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A MODIS-derived snow climatology (2000–2014) for the Australian Alps

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ABSTRACT: Although not spatially extensive, the Australian Alps are scientifically significant as they are one of the few mid-latitude mountain ranges in the Southern Hemisphere. Because they are characterised by low elevations relative to other mountain ranges, the Australian Alps are a marginal area for seasonal snow-cover and are likely to be amongst the first areas to experience the effects of climate change. While numerous studies have examined temporal trends in Australian snow depths using ground-based observations, few have explored both the spatial and temporal trends in snow-covered area using remotely sensed observations. In this study, remotely sensed snow climatology for the Australian Alps was derived. The image time-series spanned 2000–2014 and was generated from imagery obtained by the Moderate Resolution Imaging Spectroradiometer (MODIS). Spatial and temporal trends in snow seasonality and snow-covered area were analysed, with results indicating that both the duration of snow cover and the amount of snow covering the Australian Alps was highly variable. The analysis further indicated that the snow-covered area decreased at a rate of 2.5% decade^{-1} across the study period. Although this trend was not statistically significant, it is the first time that the reduction in snow-covered area has been quantified for Australia. Furthermore, the automated methods employed in this study can be used to consistently process remotely sensed imagery, which can then be employed to monitor changes in Australian snow seasonality in the future.

KEY WORDS: Snow-covered area · Snow seasonality · Time-series · Trend analysis · Moderate Resolution Imaging Sectroradiometer · MODIS · Australia

1. INTRODUCTION

Seasonal snow-cover is an important phenomenon that both influences, and is influenced by, climate and thermodynamics at the Earth's surface (Déry & Brown 2007, Groisman et al. 1994). Because snow-cover and atmospheric dynamics are tightly coupled, numerous studies have explored changes in seasonal snow-cover (e.g. Brown 2000, Hantel et al. 2000, Robinson & Frei 2000, Husler et al. 2014, Ke & Liu 2014). An important aim of these studies has been to characterise regional changes in seasonal snow-cover, which is also an integral component of the Intergovernmental Panel on Climate Change (IPCC) assessment process (Vaughan et al. 2013). To date, evidence from the Southern Hemisphere has been too sparse to conclusively indicate whether climate change is impacting snow cover there (Vaughan et al. 2013).

In addition to having an influence on atmospheric and climate dynamics, where it occurs, seasonal snow-cover also affects the biosphere. Winter snow-cover plays an important role in faunal hibernation and dormancy (Aitchison 2001) as its insulating properties help buffer against harsh winter temperatures (Shi et al. 2014). Snow-cover impacts aboveground microclimate, subsurface hydrology and soil geochemistry and affects vegetative growth and development (Pomeroy & Brun 2001, Walker et al. 2001). In mountain environments, climate-related changes

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to snowfall regimes and snow seasonality may exert greater influence on mountainous vegetation than the projected regional temperature increases (Körner 2005). Annually, snow-cover is the single most important factor governing plant phenology at higher elevations as it determines the length of the growing period (Inouye & Wielgolaski 2003). In some landscapes, changing snowfall regimes and increased rates of snow ablation have altered flora and fauna assemblages along elevation gradients, thereby changing the composition of the biotic communities within them (Root et al. 2003, Parmesan & Yohe 2003, Pauli et al. 2007, Inouye 2008).

In this context, understanding and characterising changes in snow-cover in mountainous environments has intrinsic value. Seasonal snowfall is highly variable in the Australian Alps (Budin 1985), primarily because of their relatively low elevation compared to other mountain ranges (Costin 1989). Annual snowfalls are influenced by the geographic location of a winter sub-tropical ridge over central Australia (28–30° S) relative to the Australian Alps. The position of this ridge largely determines the amount of yearly snowfall, and a shift of 1° northward can result in an additional 14–20 cm of annual snowfall (Budin 1985).

Predictors of yearly snowfall quantities remain elusive. Early studies reported biennial and 4 yr patterns in snow-depth observations (Colquhoun 1978) that have not been reported in recent studies (i.e. Green & Pickering, 2009, Nicholls 2005, 2009). Budin (1985) stated that snowfalls in the Alps were unpredictable, exhibiting little correlation with the Southern Oscillation Index (SOI), with the exception that years with large snowfalls occasionally preceded El Niño events. In Australia, the SOI and Southern Annular Mode (SAM) are significant drivers of precipitation and temperatures, particularly during the winter months (Hendon et al. 2007). Ummenhofer et al. (2009) also identified interactions between the SOI and the Indian Ocean Dipole (IOD) as contributing to substantial moisture deficits in southeastern Australia, resulting in the significant droughts observed during the 20th century. More recently, a temporal analysis conducted by Gallant et al. (2013) indicated that in Australia, interactions between the SOI and SAM are non-stationary, with variability between local and remote climate indices being the norm.

