analysis on reanalysis data with a view to identifying the synoptic systems responsible for specific precipitation events. This set, along with the compilations of McIntosh et al. (2008), Berry et al. (2011a), and Simmonds et al. (2012), provides an excellent reference base for the present investigation. The aim of this study is to utilize these datasets plus two other automated methods of identifying fronts to compare the frontal numbers identified by each method and to determine what aspects of the synoptic systems each method captures and how they relate to rainfall. This will ultimately help guide which methods will be useful in climate studies of the past, present, and future. Our overall goal is to provide perspectives of what different automated front identification methods can offer, with particular relevance to systems in the Southern Hemisphere extratropics.

In Australia, the southern coastal regions are all impacted by frontal systems embedded in the westerlies. On the large scale, Australia is downstream of the baroclinically active Indian Ocean, with its high density of synoptic systems (e.g., Simmonds and Keay 2000; Lim and Simmonds 2007). Australia’s west coast is also the location of a quasi-permanent climatological trough that is, in fact, the most persistent in the Southern Hemisphere (identified in surface fields by Wright 1974). In the SWWA, frontal systems are associated with a large proportion of high rainfall events over the region (Pook et al. 2012). SWWA rainfall is also sensitive to spatial shifts in the preferred paths of frontal systems. Thus, SWWA serves as an ideal and illustrative region over which to examine the ability of automated and other methods to capture extratropical frontal systems. Analyses conducted over this region are also valuable in that they allow us to identify and explore trends in frontal behavior and to also quantify fronts–rainfall relationships over this region of agricultural importance.

Determining the characteristics of fronts and their trends can also contribute to the understanding of the nature of rainfall trends and related circulation changes. This aspect is particularly important in SWWA, as the region experienced a marked decline in early winter (May–July) rainfall in the late 1960s (IOCI 2002; Ryan and Hope 2005, 2006; Bates et al. 2008). It was found that the decline was due primarily to a reduction in the baroclinic instability of the region and to a corresponding decrease in cyclogenesis growth modes on the subtropical jet (Frederiksen and Frederiksen 2007, 2011). Consistent with this, a reduction has been found in the number of surface low-pressure systems, including fronts and cutoff lows that cross the region (Hope et al. 2006). Rainfall totals across SWWA shifted to a lower level again in the late 1990s and have been low since then (Hope and Ganter 2010). SWWA rainfall is projected to decrease under enhanced greenhouse gas scenarios (Timbal 2004; Hope 2006; Alley et al. 2007). Pook et al. (2012) classified the rain-bearing synoptic systems in the region into fronts, cutoff lows, and other systems and found that fronts contribute more than 50% of rainfall during June and July. They found that the rainfall from cutoff lows decreased over the period 1965–2009, while the contribution from frontal systems changed little. Thus, the contribution from frontal rainfall has become increasingly important, particularly in the decade 1999–2009. Using one of the methods employed in this study, it was found that the annual average frequency of fronts increased by about 30% from 1989 to 2009 in a band at the northern extent of the SWWA region (Berry et al. 2011b).

Determining the veracity of a given frontal recognition method is a difficult task. A front can be characterized in a number of ways, but it is generally accepted that a front is expressed as a discontinuity in temperature and will often also have a wind discontinuity associated with it (e.g., Anderson et al. 1955). Hewson (1998) referred to literature where authors had compared against manual frontal analyses. This is a reasonable first step for determining whether a particular automated system can capture the approximate number of fronts in a season and their interannual variability. In this study, we include the series of manually identified fronts produced by Pook et al. (2012), as they provide reference for much of the analysis and comparison. The different methods considered in this study employ a range of measures to capture the front. Some identify specific fronts, while others point to regions where a front is highly likely to form. The occurrence of a front on each day over the SWWA region for each method will be considered and compared. Although limited to a regional focus, this study highlights the value of these methods and their use for climatological studies.

The paper is laid out as follows. The data used in this study are detailed in section 2. The description of the frontal recognition methods are each described individually in section 3. The intercomparison of the methods on both seasonal and daily time scales is described in
section 4, including discussion on their links to rainfall. The reasons for some of the differences between each method and their capacity for use in other studies are discussed in section 5.

2. Data

Rainfall data were obtained for eight stations across the Central Wheatbelt (CWB) of SWWA from the Australian Bureau of Meteorology archive. This region is reasonably flat, with a low scarp running north–south along the west coast to the west of the region. The mean winter rainfall is higher in the west, while the contribution from frontal systems to the total rainfall is upward of 50% across the whole CWB (Pook et al. 2012). The rainfall stations were Wongan Hills, Bencubbin, Meckering, Cunderdin, Kellerberrin, Merredin, and Southern Cross (see Fig. 1 of Pook et al. 2012). The Patched Point Dataset supplied by the Queensland Department of Environment and Resource Management (Jeffrey et al. 2001) was employed to provide a consistent technique to insert estimates of missing data. This set uses original Bureau of Meteorology measurements for a particular meteorological station, but interpolated data are used to fill any gaps in the observation record, as described by Jeffrey et al. (2001). The station data were then averaged, and if the average rainfall for the region on any given day was greater than 0.2 mm, it was deemed a “rain day.” Daily rainfall was recorded at 0900 local time (0100 UTC) and was the total of the rainfall that fell during the preceding 24 h.

National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalyses (Kalnay et al. 1996) were used for all fields required by the frontal recognition methods in this study. The fields considered were the zonal and meridional wind components at 850 hPa (U850 and V850), temperature at 850 hPa (T850), specific humidity (Q850), mean sea level pressure (MSLP), geopotential height at 500 hPa (Z500), and thickness (Z1000–Z500). The NCEP–NCAR reanalysis was used for two reasons: it has a broad spatial scale (2.5° latitude × 2.5° longitude) that is comparable to many climate models and it was accessible by all groups contributing results of their methods to this study. We limit the analysis to the years 1979–2006 because of the length of the series of manually identified fronts that was available, which provides 28 seasons over which to compare the methods. Six-hourly or once-daily data from June and July (hereafter referred to as winter) were considered. These are the months when the subtropical ridge is at its most northerly latitude and thus when frontal systems might be expected to have their greatest impact on this region. Pook et al. (2012) showed that the proportion of rainfall associated with fronts is higher in winter than any other season.

3. Methods

In this section, we describe the six frontal identification methods in detail. For all methods, if a front was identified on a particular day, it was denoted with a 1; otherwise, it was 0. In the manual method, the search for fronts was conducted only for rain days. The frontal search with the automated schemes was carried out for all days, and the subset on rain days was extracted for comparison with the manual method. The region of consideration was the region 25°–40°S and 105°–125°E (boxed area in Fig. 1). It is particularly midlatitude fronts that are of interest in this study.

a. Manual

The manual (MAN) method provides a baseline against which one can compare the automated schemes. While there is still subjectivity, a manual analysis by a trained and experienced synoptician has a certain authority to it and is an important first step toward developing and assessing an automated system.