Under current climatic conditions the Australian Alps do not support permanent glaciers, and evidence suggests that glacial activity was confined to the highest elevation areas during the last glacial period (Galloway 1965). In this sense, the Australian Alps are a marginal area for seasonal snow-cover, and are likely to be amongst the first alpine areas in the Southern Hemisphere where the effects of climatic change will be observed. Measuring the impacts of climate-related changes in snow-cover in the Southern Hemisphere is also a challenge, as there are relatively few long-term ground-based monitoring locations (Vaughan et al. 2013). Remote sensing offers a means of observing changes in snow regimes in the Southern Hemisphere, though there have been few studies utilizing this technique to date. An exception is the work of Foster et al. (2009), who observed a negative trend in the winter snow-covered area in Patagonia. Using imagery from the Scanning Multichannel Microwave Radiometer (SMMR) and Special Sensor Microwave Imagers (SSM/I), Foster et al. (2009) reported a negative trend of $-1962\ km^2\ yr^{-1}$ between 1979–2005.

Although analysing seasonal variability in snow-cover has intrinsic scientific merit, changing snow-cover has implications for Australia. Climate-related changes in snow-cover are likely to impact the survival of endangered Mountain Pygmy Possum *Burramys parvus* because persistent snow-cover provides a buffer against winter temperatures (Shi et al. 2014). Additionally, the Australian Alps have hydrologic importance. Snow-melt from these areas is used for hydroelectric power generation (Gare 1992), drives agricultural production in the Murray-Darling Basin, one of Australia's most important agricultural areas (Brennan & Scoccimarro 1999), and plays a significant role in water supply for southeastern Australia (Williams & Wahren 2005). Therefore, characterising decadal variability in Australian snow-cover is important as climate change and altered snow regimes will ultimately impact these phenomena.

In Australia, concerns about the shifting nature of snow-cover and links to climate change have at least been partially substantiated by analyses of historical *in situ* snow-depth observations. Ruddell et al. (1990) extended maximum snow depth measurements for Rocky Valley (Victoria) and Deep Creek (New South Wales, NSW) back to 1910 using meteorological and hydrological observations. Their analysis of maximum snow depth between 1910–1989 indicated declining snow-depth, particularly over the last 40 yr of the record, although this trend was not statistically significant. Duus (1992) used Spencer's Creek (NSW) snow-depth observations to derive an empirical model for snow-cover from 1910–1991. His analysis identified distinct categories of snowfall regimes that ranged from periods characterised by high snowfall, periods with lower snowfall, and periods with considerable interannual variability in snowfall. Nicholls (2005) also analysed the snow depth record for

Spencer's Creek between 1962 and 2002. His results indicated a slight downward trend in the seasonal maximum snow-depth, and identified a 40% reduction in spring snow depths. Nicholls (2005) attributed both phenomena to the combination of increased temperatures between July and September and changes in synoptic patterns over this time, suggesting that Australia might already be experiencing the impacts of climate change. Green & Pickering (2009) analysed the Spencer's Creek data and determined that the number of snow-cover days had declined from an average of 213 metre-days early in the time-series to 146 metre-days at the end of their record.

Using an experimental snow-detection algorithm and remotely sensed data collected by the MODerate Resolution Imaging Spectroradiometer (MODIS), Bormann et al. (2012) also reported a shift towards an earlier end to the snow-covered period for elevations above 1580 m between 2000 and 2010. Bormann et al. (2012) further examined maximum snow-cover extent, reporting a statistically significant decline in maximum extent during that period. Modelling predictions incorporating the IPCC's projections for temperature increases indicate that the number of days with persistent snow-cover will likely decline across the Australian Alps, with the magnitude of decline being a function of both elevation and projected temperature increases (Whetton et al. 1996, Hennessy et al. 2008).

While previous studies have characterised changes in seasonal snow-cover or made predictions about snow-cover in a changing climate, none have presented a comprehensive spatio-temporal analysis of snow-climatology in the Australian Alps. In part, this is likely because Australia's alpine areas are not spatially extensive, which effectively precluded the regular detection of snow-cover with early generations of optical sensors on space-based orbital platforms (Dewey & Heim 1983). The advent of MODIS, with its improved spatial resolution, on-board radiometric calibration, large number of spectral bands (36), frequent overpasses and improved cloud-detection (Justice et al. 2002) have resulted in the ability to generate daily map time-series of snow-cover globally (Hall et al. 2002). Characterising both seasonal variations in snowfall and the spatial patterns of snow persistence are important for understanding how climate change will impact Australia's alpine vegetation (Edmonds et al. 2006). MODIS data are suitable for this purpose.

This study analyses a 15 yr MODIS-derived snow climatology for the Australian Alps. The spatial resolution of the image time-series is 500 m and spans the period from 2000–2014. Snow-cover was detected and mapped using an implementation of the standard MODIS snow-mapping algorithm of Hall et al. (2001) in conjunction with the improved liberal cloud-mask (ILCM) described by Thompson et al. (2015a), which addresses scale-related snow/cloud confusion problems associated with the MODIS cloud-masking algorithm over Australia. The objectives of this study were to (1) generate an automated and consistently processed snow-cover image time-series for the Australian Alps; (2) employ this time-series to characterise spatio-temporal variability in snow-cover for the region; and (3) explore the meteorological and climatological factors influencing the time-series. Specifically, the spatial and temporal patterns and trends in snow seasonality descriptors associated with the start and end of seasonally persistent snow-cover (e.g. snow onset/offset), duration of the snow-covered period, and the seasonal changes in the areal fraction of snow-cover are assessed alongside the drivers of monthly and annual snow-covered area.