The method involves the synoptician (Pook) examining a range of NCEP–NCAR reanalysis fields on any given rain day and identifying the synoptic system responsible for the precipitation event. The nature of this task dictated that the manual approach was only possible on a rain day whereas no such constraint applies to the automated methods. Synoptic systems were classified according to the scheme originally developed by Pook et al. (2006) and applied to the CWB by Pook et al.
The method of identifying a front in the NCEP–
NCAR reanalysis followed the established analysis
and forecasting practice of locating a trough in MSLP
(indicating a wind shift from approximately northwest
to southwest with low-level cold advection in a region
of marked 1000–500-hPa thickness gradient). The
analysis of fronts was supplemented by examination of
of marked 1000–500-hPa thickness gradient). The
wind-shift (WND) method searches for 6-h
changes in the direction of the horizontal wind from the
northwest quadrant to the southwest combined with
shifts in the strength of the meridional wind of greater
than 2 m s$^{-1}$. The algorithm then maps a spatially con-
tinuous group of such shifts and thus determines the
location of a front (Simmonds et al. 2012). The time
rates of change of dynamic (and thermal) variables at
grid points is an Eulerian approach that has been adopted
in other contexts (e.g., Fraedrich et al. 1986; Huang and
Mills 2006a,b; Ma et al. 2010). Basing the algorithm on
the behavior of the meridional component of the wind is
consistent with a number of studies that have shown that
this parameter, both filtered and unfiltered, contains
much dynamic information about synoptic processes and
frontal systems in particular (e.g., Trenberth 1991;
Berbery and Vera 1996; Yin and Battisti 2004; Hoskins
and Hodges 2005; Carmo and de Souza 2009; Petoukhov
et al. 2013).

This method identifies individual fronts via the com-
ponent (or object) labeling technique (McAndrew
2004), which was applied to the grid points flagged by the
wind change considerations above. Each pixel so flagged
is related to its eight neighbors and an eastern edge
found and smoothed (Simmonds et al. 2012). Single-
point fronts are deleted from consideration. For these
frontal objects, the length, their center of gravity, and
a net intensity are quantified by the algorithm (Simmonds
et al. 2012). The fronts can then also be tracked effec-
tively by tracking the center of gravity of the component
frontal points.

For this study, we have used NCEP–NCAR reanalysis
6-hourly wind at 850 hPa. The method produces a great
deal of information about the characteristics of the
front, which is of considerable value in a range of contexts,
but here we are only interested in whether the
method identified a front on a day or not. To this end,
for comparison with the other methods, only fronts
with their centroids within the region of consideration
(Fig. 1) and a length greater than 1000 km were con-
sidered, and only one front was counted per day. The
length limitation meant that short-lived and weak troughs
would not be counted as fronts.

c. Wet-bulb potential temperature gradient

Wet-bulb potential temperature (WPT) gradient fronts
are identified using the method of Berry et al. (2011a),
which employs the same principles as those presented in
Hewson (1998). First, the thermal front parameter (as
defined by Renard and Clarke 1965) is calculated using
850-hPa wet-bulb potential temperature $\theta_w$ as the base
variable. The field is masked where the thermal front
parameter is greater than a prescribed threshold ($-8 \times 10^{-12}$ K m$^{-2}$). Fronts are then identified numerically
where the gradient of the thermal front parameter is zero,
and a line-joining algorithm is employed to link
contiguous points into individual fronts. This grouping is
based on the proximity of frontal points, and fronts
comprising fewer than three points are removed. Fronts
are then separated into cold, warm, and quasi-stationary
fronts according to a threshold front speed parameter.
The warm and cold fronts are separated depending on
whether they are traveling toward cold air or warm air,
and the frontal speed parameter threshold is $\pm 1.5$ m s$^{-1}$.

For this study, all front segments were considered
together, allowing features such as frontal waves to be
identified. The front was required to have at least 650 km
of its length within the “box.” Under this criterion, 754
fronts were identified. As the WPT method can also
distinguish between warm, cold, and stationary fronts, the individual numbers were examined, and cold fronts were found to be by far the most prevalent, as would be expected in this part of the world.

d. Temperature gradient

Mills (2005) developed the temperature gradient (TGR) method to provide a measure of frontal strength for fire weather applications in southeastern Australia. He assessed temperature gradients at 850 hPa and argued that if strong gradients were apparent at this level, in addition to at the surface, the front would possess a deeper tropospheric structure and hence be associated with greater impacts. Greater depth meant that both pre- and postfrontal winds were stronger, and the majority of major bushfire events in southeastern Australia over the last 45 years have been associated with the strongest (850-hPa temperature gradient) fronts. This method differs from that described in Hewson (1998) in that it does not attempt to locate a frontal position, but merely identifies the presence and strength of a front in a particular geographic area.

**FIG. 2.** Examples of each frontal type as defined by Pook et al. (2012): (a) cold front on 3 Sep 2003, (b) complex cold front on 11 Sep 2005, and (c) wave on cold front on 9 Jun 2008.
This measure of frontal strength has been adapted to wintertime SWWA by determining an appropriate threshold level of 1.3°C (100 km)\(^{-1}\) for the magnitude of the T850 gradient. Days upon which gradients exceed this within the region were classed as days with a front. The reasoning was that a strong thermal gradient is more likely to be associated with stronger prefrontal advection from the north and stronger ascent (Mills 2005), thereby having greater rain-producing potential, given the orientation of SWWA to an ocean moisture source to the northwest.

e. Self-organizing map

As discussed earlier, a climatological surface trough sits off the west coast of Australia during winter and thus guides weather systems that bring rainfall to SWWA. In general, the direction and passage of frontal systems in the region follow a reasonably well-defined path dictated by the location of the dominant climatological highs in the Indian Ocean and over continental Australia. Thus, two methods of identifying fronts using static patterns were developed. The application of pattern recognition to identify frontal systems has been used with some success by identifying features such as “stripes” (e.g., Jann 2002) or segments of arcs (Wong et al. 2008). However, given the strong climatological features of the region, a method to detect patterns specific to the SWWA has been developed here. Because of the dates on which the MAN analysis was at first available, these methods have been trained and developed using data within the analysis period (1979–89).

The first method employs a self-organizing map (SOM) approach (e.g., Kohonen 2001; Hewitson and Crane 2002; Hope et al. 2006), which organizes all data into a pre-defined number of types using a neural network, where similar types sit more closely and more distinct types are placed farther apart across the map. Three variables (MSLP, Z500, and thickness) were considered on each day and presented to the artificial neural network of the SOM software (Fortran code from http://www.cis.hut.fi/research/som-research/). The SOM was chosen to consist of 20 types, a number guided by minimizing the error during the learning process. Only data on CWB rain days were included (more details on this method are presented in McIntosh et al. 2008).

With such a broadscale measure as a spatial pattern trained on many days of data, a larger region was required to begin to uniquely classify fronts. It spanned 15°–50°S (15 grid points in NCEP–NCAR reanalysis) and 90°–130°E (17 grid points). In the MSLP component of the SOM (Fig. 3), clear trough-like structures can be seen on the right-hand side (e.g., nodes D5, D4, and D3), with more northwesterly flow over SWWA in the bottom-right corner (D2 and D1). In the bottom-left corner of Fig. 2, flow across SWWA would be more from the southwest (A1, A2, and B1), while the top left indicates structures that might reflect cutoff lows (e.g., nodes A5, A4, and B4; Table 1). In the midtroposphere, the Z500 SOM (not shown) broadly reflects the features seen in the MSLP. While thickness is effectively the difference between Z500 and MSLP, its anomalies reflect the temperature of the air mass (Fig. 4) and show strong gradients in many of the patterns across the SOM. At the top of the SOM there are many closed anomalies of cool air, a pattern indicative of cutoff lows, particularly when accompanied by positive anomalies on the poleward side.

During the training period, the MAN types were allocated to a SOM node for each rain day. For each SOM node in which more than 50% of the days were classified as MAN front types (complex front, cold front, and frontal wave) and fewer than 20% of days were classified as cutoff lows, these nodes were deemed representative of a front in the SOM (Table 1). The nodes that had greater than 50% of the days classified as cutoff lows are deemed representative of cutoff situations (McIntosh et al. 2008) and were found to correspond very well with those identified manually. Six nodes represent fronts in the SOM (A2, A1, B1, C1, D1, and C5 in Figs. 3 and 4). The nodes in the bottom right (C1 and D1) and the one on the top row (C5) demonstrate deep surface lows reasonably close to the southwest coast and strong MSLP gradients (Fig. 3), while the surface patterns of the nodes in the bottom left of the SOM (A2, A1, and B1) display weak gradients and little curvature, but there is a strong shift from negative to positive anomalies in the thickness (Fig. 4). This highlights that it is not necessarily only the surface features that will identify a front. Across the spatial patterns of each node a number of features can be represented. For instance, the pattern in node B1 could be interpreted as a warm front, as there is clearly warm advection occurring in the westerly flow southwest of Australia. In this pattern, the northern part of the front can also be poorly defined and yet still influence rainfall over SWWA. The application of the classical theory of fronts in the relatively low-latitude Western Australian context can pose problems when what are seen as warm fronts by local analysts are often features characterized by a zone of increasing moisture rather than a significant temperature discontinuity.

There were 671 June and July days between 1979 and 1989, 300 of which were classified as rain days used in the SOM. On these days, the manual analysis found 134 fronts, made up of cold fronts (64), frontal waves (29), and complex fronts (41).
FIG. 3. The MSLP component of the SOM. The SOM was developed with 1979–89 MSLP (hPa), Z500 (dm), and thickness (dm). Only days on which the mean rainfall across an eight-station average through the Central Wheatbelt was greater or equal to 0.2 mm were included. Annotated nodes correspond to nodes for which more than 50% of days falling into these nodes had fronts identified via the MAN method.
Once the SOM was developed on the training period of 1979–89 data, data on each day (both rain days and dry days) for the full 1979–2006 period were assigned a node from the SOM based on the smallest Euclidean distance. If that node was a frontal node, the day was denoted as having a front under the SOM method.

f. Pattern match to manual composite

The second method of recognizing patterns specific to the SWWA region is more direct than the SOM approach. The MSLP, Z500, and thickness fields on days where a particular frontal weather system was identified using the manual analysis were composited for June and July in the period 1979–89 to produce a “mean” pattern of each of the types (Fig. 5). These patterns were compared directly with data on each day for the full 1979–2006 period, including dry days as well as rain days using the same Euclidean distance method as the SOM technique. Each day was assigned to its closest-matched type.

There are some limitations to the SOM and pattern match to manual (PMM) composite methods as they rely on pattern matching to capture the frontal systems affecting SWWA. As the pattern is fixed in space, these methods cannot capture systems that do not align spatially with the predefined locations of the system. Shifts in magnitude are accommodated for, however, by the removal of the mean and division by the standard deviation of each field. Although it would be ideal to develop the SOM and PMM patterns on a period of data distinct from the analysis period, we only have a short period over which the SOM and PMM were developed. This allows a longer period of analysis, but this overlap might mean a slightly inflated skill in this comparison.

### 4. Analysis and results

a. Central Wheatbelt rainfall

Mean winter rainfall across the eight stations in the CWB is 106 mm. The region extends a considerable distance inland, and winter rainfall is lower farther from the coast (e.g., Fig. 1 of Pook et al. 2012). Pook et al. (2012) suggest that these stations are ideally situated to reflect days on which a front crosses the region, as a front will likely extend its impact on rainfall well inland, unlike some rainfall stimulated by the effects of the coast and the scarp that runs north–south along the west coast.

CWB winter rainfall has declined over the period 1979–2006 (Fig. 6), with a linear trend of $-7 \text{ mm decade}^{-1}$; however, this is not significant. This downward trend is influenced by the fact that all years since 2000 except 2004 (116 mm) have experienced below-average rainfall. The driest year between 1979 and 2006 was 2006, with a total of 41.6 mm. Rainfall since 2006 has continued to be low, with 2010 being SWWA’s lowest year on record (Hope and Ganter 2010).

The number of rain days (Fig. 6) is important when comparing the number of fronts identified by each method in a season when only conditions on rain days were assessed for the presence of a front. There were a total of 819 rain days over the 28 years, with 29.3 rain days per winter on average: hence, rain fell on almost
Fig. 4. As in Fig. 3, but showing the Z1000–Z500 thickness full field and anomaly (m).
every second day. However, the number of rain days varied from 42 in 1991 down to 13 in 2006, with a standard deviation of six. Thus, in 2006, the maximum possible number of fronts that could be identified was 13, which is lower than the mean seasonal number of fronts using some methods. To account for this, in some cases the numbers of fronts per season are divided by the number of rain days in that season.

**b. Comparison of methods**

We first focus on the rain day fronts identified in the six schemes. Across the methods there were, on average, 13.2 such frontal days identified per winter (61 days). Thus, on average, rain days had fronts on them 45% of the time (=13.2/29.3). Table 2 (top) and Fig. 7a show that the various methods identify different numbers of fronts each season, with PMM consistently identifying fewer fronts. The lower numbers identified using the pattern match methods may be due to the fact that only one time each day was assessed, rather than four, and also due to their fixed nature in space, which may provide a match to the data less often. The mean number of fronts as identified in the WND, WPT, and TGR methods were, to some extent, adjusted to match the number identified with the MAN method (length criteria for WND and WPT and gradient threshold for TGR). There were no significant trends in the numbers of rain day fronts using any method. Although not statistically significant, the trends in numbers identified using the WPT and TGR methods were negative, while they were positive for the other methods.