2. STUDY AREA

The Australian Alps encompass an area of 12 147 km^2, are situated in the southeastern corner of the continent (Fig. 1) and are globally significant, comprising one of the few mid-latitude mountainous regions in the Southern Hemisphere (Costin 1989). Being a dissected plateau, the elevation range within

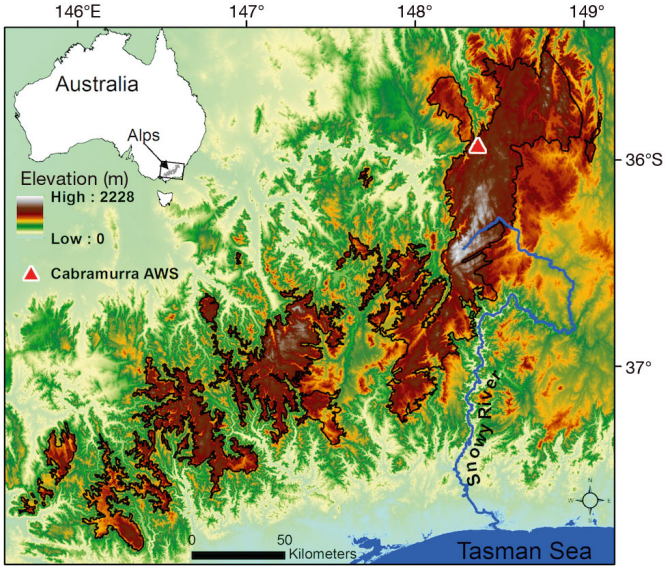

Fig. 1. Study area is the Australian Alps (black) located in southeastern Australia. Note the low elevation relative to other mountain ranges

the study area is limited, with Mt. Kosciuszko as the highest peak at 2228 m above sea level (a.s.l.). These low elevations (see Fig. S1 in the Supplement at www.int-res.com/articles/suppl/c068p025_supp.pdf) impact Australia's snow-climatology, which is characterised by considerable interannual variability in both snowfall and snow-depth (Duus 1992, Davis 1998, Nicholls 2005). As previously noted, under current climatic conditions Mt. Kosciuszko's elevation is too low to support glacial activity, though there is evi-dence of previous activity during the last glacial cycle (Galloway 1965). Long-term monthly precipitation for the austral winter (June–August) ranges from 165–205 mm, average minimum temperatures are between −1.8 and −0.4°C with average maximum temperatures ranging from 3.1–4.9°C. Land cover types vary within the Australian Alps, and include open forests (45.8%), low open forests (33.3%) and woodlands (9.2%; note that woodlands have fewer trees relative to forests). Globally, the study area is unique in that it is the only mountain environment dominated by evergreen *Eucalyptus* species (Costin 1989). Areas with true alpine vegetation are confined to Mt. Kosciuszko (Costin et al. 2000).

In the study area, there is significant intra-regional variability in the duration of the snow season (Budin 1985, Slatyer et al. 1985, Ruddell et al. 1990, Duus 1992, Nicholls 2005, Green & Pickering 2009). This is primarily a result of the elevation gradient that occurs across the study area (Slatyer et al. 1985). In terms of the climate events that bring snow to the region, Davis (1998) suggested that the alpine areas can generally be considered as a single entity when it comes to snow-bearing weather systems.

As a consequence of the relatively low elevation and geographic location of the study area, the Alps are sensitive to changes in atmospheric temperatures; small changes in weather patterns can significantly impact the snow season, and the storms that bring snow to the area often deposit snow across the entire region (Davis 1998). As previously noted, the location of the sub-tropical ridge in central Australia is an important driver of winter snow-depth, with small shifts in the ridge resulting in higher snow deposition in the northern portions of the range (Budin 1985).

3. DATA

3.1. MODIS data

Although a daily MODIS snow cover (MOD10A1) product exists for most of the globe (Hall et al. 2002), this product has significant errors over the Australian Alps (Bormann et al. 2012, Thompson et al. 2015a). As such, MODIS daily surface reflectance (MOD09GA) data from Collection 5 (Vermote & Vermeulen 1999, Vermote & Kotchenova 2008, Vermote et al. 2011) were used to map snow-cover within the study area. These data are Level 2 products that provide top of the atmosphere (TOA) reflectance values for the first 7 MODIS bands (Vermote et al. 2011). They are corrected for: variations induced by the Bidirectional Reflectance Distribution Function (BRDF) effects from adjacent land cover types and coupling effects within the atmosphere; and contamination by thin cirrus clouds (Vermote & Vermeulen 1999). The MOD09 processing stream uses a vectorised 6S radiative transfer model with estimates of atmospheric and meteorological conditions to approximate TOA reflectance values corresponding with underlying land cover type that are adjusted for the angle of incident solar radiation (Vermote & Kotchenova 2008). The MOD09GA products have been used to study other seasonally snow-covered landscapes (e.g. Dozier et al. 2008, Rittger et al. 2013) and were thought to be suitable for the present study. All daily MOD09 data for 2000–2014 were used in the analysis.

3.2. Meteorological data

Meteorological data were obtained from the Cabramurra Automatic Weather Station (AWS) (Fig. 1; Station ID 072161). Cabramurra is a high elevation (1482 m) meteorological station located in the northern part of the study area (Australian Bureau of Meteorology 2015). It is one of the few high elevation stations with a long observation history (manual station: 1955–1999, automatic: 1998–current) and has been used in previous studies to characterise climatic conditions in relation to changes in ground-based snow measurements (e.g. Nicholls 2005, 2009). For this analysis, total monthly precipitation along with average monthly maximum and minimum temperatures from the Cabramurra AWS were used.