The structure of the interannual variability differs between the methods. The MAN method identifies between 5 and 25 fronts per season [Table 2 (top)], with a standard deviation of five. The automated methods tend to have slightly lower interannual variability (standard deviation) to MAN, except the WND method. The distribution of the seasonal number of fronts identified by the WND and WPT methods is skewed to higher values, and in some years (1989 and 2002) the number of fronts identified with the WND and WPT methods are both more than the MAN method. The pattern-matching methods, SOM and PMM, for which lower numbers of fronts were identified, also have lower variability.

One factor influencing the interannual variability of counts on rain days is, of course, the variability of the number of rain days themselves. To quantify the influence this has on the total counts, the data in Fig. 7a were normalized by dividing by the number of rain days each season (Fig. 7b). This means that the very low values in 2006 are now not so evident. Some years (e.g., 1990) now show a distinct peak in numbers that was not as evident in Fig. 7a. This is because there were fewer rain days in 1990 as compared to 1991 (Fig. 6). The trends in the number of fronts per rain day were of the same sign as those of the total fronts for each method. However, the magnitude of the trend was even closer to zero.
We now investigate the total number of fronts (all days included) identified in the automated algorithms. Using the TGR, SOM, and PMM methods, these are approximately double those identified on rain days, while only about a third larger using the WND and WPT schemes [Table 2 (bottom); cf. Figs. 7a,c]. This suggests that fronts identified with these last two methods are more closely tied to rain days than the other methods. The interannual variability in the number of fronts identified on all days is larger for all methods except WND when compared to the variability when only rain days were considered [Table 2 (bottom)]. This was particularly true of the pattern-matching methods. It might be expected that there would be such an increase given that the total numbers more than double when all days are considered. Although 28 years is a short period over which to calculate trends, including all days for the assessment of fronts leads to consistent negative trends across the five methods. These trends are negative, although only the trend for the number of fronts as identified using the TGR method is significant at the 10% level (trend = 0.237 fronts per year, p = 0.07). In the first year in the time series, 1979, the highest numbers of fronts of any season were identified using the TGR method.

Correlations between the seasonal time series produced using each of the methods on rain days only are all positive, all but four are significant with a two-tailed test at the 5% (p = 0.05) level, and only one correlation (that between TGR and SOM) is not significant at the 10% (p = 0.10) level [Table 3 (top)]. A two-tailed test was used because, although we would assume that all correlations with any meaning should be positive, if there was a negative correlation we might begin to ask some different questions. If a one-tailed test had been used, the p value would be half that found with a two-tailed test. There is little serial correlation and little trend in any of the series; thus, removing the trend using first differences makes little difference to the correlations (not shown). All automated methods correlate significantly with MAN. The WND, WPT, and PMM methods cross correlate significantly. This result suggests that any one of the methods would be a useful tool to provide insight into the variability of fronts as might be found using the MAN method.

As the fronts were only identified on rain days, the interannual variability of the number of rain days (Fig. 6) will influence the correlations. To limit this aspect of the variability, the series were all divided by the number of rain days (Fig. 7b). The correlations between the new

Table 2. (top) Mean statistics for the 1979–2006 period for each frontal recognition method when computed only on rain days. (bottom) As in (top), but computed for all days.

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<th>TGR</th>
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<td>16.0</td>
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values [equivalent to the proportion of rain days associated with a front; Table 3 (middle)] are indeed much reduced compared to those in Table 3 (top). However, the MAN series is still significantly correlated with all series created using the automated methods, except TGR. Correlations between the WND and WPT, WND and PMM, or WPT and SOM series also remain significant. The correlation between the MAN and PMM series is the highest ($r = 0.62$).

As pointed out above, the SOM and PMM techniques were trained and developed using data from a period within the analysis period (1979–89). Thus, during this
Table 3. (top) Correlations between the seasonal rain day time series of fronts identified by each method over the 1979–2006 period and every other method. (middle) As in (top), but normalized (i.e., number of fronts divided by number of rain days). (bottom) As in (top), but computed for all days. Numbers are repeated in both the top and bottom of the diagonal for ease of comparison. Correlations significant at the 5% (10%) level are marked in boldface (italics).

<table>
<thead>
<tr>
<th></th>
<th>MAN</th>
<th>WND</th>
<th>WPT</th>
<th>TGR</th>
<th>SOM</th>
<th>PMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAN</td>
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<td>0.81</td>
<td>0.62</td>
<td>0.53</td>
<td>0.42</td>
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<tr>
<td>TGR</td>
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<tr>
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<td>0.58</td>
<td>0.13</td>
<td>1.00</td>
<td>0.37</td>
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<tr>
<td>PMM</td>
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<td>0.51</td>
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<table>
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<th>TGR</th>
<th>SOM</th>
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<tr>
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<td>0.28</td>
<td>0.42</td>
<td>0.62</td>
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<tr>
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<td>0.22</td>
<td>0.22</td>
<td>0.38</td>
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<tr>
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<td>−0.11</td>
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<td>0.55</td>
<td>0.10</td>
<td>1.00</td>
<td>0.21</td>
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<tr>
<td>PMM</td>
<td>0.62</td>
<td>0.38</td>
<td>0.23</td>
<td>0.21</td>
<td>0.21</td>
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</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>WND</th>
<th>WPT</th>
<th>TGR</th>
<th>SOM</th>
<th>PMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>WND</td>
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<td>0.15</td>
<td>−0.04</td>
<td>0.48</td>
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<tr>
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<td>0.30</td>
<td>1.00</td>
<td>0.16</td>
</tr>
<tr>
<td>PMM</td>
<td>0.48</td>
<td>0.20</td>
<td>0.37</td>
<td>0.16</td>
<td>1.00</td>
</tr>
</tbody>
</table>

period of overlap they might be expected to perform better than if the analysis period was wholly outside of the training period. Although 11 years is very short to calculate a correlation, correlations were done between the seasonal MAN series and each of the SOM and PMM series (on rain days, but divided by rain days) for the development period and then for the other years and compared. For PMM the correlation over 1979–89 is $r = 0.65$, while for the later period, 1990–2006, it is 0.48. This suggests that the PMM method is still robust outside of the training period. However, for the SOM series there is a correlation of $r = 0.84$ over 1979–89 and $r = 0.04$ in the later period. The very low correlation between SOM and MAN in the later period appears to be due to a few years with opposite responses (e.g., 1997, Fig. 7b), while the years since 2000 align quite well. The reason why the SOM method produced a large count in 1997 compared to MAN is because, although only three occurrences of fronts identified with the MAN method were missed by the SOM method, 9 days with other synoptic types such as cutoff lows and an upper trough were also classified as fronts. Thus, the pattern-matching methods do capture fronts better during the training period. Outside of this, the SOM method has difficulty distinguishing between fronts and other synoptic types in some years.

Correlations between the time series of frontal number using the five automated methods on all days [Table 3 (bottom)] are much weaker in general than the correlations of the series produced on rain days [Table 3 (top)]. However, all the significant correlations between the series on rain days divided by the number of rain days [Table 3 (middle)] remain. The correlation between the WND and TGR series is significant at the 5% level, as is the correlation between the PMM series and the WND and TGR series. It can be argued that fronts on rain days have a stronger and more distinct signature and hence are more likely to be captured by the automated methods. To explore this issue, in the next section some of the day-by-day matches and misses are identified and the reason behind them is explored.

c. Daily matches

We have seen that the frontal identification methods do not identify the same number of fronts in the June–July period. To appreciate which methods do match on a day-by-day basis, the daily series of ones and zeros were multiplied for each method and then summed, for example, $\Sigma(MAN \times PMM)$. Table 4 (top) shows, on the diagonal, the total number of rain days on which a front was recognized by each method (recall the total number of rain days is 819). The method that identified the most fronts was WND with 461 days, while PMM only has 223 days on which a front was identified. The highest number of days when two methods agree is between WND and WPT with 305 days, followed by WND and MAN with 282. Thus, with any two methods, fronts are identified on the same day more than half the time. There were 24 days when a front was identified by all six of the methods, only 3% of the total 819 rain days.

There are a number of statistical analyses one can perform to ascertain how well the schemes match on a day-to-day basis. The maximum possible number of
matches is the lowest total of the two methods being compared. In the upper cells of Table 4 (top and bottom), the equitable threat score (ETS; also known as the Gilbert skill score, see Eq. (1)) is used to compare methods, based on their contingency table, accounting for misses and false alarms, as well as the number of hits that might be expected due to chance (see http://www.cawcr.gov.au/projects/verification/#Methods). It ranges from $-1/3$ to 1, where 1 is a perfect match, while a score of 0 indicates no match beyond that expected by chance:

$$\text{ETS} = \frac{\text{hits} - \text{hits}_{\text{random}}}{\text{hits} + \text{misses} + \text{false alarms} - \text{hits}_{\text{random}}}, \quad (1)$$

where

$$\text{hits}_{\text{random}} = \frac{\text{(hits} + \text{misses})(\text{hits} + \text{false alarms})}{\text{total}}.$$

On rain days, the days on which fronts were identified by the WND and WPT methods align most closely with each other and also with those identified with the MAN method. The front days align least well using the SOM and PMM methods. For all days [Table 4 (bottom)], the match between the days on which any two methods identify fronts is poor compared to only comparing rain days. Again, the WND and WPT series align well with each other, while the days on which fronts are identified with the TGR and SOM methods do not align well with other methods.

Thus, the number of fronts identified by each method aligns better with other methods on rain days than on dry days. This is consistent with our comments that a front that brings rainfall will likely have a clearer and stronger signature in the temperature, thickness, wind, and MSLP fields.

To better understand why some methods identify the same front on a particular day while others do not, five days were chosen as case studies. We chose only days that were identified by the MAN method as a front to allow further examination by the synoptician. These various situations show that the automated systems have difficulty with weak and weakening fronts, particularly, for this region, at the northern extensions. In these cases, the manual method takes more into account than just the wind and temperature contrasts, although these still strongly influence the interpretation. We also describe three days when a front is identified with all methods.

(i) The first case is one where the system was identified as a front by MAN and WPT, but the limitations set on each method for the comparison in this study might have made it difficult for the other methods to capture it. On 4 June 2005, a front crossed early in the period and was followed by rapid ridging. The wind shift was quite sharp (from northwest to south-southeast) and there was good evidence of cold advection at 0600 UTC on 5 June, but the airmass contrast weakened on subsequent analyses. Obviously, the methods that were only analyzed at 0000 UTC would not have captured this. As the front was very long, the centroid as defined by the WND and WPT methods was outside the region; thus, these methods would have missed this front when that criteria was applied. In this study, this was a requirement of the WND method; however, for the WPT method, 650 km of the front had to be within the box, so it captured this front. All the methods except the WND method captured some measure of the temperature gradient, while the WND method captured the wind shifts well.

(ii) Second, a case is considered where a front was identified by the WND method and the MAN method, but all other automated methods did not capture it. On 5 July 1988, a relatively weak front where the wind change from northwest to southwest was well defined, but the 1000–500-hPa thickness gradient was quite weak in the vicinity of SWWA. Hence, cold advection was poorly defined in this case. Weather forecasters would invariably analyze this system as a cold front, as the Australian Bureau of Meteorology forecasters did on that day. For all other methods, cases of strong temperature gradient or advection were likely to be better captured. The WPT and WND methods had an advantage over the other methods here in that they were first applied to the whole of the hemisphere before fronts were counted in the box of interest. Thus, information to the south of the region might be captured with those methods, but the other methods would not see those gradients at all.

(iii) The third case considered was another day on which only the MAN and WPT methods recognized a front. The front is identified by the WPT method and not the other automated methods in this case, not because of the limitations placed on the other methods, but because of the particular features of the WPT technique. On 27 June 2002, the front was well defined in wind change and thickness gradient to the south of Western Australia, but the northern extension only just reached SWWA. A weather forecaster would have looked for the extension of this front in the station observations (including rainfall), but the automated methods are likely to struggle with the northern portion. Thus, the temperature contrast to the south of the region was captured by the WPT method, while the other
methods would not have seen that at all. The TGR and WPT methods both assess the temperature gradient at 850 hPa and thus might be expected to identify similar fronts. This is not necessarily true, as can be seen in Table 4 (top). TGR and WPT have a Gilbert skill score of 0.27 [Table 4 (top)], similar to the scores between TGR and MAN or TGR and WND. There were 11 cases when a front was identified using the MAN, TGR, and WPT methods only.

(iv) In three cases that were examined when a front was identified by only the MAN and TGR methods, there were similar weather conditions. In these cases the wind shift was weak, but the temperature change was marked. This fourth case illustrates the synoptic conditions on such days well. On 22 July 2003, there was a cold front moving quickly northward in a southwesterly stream, with strong ridging ensuring only a slight wind shift from southwest to south. Decreasing thickness and some cold advection favors the TGR method.

(v) For the pattern-matching methods, there were only four cases when a front was identified only by the SOM and PMM or MAN methods. There were no days on which both the PMM and MAN methods identified a front while no other methods did. This suggests that the pattern-matching methods capture aspects of the front that the other methods do also. For a front to be identified using the SOM or PMM method, the broadscale pattern on the day must match the patterns in the SOM or PMM grid. For these methods to capture a front identified using MAN, while other methods do not, the wind shift must be relatively weak so that they are missed by the WND method, and the airmass contrast must also be relatively weak. The fifth case is one where a front was identified with the MAN method and the SOM method only. On 5 June 2004, the frontal change associated with the frontal wave appeared very weak, the wind shift was little more than west-northwest to west-southwest, and there was no discernible airmass change. Thus, there is no discernible airmass contrast, but there is a clear trough structure near SWWA. The heavy rain is likely explained by the moisture being sourced from the above-average sea surface temperatures to the WNW on this day (e.g., Ummenhofer et al. 2008).

(vi) As stated above, there were 24 days when a front was identified by all methods. A few of these cases were examined more closely.