4. METHODS

4.1. Snow/cloud discrimination

To overcome the limitations of the cloud mask used in the standard MOD10A1 products, the automated ICLM algorithm of Thompson et al. (2015a) was used to identify misclassified snow-cover in the standard

MODIS cloud-mask (MOD35). The ICLM uses reflectance thresholds from MODIS bands 6 (ρ_{b6}: 1.628–1.652 µm) and 7 (ρ_{b7}: 2.105–2.155 µm) in conjunction with the Normalised Difference Snow Index, NDSI:

$$\mathrm{NDSI} = \frac{(\rho_{b4} - \rho_{b6})}{(\rho_{b4} + \rho_{b6})} \quad (1)$$

where ρ_{b4} is band 4 (0.545–0. 565 µm) and ρ_{b6} is band 6 reflectance. Because actively precipitating clouds have droplet sizes similar to those of fine snow (Chahine et al. 1983) and are thus spectrally similar to snow-cover (Dozier 1989), the ILCM can misclassify these types of clouds as snow. However, the benefits of automation are preferable to visually identifying cloud cover (e.g. Bormann et al. 2012), as the accuracy of manual cloud identification depends on the skill of the analyst (Ackerman et al. 1998).

4.2. Snow detection

For snow detection, a modified version of the MOD10A1 snow-mapping algorithm (Riggs et al. 2006) was used. With the exception of the temperature thresholds used to differentiate snow-cover from other bright surfaces (e.g. coastal beach or desert sands) that do not occur in the study area, all other thresholds described by Riggs et al. (2006) were used to detect snow. While the snow-mapping algorithm primarily uses the NDSI, it also employs the Normalised Difference Vegetation Index (NDVI) to identify snow-cover in forested areas (Klein et al. 1998). The NDVI is calculated as:

$$\mathrm{NDVI} = \frac{(\rho_{b2} - \rho_{b1})}{(\rho_{b2} + \rho_{b1})} \quad (2)$$

where ρ_{b1} is band 1 (0.545–0.565 µm) and ρ_{b2} is band 2 (1.628–1.652 µm) from the Terra satellite's MODIS sensor.

The combination of the ILCM and the snow-mapping algorithm results in an improved ability to distinguish snow from cloud in Australia. Under clear-sky conditions, the accuracy of detecting snow using these combined methods is 83.8%, whereas the accuracy of the standard MOD10A1 product is 15.1% (Thompson et al. 2015a). Because the ICLM is not a clear-sky conservative algorithm, it does result in higher rates of cloud misclassification. When compared against a 3 yr time-series of *in situ* observations, Thompson et al. (2015a) reported that the producer's accuracy (a measure of omission) for cloud-cover detected by the combined methods was 57.8 versus 76.0% for the standard MODIS product. Thompson et al. (2015a) also found that the user's accuracies (a measure of commission errors) for cloud detection was 95.4% for the combined method and 73.1% for the standard MODIS product. It is important to note that inaccuracies in the global MODIS snow products (MOD10A1) are predominantly a result of erroneous cloud/snow confusion in the global MODIS cloud-masking algorithm (MOD35; Ackerman et al. 2006). The ICLM provides a mechanism for redressing snow/cloud misclassification, thereby enabling the use of the established, documented and well-understood snow detection algorithm described by Riggs et al. (2006). Because the accuracy of the combined methods (83.8%) is similar to the accuracy of the standard MODIS products (~93%) under clear sky-conditions, the snow-cover time-series used in this study should be comparable to those used in other remotely sensed snow-climatology studies (e.g. Wang & Xie 2009, Gao et al. 2012, Husler et al. 2014).

4.3. Snow seasonality descriptors

The snow-cover image time-series was used to estimate snow seasonality descriptors. These descriptors are increasingly of interest to the scientific community (e.g. Gao et al. 2012, Husler et al. 2014, Wang & Xie 2009); in particular, those corresponding with the onset of snow-cover (SCOD), the snow-cover melt date (SCMD) and the duration of the snow-covered period (SCD). A number of different methods have been proposed for determining the dates of both SCOD and SCMD, though most fail to account for the fact that snow-cover can be ephemeral—particularly at the beginning and end of the snow-covered period (Thompson & Lees 2014). Choi et al. (2010) demonstrated that failing to account for ephemeral snow events skews the results of trend analyses.

In this study, SCOD and SCMD were determined using the algorithm described by Thompson & Lees (2014) in order to account for early- and late-season ephemeral snow-cover events. In short, the algorithm employs object-based segmentation in the temporal domain to eliminate ephemeral snow-cover events, and thus more accurately identifies the period of persistent snow-cover. Essentially, it examines a pixel's yearly snow-cover time-series, identifying any 'no-snow' detections in the series associated with ephemeral snowfalls. The algorithm ignores ephemeral events and identifies the start and end of the persistent SCD. The start and end of this period are then defined as the SCOD and SCMD respectively. A

complete description of the algorithm is provided in Thompson & Lees (2014).

Thompson & Lees (2014) reported good correspondence between remotely derived snow seasonality descriptors and those estimated from *in situ* observations in the Australian Alps, and they are similar to those proposed by both Wang & Xie (2009) and by Gao et al. (2012). As such, the terminology of Wang & Xie (2009) and Gao et al. (2012) has been adopted here, although the method for estimating the snow seasonality descriptors differed from those proposed by Wang & Xie (2009) and Gao et al. (2012). SCD was also derived using the MODIS observations. Because the austral winter does not span calendar years, the duration of the snow-cover can be directly determined using the formula:

$$\mathrm{SCD} = \mathrm{SCMD} - \mathrm{SCOD} \tag{3}$$

Further discussion of snow seasonality descriptors is presented in the Supplement at www.int-res.com/articles/suppl/c068p025_supp.pdf, including a discussion regarding limiting the influence of off-NADIR view-angles (i.e. those not directly beneath the sensor) on the time-series.

4.4. Snow-covered area

Snow-covered area (SCA) is a descriptor frequently used to characterise snow-cover in mountainous environments (Gao et al. 2012, Husler et al. 2014). As noted above, the method of Thompson & Lees (2014) explicitly assumes the presence of snow underneath obscuring cloud-cover until a clear-sky view of the surface is obtained. This assumption is used to gap-fill a time-series, thereby enabling the creation of a SCA time-series; this is discussed in more detail in the Supplement.

4.5. Time-series analysis

Spatio-temporal analyses were conducted for both the snow seasonality descriptors and SCA data. In climatological time-series analysis, it is common to report standardised anomalies to facilitate inter-temporal and inter-regional comparisons. Standardised anomalies are calculated as:

$$\mathrm{SA} = \frac{(\bar{x} - \mu)}{\sigma} \tag{4}$$

where μ is the long-term population mean, σ is the long-term population standard deviation, and $\bar{x}$ is the mean value for the period, which depends on the time-series (i.e. monthly or yearly). For the snow seasonality descriptors, the data were analysed per-pixel, and were also analysed for elevation classes. For the elevation analysis, data were aggregated into 4 classes: 1200–1399, 1400–1599, 1600–1799 and ≥1800 m. Because the ILCM has difficulties separating actively precipitating clouds from on-ground snow-cover, the seasonality algorithm was further constrained to only examine data between 1 April and 30 November each year. To prevent short ephemeral snow-cover events from skewing the analysis, only pixels with a SCD ≥10 were analysed. Previous work indicated that this threshold helped to reduce the 'noise' associated with ephemeral snowfalls that occur late in the season (Thompson et al. 2015b).

For the SCA trend analysis, data were aggregated using only July–September observations. Previous studies indicated that Australian snow-cover has declined through time, particularly at the beginning and end of the snow-covered period (Nicholls 2005, Green & Pickering 2009). It was felt that including data outside the core winter months would potentially bias the analysis of the areal data. To account for temporal autocorrelation, the trend was determined using an auto-regressive generalised least squares model (Cowpertwait & Metcalfe 2009). The regression results were then used to calculate the minimum length of time-series (n) required to detect a trend with 95% confidence, using the formula of Weatherhead et al. (1998):

$$n = \left(\frac{3.3\sigma_N}{|\omega_0|} \sqrt{\frac{1+\phi}{1-\phi}} \right)^{2/3} \tag{5}$$

where σ_N is the standard deviation of the residuals, ω_0 is the trend and ϕ is the autocorrelation in the monthly series.

4.6. Meteorological and climatological analysis

To understand the important meteorological factors that contribute to monthly MODIS SCA in Australia, a statistical analysis was conducted using the May–October meteorological data from the Cabramurra AWS. Analysis of variance (ANOVA) was used to characterise the main meteorological factors influencing SCA. The factors included in the ANOVA to understand SCA were:

$$\mathrm{SCA_m} \sim P_\mathrm{m} + \min T_\mathrm{m} + \max T_\mathrm{m} + \min T_\mathrm{m} : \max T_\mathrm{m} \tag{6}$$

where $\mathrm{SCA_m}$ is the monthly SCA derived from MODIS, P_m is total monthly precipitation, $\min T_\mathrm{m}$ and

maxT_m are average monthly minimum and maximum temperatures respectively for Cabramurra, and minT_m:maxT_m is an interaction between average monthly minimum and maximum temperatures.

5. RESULTS

5.1. Snow seasonality descriptors

The results of the snow seasonality descriptor analyses are presented in Figs. 2–4. Fig. 2 depicts the mapped results for the snow seasonality descriptors. These results indicate that the higher elevation areas generally exhibit an earlier SCOD, a later SCMD and corresponding longer duration of SCD. Geographic differences were also evident in the results, as the eastern edges of the main range exhibited an overall tendency towards earlier melt dates (Fig. 2b). This phenomenon was particularly evident in in the northern parts of the Australian Alps.

Standardised anomalies for the snow seasonality descriptors are presented in Fig. 3. For the standardised SCOD (Fig. 3a), few consistent patterns were evident across the 4 elevation classes, though there was a tendency for a later onset of SCOD at some elevations later in the time-series. Similarly, the standardised anomalies for SCMD (Fig. 3b) also indicated an earlier end to the snow-cover period at most elevations, particularly from 2005–2007. Patterns for SCD (Fig. 3c) were more mixed, with more SCD anomalies occurring at the highest elevations later in the time-series.