- 29 June 1993: This case is illustrated in Fig. 1. This was a frontal wave with a major trough through the troposphere and strong airmass contrast. The wind change was not particularly sharp, front west-northwest to southwest at most.
- 13 June 2004: A classic case of a cold front with a well-defined trough in the upper air and good cold advection. The wind change is more marked on the prefrontal trough rather than on the front itself. The WND method may have been influenced by this change on the trough as it was only a short distance ahead of the front.
- 3 July 2004: A frontal wave with a well-defined upper trough and strong cold advection. The airmass contrast is stark, but the wind shift is probably more associated with a prefrontal trough than the front itself.

One consistent point on days when all methods identify a front is that there is a strong airmass contrast. In some of these cases it could well be that the prefrontal trough has been identified by the WND method rather than the front itself. This ability to capture prefrontal troughs may be advantageous if a study was particularly interested in the links of prefrontal troughs to rainfall, as rainfall is often associated with these systems.

### d. Classes of fronts and other synoptic types

Three different frontal types have been combined to produce the “front” number in the MAN method (frontal wave, complex front, and cold front). Pook et al. (2012) comment that the classic cold front is the most common type in winter, while the class of complex fronts includes those systems with a trough ahead of the front, which is more common in summer (a cool change). As outlined in the section above, some of the automated methods may capture particular aspects of these different types of fronts. To address this, each manually defined frontal type was considered separately. This association is, of course, dependent on an automated method aligning with the MAN method.

For the years 1979–2006, cold fronts were more common, on average, than the other frontal types (39.4%), then frontal waves (32.4%) and complex fronts (28.2%). The average number of fronts in a season is 14.3, made up of 5.7 cold fronts, 4.6 frontal waves, and 4.0 complex fronts. Fig. 8 shows how their numbers vary across the record. In the five years prior to 1984, cold fronts contributed most to the mix (except in 1980), while in 1995, 1999, 2004, and 2005 frontal waves were the most common type. Complex fronts were generally close to or within the values of the other frontal types, except in 1993 and 2004, when there were a good deal fewer than other types (zero in 2004), which means that frontal
recognition methods that better capture complex fronts than other types of fronts might identify fewer total fronts in these years.

The correlation of the number of fronts in each class as identified by the manual method and the total number of fronts identified by the five automated methods are shown in Table 5. While all automated methods are significantly positively correlated with the MAN series [Table 3 (top)], once the MAN series is broken into classes, some methods correlate well with some types and not with others. The WND method correlates reasonably well with all classes, as does PMM. The WPT method has the highest correlation with complex fronts, while it correlates less well with other types, although it has been used successfully to identify frontal waves in other studies (Hewson 1997). The TGR method also has a high correlation with the complex front, but lower correlations with others. The SOM method has the lowest correlation with the MAN series of all the automated methods (even though day-by-day it has a relatively high number of matching days), and it only has a significant correlation with cold fronts.

We saw in Fig. 7a that in some years the methods with the larger totals (MAN, TGR, WND, and WPT) align, while in others, such as 1996, the WPT method is much lower than the others. Fig. 8 reveals that there were fewer complex fronts identified in that year relative to other types which, given the high correlation between WPT and complex fronts, may have contributed to this difference. In 2004, there were zero complex fronts, but this did not produce the same reduced number in fronts identified with the WPT method.

Pook et al. (2012) classified each rain day with one of 13 different types of synoptic systems. While only the three frontal types are included in the MAN component of this analysis, all 13 types are identified as a front by the automated frontal recognition methods, except PMM. These instances of alternate synoptic systems being classified as fronts are not common except for the case of cutoff lows (Table 6). WND and TGR methods both identify cutoff lows as often as some of the frontal

![Figure 8: Decomposed MAN front series (into complex front, frontal wave, and cold front classes). The full MAN series is also shown.](image)

**Table 5.** Correlation of the winter number of fronts using each automated method and the count of the decomposed MAN fronts (into complex front, frontal wave, and cold front classes). Significant values at the 5% (10%) level are indicated in boldface (italics).

<table>
<thead>
<tr>
<th></th>
<th>Complex front</th>
<th>Frontal wave</th>
<th>Cold front</th>
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<tbody>
<tr>
<td><strong>Correlation</strong></td>
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<td>0.32</td>
<td>0.54</td>
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<tr>
<td><strong>p value</strong></td>
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<td>0.10</td>
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<td><strong>WND</strong></td>
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<tr>
<td><strong>WPT</strong></td>
<td>0.71</td>
<td>0.56</td>
<td>0.28</td>
</tr>
<tr>
<td><strong>TGR</strong></td>
<td>0.40</td>
<td>0.25</td>
<td>0.30</td>
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<td><strong>SOM</strong></td>
<td>0.25</td>
<td>0.06</td>
<td>0.42</td>
</tr>
<tr>
<td><strong>PMM</strong></td>
<td>0.34</td>
<td>0.06</td>
<td>0.57</td>
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</table>

**Table 6.** Number of key synoptic types as classified by MAN captured by the automated frontal recognition methods. The numbers of each front type identified by MAN are included for reference.

<table>
<thead>
<tr>
<th></th>
<th>MAN</th>
<th>WND</th>
<th>WPT</th>
<th>TGR</th>
<th>SOM</th>
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<td>113</td>
<td>81</td>
<td>88</td>
<td>69</td>
<td>48</td>
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<td>90</td>
</tr>
<tr>
<td>Cutoff low</td>
<td>0</td>
<td>85</td>
<td>68</td>
<td>78</td>
<td>26</td>
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<tr>
<td>Trough</td>
<td>0</td>
<td>33</td>
<td>22</td>
<td>12</td>
<td>14</td>
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</table>
Table 7. The percentage of fronts identified (on rain days) by each method compared to the maximum possible in a season (the number of rain days) and the percentage of rainfall in a season that fell on days when a front was identified using the various methods as a percentage of total rain (i.e., this could be classed as frontal rain).

<table>
<thead>
<tr>
<th>1979–2006</th>
<th>MAN</th>
<th>WND</th>
<th>WPT</th>
<th>TGR</th>
<th>SOM</th>
<th>PMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of fronts/rain day</td>
<td>49</td>
<td>56</td>
<td>54</td>
<td>49</td>
<td>39</td>
<td>27</td>
</tr>
<tr>
<td>Percentage frontal/total rain</td>
<td>53</td>
<td>68</td>
<td>62</td>
<td>60</td>
<td>29</td>
<td>32</td>
</tr>
</tbody>
</table>

types. Cutoff lows occur commonly in SWWA (Qi et al. 1999) and are an important source of rainfall (Pook et al. 2012). A cutoff low has a closed low by definition, but there are often strong gradients associated with it, which could be identified as a front by automated software. Thus, any correlations of seasonal averages might be capturing a signal from the number of cutoff lows, rather than purely from fronts. Troughs are also of interest as they are often also associated with rainfall. Most methods do not capture many troughs, although the WND method identifies the most days with a trough as a front, as might be expected with a wind-shift method.

e. CWB rainfall and fronts

Frontal systems are often associated with rainfall, and the strength of this association is of interest in many climatological studies (e.g., Pook et al. 2012; Catto et al. 2012). To explore this, the rainfall associated with fronts will be assessed in this section. As a simple measure of the amount of rain associated with a front, the average rainfall total across the CWB stations on the day the front was identified was attributed to that front. This measure may underestimate the amount of rainfall associated with a front as the rainfall on the day before or after may also be associated with the system (e.g., Hope et al. 2006).