The mapped results of per-pixel differences in the snow seasonality descriptors from their long-term mean are represented in Fig. 4. In some years, there was considerable spatial heterogeneity in the seasonality descriptors, but the effects of the elevation gradients were evident across all years. For example, SCD anomalies were particularly evident in the northeastern parts of the Alps, while in 2013 most of the lower elevation areas of the northern sections ex-

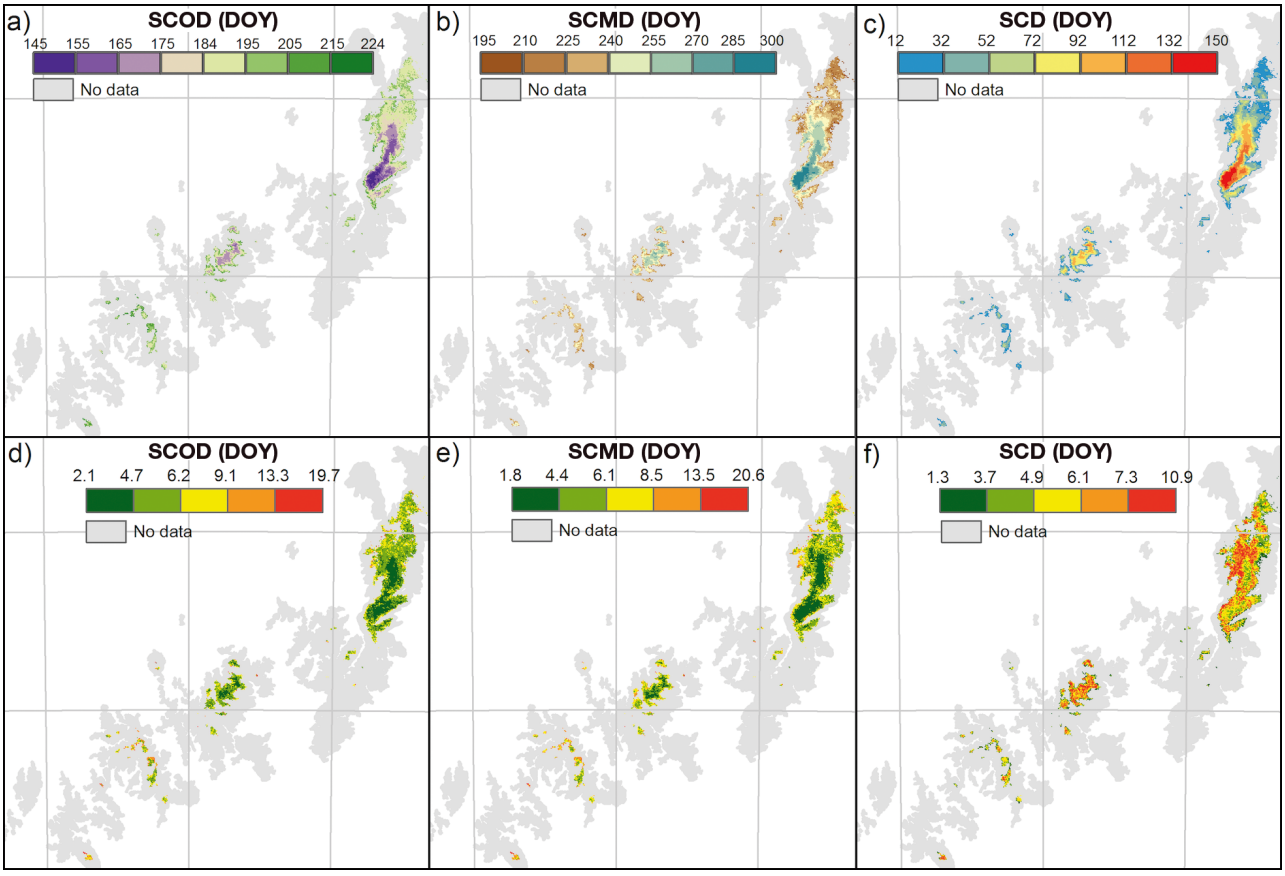

Fig. 2. Mean (a) snow-cover onset date (SCOD), (b) snow-cover melt date (SCMD), and (c) snow-cover duration (SCD) for the study period (2000–2014). Means were derived on a per-pixel basis, using the statistics of the individual pixels; (d–f) represent the standard error (SE) estimates for the descriptors in (a–c), respectively, which were also determined on a per-pixel basis. DOY: day of the year. See Fig. 1 for latitude/longitude indications

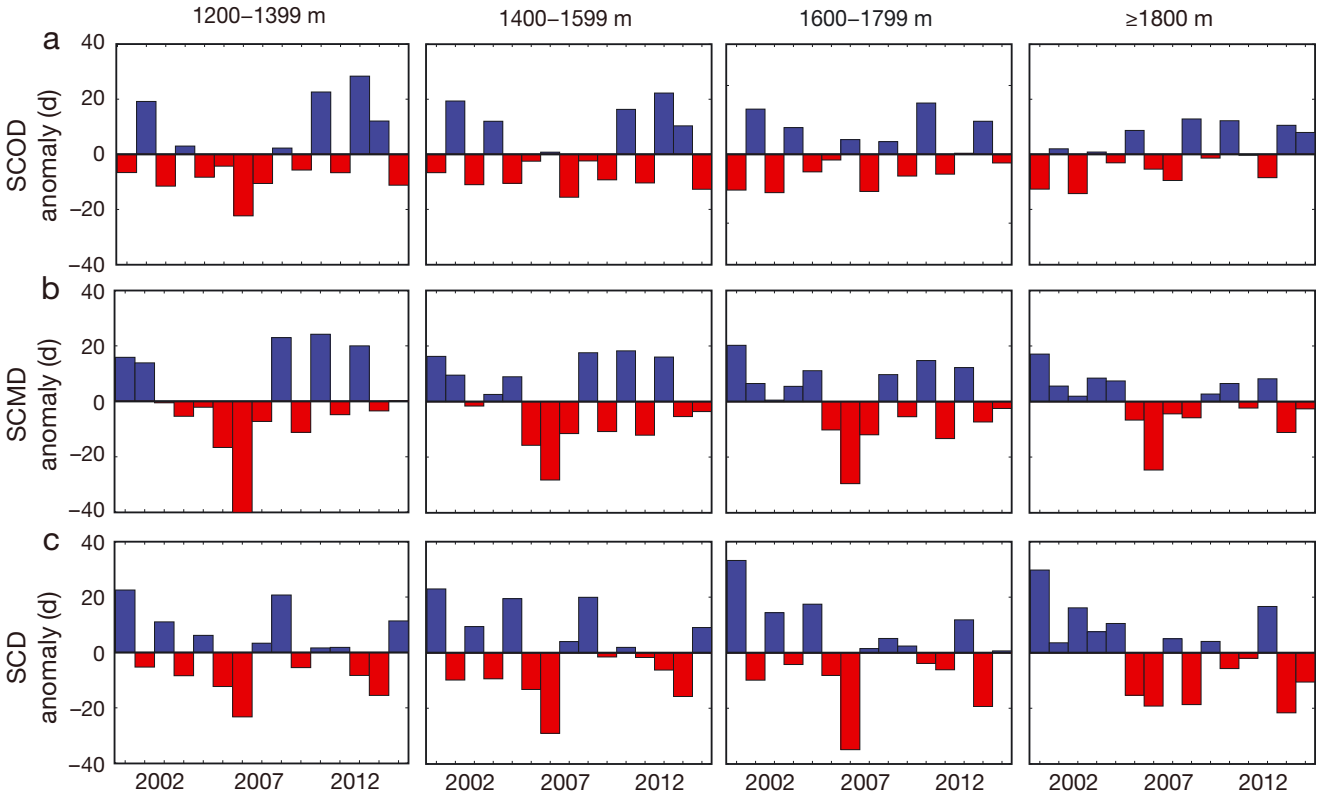

Fig. 3. Interannual comparison of observed anomalies from 2000–2014 for the (a) snow-cover onset date (SCOD), (b) snow-cover melt date (SCMD) and (c) snow-cover duration (SCD) for different elevations. Blue and red: positive and negative values, respectively

perienced a shorter SCD period. In contrast, during 2008 the lower elevation areas of these northern sections experienced a longer SCD period, while a shorter period was observed at higher elevations.

5.2. Snow-covered area

The distributions of monthly SCA for the entire study period are presented in Fig. 5. Overall, July and August were the months when most snow cover was observed during the study period. Though the median SCA value for July was higher than August, there was more variability in July SCA. A comparison of the 10 highest and lowest SCA values for July and August revealed that July had 6 of the 10 highest and lowest SCA values during the study period (data not shown). In contrast, most August SCA values were observed to be solidly within the middle of the distribution of SCA values.

Fig. 6 presents the results of both the monthly-standardised SCA anomaly analysis (Fig. 6a) and the overall trend in SCA across the time-series (Fig. 6b). Table 1 contains the regression parameters for the trend analysis, which is depicted graphically in Fig. 6b. Fig. 6a shows an overall decrease in monthly SCA for most months across the time-series. This monthly decline was also evident in the SCA trend analysis, with the regression indicating that the SCA declined at a rate of 2.52% decade^{-1} (Table 1) across the time-series. This trend was not statistically significant.

5.3. Meteorology and SCA

The results of the comparison of SCA with the meteorological data from Cabramurra AWS are presented in Table 2. Overall, the meteorological variables explained 73.4% of the variability in monthly SCA, with average minimum monthly temperatures explaining most (57.0%) of the variability in the data. In contrast, average maximum temperature alone held no significant explanatory power (0.1%), though interactions between average maximum and minimum temperature explained some variability (10.2%) in monthly SCA. Monthly average maximum temperature was highly correlated with average minimum temperatures (Kendall's $\tau = 0.816$). In addition, an analysis of ANOVA errors revealed temporal structure within the