The rainfall on days where a front was identified with the MAN method accounts for 53% (Table 7) of the total winter rainfall in the CWB (1979–2006). Over time, this proportion has ranged from 12% to 80% (compare the two blue lines in Fig. 6). The average amount of daily rainfall associated with a front defined using the MAN method varies more modestly from year to year, from 2.3 to 7.3 millimeters per front. In general, the values hover between 2.3 and 5.3; however, there were three years prior to 1996 with mean values greater than 6.5. The trend in CWB rainfall on days when a MAN front was identified is not significant (Fig. 6).

For the fronts identified only on rain days, the number of fronts identified by each method is shown as a percentage of all rain days in Table 7 (these same numbers could be gleaned from the first row of Table 2 (top), by dividing by the average rain days each season, 29.3). The amount of rainfall on each front day was then calculated and divided by the total CWB rainfall (Table 7). This then gives an appreciation of the intensity of rainfall on the days that each different method identified a front. For example, more rain fell on days identified with a front using the MAN method than other rain days, as from 49% of the total rain days, 53% of the rain was derived. This is true for all methods except SOM. These figures suggest that the series of frontal number might correlate well with the total CWB rainfall for all methods but SOM.

The correlations between the number of fronts identified on rain days each winter by each method and the total CWB rainfall are shown in Table 8 (top). As suggested above, there is a positive correlation between the number of fronts and total rainfall for all methods except SOM. The strongest correlations are between the WND series and rainfall and the TGR series and rainfall. This is not surprising, given that the rainfall falling on frontal days identified with these methods accounts for 68% and 60% of the total rainfall, respectively (Table 7). The correlation between the MAN series and rainfall is also significant, but only at the 10% level. Interestingly, although rainfall on days as associated with fronts by the WPT method account for 62% of the rainfall, the correlation between WPT fronts and rainfall is not significant. Removing any trend by applying first differences does not alter the correlations markedly, except TGR, for which the correlation between CWB rain and fronts on rain days is no longer significant. Thus, the frontal identification method on rain days that best correlates to rainfall is the WND method.

The amount of rainfall was also considered across the three different frontal types identified with the MAN method. Complex fronts are associated with far more rainfall (4.54 millimeters per front) than other types of fronts (3.11 millimeters per front for frontal wave and 3.01 millimeters per front for cold front) (Table 9). However, the high total for complex fronts is skewed by four years with totals of 10 millimeters per front or greater.
including two years with an average of 20 millimeters per front or greater—1983 and 2001 (not shown). As seen in the previous section, the automated methods at times identify fronts on rain days that have been manually identified as a different synoptic type. The rainfall associated with these alternate synoptic types can be reasonably high, for example, the average rainfall on the 68 cutoff low days that the WND method captured is 5.12 mm, higher than either the cold fronts or frontal wave types.

Prefrontal troughs may also be identified by some methods, but not by others. Schultz (2005) provides a review of the nature and causes of these troughs and the fields in which they are expressed. He suggests that a trough in the surface pressure and wind shift can form in the warm air preceding a front. A good illustration for the SWWA region is described by Hanstrum et al. (1990). Thus, WND might capture these prefrontal troughs as well as the front itself (as we commented above), whereas WPT and TGR are less likely to. The MAN, SOM, and PMM methods all assess the sea level pressure; thus, they may also pick these up. However, the thickness field also forms part of their assessment, which may then limit the identification of these troughs. Prefrontal troughs are often associated with rainfall, although the averages shown in Table 9 are lower than those for cutoff lows, so the correlation with rainfall may be more dictated by the number of cutoff lows identified by these automated frontal recognition systems.

Removing the variability signal introduced by fronts only being sought on rain days by dividing the frontal numbers by the rain days each season results in all correlations becoming negative or nonsignificant. The correlation between the WND series and rainfall drops to \( r = 0.16 \), with a \( p \) value of 0.43. The correlation between the SOM series and rainfall is significant at the 10% level, but negative. A negative correlation is not expected and suggests that the number of fronts identified in any one season with this method is not relevant to how much rainfall falls in that same season.

Considering fronts on all days, the magnitude of the correlations with total rainfall drop [Table 8 (bottom)]. This is not surprising as the number of fronts on dry days will not contribute to the variability of total rainfall. Fronds are identified on dry days about as often as on rain days using the SOM, PMM, and TGR methods, while using the WND and WPT methods, only about a third of the fronts identified fall on dry days (cf. Table 2). Correspondingly, the magnitudes of the correlations between the number of fronts identified using the SOM, PMM, or TGR methods and CWB rainfall drop dramatically, with SOM becoming significant but negative. The correlation between the WPT front time series and rainfall changes little when all days are included [Table 8 (bottom) compared to Table 8 (top)], and the correlation between the WND front time series and rainfall remains positive and significant at the 10% level.

### 5. Discussion and conclusions

Six diverse methods of front identification have been applied to the region of SWWA over the winter months (June and July) from 1979 to 2006. One of the methods, MAN, used a manual identification technique applied by an experienced synoptician. The other five methods used automated techniques to identify fronts based on a range of large-scale atmospheric variables. The identification of fronts was performed on all days for the automated methods and on days on which rain fell in the CWB region of SWWA (rain days) for the MAN method. The numbers of fronts were compared between the methods, and the interannual variability and trends in the front numbers and links to rainfall were investigated.

The interannual variability of seasonal time series of fronts on rain days is related between all methods, with correlations significant at least at the 10% level (except between the TGR and SOM counts). These significant correlations between the MAN time series of fronts show that each automated method holds some level of skill at analyzing a front for a seasonal time series. Analyzing fronts on all days was possible for each automated method, but the correlations were lower. The WND and WPT time series were also still correlated with each other at a significant level, as were the WND and TGR time series with the PMM time series and the SOM and WPT time series. The trends in the numbers of fronts on rain days were not significant. The trends in fronts when all days were analyzed were all negative, and for the TGR time series this trend was significant, but not for the others.

Relating the number of fronts to rainfall across the CWB, the winter front count identified with the WND method has the strongest correlation with rainfall. This may be due to the ability of the WND method to identify not only fronts, but also prefrontal troughs, which can be

### Table 9. The average amount of rainfall (mm) associated with each synoptic type as identified by MAN on front days identified by the automated methods. The average rainfall associated with each front type identified by MAN is included for reference.

<table>
<thead>
<tr>
<th>Front Type</th>
<th>MAN</th>
<th>WND</th>
<th>WPT</th>
<th>TGR</th>
<th>SOM</th>
<th>PMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complex front</td>
<td>4.54</td>
<td>5.44</td>
<td>5.23</td>
<td>5.43</td>
<td>4.37</td>
<td>5.83</td>
</tr>
<tr>
<td>Wave on front</td>
<td>3.11</td>
<td>3.31</td>
<td>3.3</td>
<td>3.29</td>
<td>2.37</td>
<td>3.31</td>
</tr>
<tr>
<td>Cold front</td>
<td>3.01</td>
<td>3.56</td>
<td>3.26</td>
<td>3.63</td>
<td>2.45</td>
<td>3.18</td>
</tr>
<tr>
<td>Cutoff low</td>
<td>---</td>
<td>5.12</td>
<td>5.53</td>
<td>5.2</td>
<td>3.13</td>
<td>7.13</td>
</tr>
<tr>
<td>Trough</td>
<td>---</td>
<td>2.82</td>
<td>2.5</td>
<td>3.7</td>
<td>1.02</td>
<td>1.21</td>
</tr>
</tbody>
</table>
associated with heavy rainfall (e.g., Hope et al. 2006). However, in this study, a number of days that the manual analysis of Pook et al. (2012) classified as cutoff lows were also identified as fronts by the automated methods. These days on which a cutoff occurred had, on average, much higher rainfall totals than those days with a trough. Thus, the correlations between rainfall and frontal number will be driven to some extent by the number of cutoffs identified also. To remove cutoff lows (e.g., Grose et al. 2012) from the record before applying a frontal recognition system might result in a clearer signal of how the number of fronts relate to rainfall. The observed trend in CWB rainfall for the period is not significant, although the years at the end of the time series had low rainfall, and it may well be significant if the years since 2006 could be included, as 2010 was the driest on record. This could be a topic for further research. This study has shown the difficulty associated with the identification of fronts, important atmospheric features for which there is currently no universally agreed single definition. An absence of a “correct answer” means that a thorough discussion of the advantages and disadvantages of each of the methods needs to be given. To identify a front using the MAN method, a number of features can be drawn upon that are not currently incorporated into the automated methods. One key characteristic of manual analysis is historical consistency. The manual analyst is strongly influenced by the previous analysis and has to justify clearly (in his/her own mind) why a synoptic feature has disappeared from the chart. Vestiges of fronts and trough lines often explain observed weather and, as they usually have a history of movement, can be used in weather forecasting. Before regular satellite imagery and radar coverage, this approach was more critical than today. In cases where only one or two automated methods agreed with MAN, the fronts tended to be relatively weak or in a state of frontolysis, often associated with strong ridging. This can mean that there is no significant wind shift (already south of west) although the temperature gradient can still be quite marked. Often these cases were days on which only the northern portion of the front was in the region; these portions at the full extent of the front are often relatively weak, and it is difficult to detect a marked airmass contrast. These are cases when the automated methods may not perform as well, but to perform a manual analysis of fronts on a global scale for all days would be prohibitively time consuming. Despite their shortcomings in specific situations, the automated schemes have proven to be valuable.

On days when a front is identified by all automated methods, there tends to be a strong trough and significant cold-air advection. For other cases, the different methods capture different facets of the system. The WND and WPT techniques are reasonably well established and have the advantage over the other methods in this regional study of first identifying fronts with the entire Southern Hemisphere information, rather than just the signal within the box considered. All the methods consider the thermal contrast using a range of parameters (thickness, T850, andΘe) except the WND method. While the WND method in a number of test cases appears to capture the wind shift in the prefrontal trough (if present) as well as the front, it also correlates very well with the methods that assess the thermal gradient. The time series of front counts produced with the TGR method does not correlate as well as might be expected with the other methods given that it assesses the actual temperature gradient. But since it was modified from a specific summer case (Mills 2005) for this winter study, some further work might be required for its widespread application. The SOM method was also drawn from a previous study (McIntosh et al. 2008), which focused on distinguishing between fronts and cutoff lows. There were SOM nodes on the right-hand side of the SOM that may have aligned well with complex fronts, but they were discounted because of their good match with cutoff lows. The PMM, which was formulated purely for this study as a simple test of whether a composite pattern could possibly be used for this purpose, had good results, which could be used as an initial guide to the variability of fronts in this region.

There are a number of factors that will impact upon the choice of which method to use for a particular climate study. The ease of applicability to other regions means that the WPT method is appealing as it can be used globally, with little need for adjustment for regional differences. The WND method has been applied to all Southern Hemisphere midlatitude regions (Simmonds et al. 2012). The TGR method may also be able to be tuned for global use, but it has not been developed for that purpose thus far. The pattern recognition methods can only be used regionally, as they require training on the regional synoptic patterns. The SOM method did not correlate well with the other methods in the identification of fronts, but as suggested above, it could be improved in further work. PMM is not only limited to a small region, but also requires a considerable amount of background knowledge of the fronts in the region in order to establish the particular patterns with which to identify fronts. This information may be difficult to obtain for a climate researcher, but may be readily available from a local weather forecasting service. If the information is available, it provides promise to capture features that are front-like in broadscale (both spatially and temporally) data.
A major advantage of automated front identification methods is that they can be applied to climate model output as well as reanalysis data; however, the availability of the required data may change the accessibility to some of the methods. The WPT method requires access to a greater range of fields than the other methods (i.e., moisture). All of the methods in this study use instantaneous 6-hourly data to identify fronts. For the WND method, this is very important as the identification is performed on the wind change over the 6-hourly period. The WPT and TGR methods assess gradients in instantaneous data, so once-daily data could be used rather than 6-hourly data. However, if this was the case, the size of the region of investigation would need to be considered in order to capture the passage of each front. For example, the 20° longitude region in this study (~1860 km) would likely capture the transition of a front as a front that entered the region just after one analysis time and would need to move very quickly (faster than 78 km h⁻¹) to transition out of the region before the next analysis time. However, fronts that persist for less than 24 h may not be captured. Other considerations are the number of fields required for the analysis. Static patterns (PMM and SOM) can also be assessed at lower (once daily) time resolution. Until recently, 6-hourly instantaneous data were not generally widely available from many modeling groups. However, modeling groups participating in phase 5 of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012) have provided some such high temporal resolution data. Another advantage of these new models and datasets is that their resolution is increasing, which would likely make the identification of fronts in these data a more reliable task. This new dataset allows an unprecedented opportunity to perform front identification analysis on multiple models.

The major international program to compare the automated identification of extratropical lows (Neu et al. 2013) was very extensive in its comparison across methods, and new insights have been revealed. The current comparison of fronts has been conducted over a specific region, but we have benefited from including a manual identification scheme. This study should encourage further intercomparison studies that can help climatologists appreciate exactly what features of mid-latitude and extratropical weather systems any one automated system captures.

The results here highlight that automated techniques have considerable value in understanding frontal behavior and in identifying the changes in the frequency of frontal systems through time. These methods allow for more comprehensive analyses than is practicable using manual approaches. They are conducive to the exploration of a wide range of datasets and data periods (e.g., future projections from climate models).

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