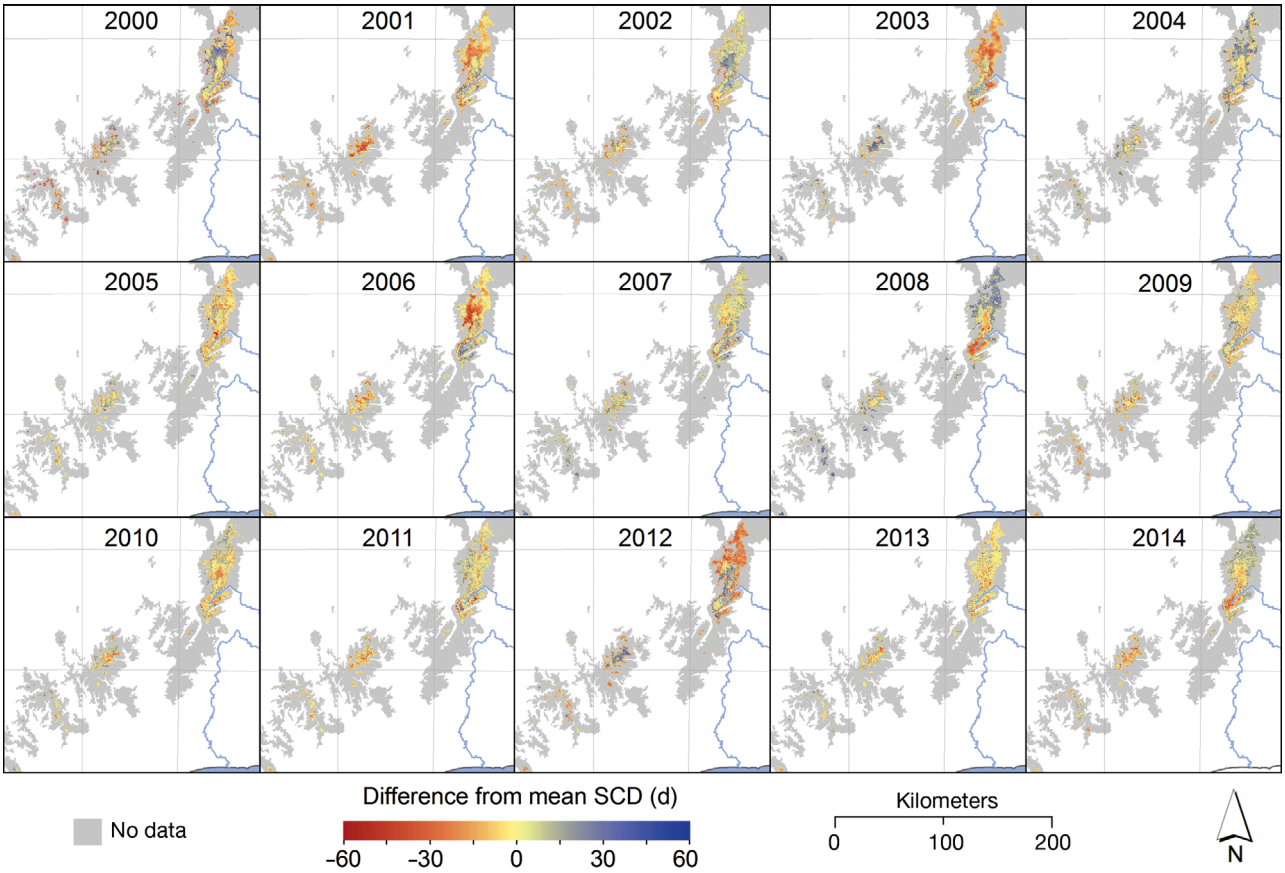

Fig. 4. Yearly duration of snow-cover with the 15 yr mean duration for the period 2000–2014. Comparisons were derived on a per-pixel basis, using the statistics for the individual pixel; grey ('no data') areas: snow-cover not observed in that year. To highlight spatial patterns and variability across the time-series, the display scale is capped at ±60 d; pixels with snow-cover duration (SCD) values exceeding these values are truncated accordingly. See Fig. 1 for latitude/longitude indications

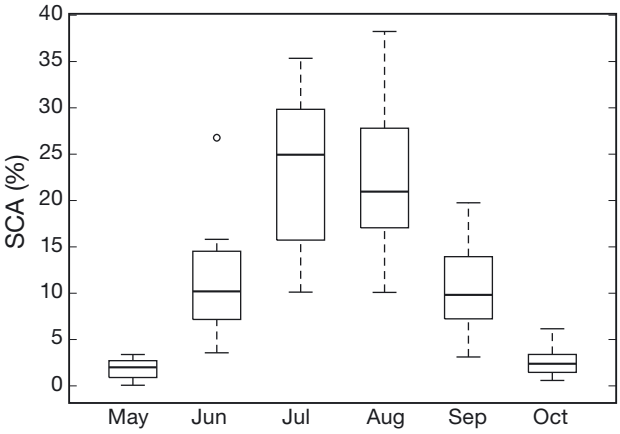

Fig. 5. Monthly snow-covered area (SCA) across the time-series (2000–2014). Note that the median SCA values (dark lines in the centre of the boxes) for both May and October are lower relative to other months. Boxes: median values as well as lower and upper quartiles (25 and 75%); whiskers: minimum and maximum values; circles: values more than 1.5 times larger than the difference between the lower and upper quartiles

data; an 18 mo lag (~3 yr) in the monthly SCA residual values was observed. This correlation was investigated, but no physically meaningful relationship was found (e.g. no relation to climate indices was detected).

6. DISCUSSION

Overall, these results highlight the fact that both the snow-covered period and the amount of snow covering the Australian Alps were variable during the study period. Much of this variability was a function of average monthly minimum temperature. For the snow seasonality descriptors (Fig. 3), very few clear patterns were evident in the results, particularly for lower elevations areas. For pixels above 1400 m, the SCMD tended to exert a stronger influence on the SCD than the SCOD (Fig. 3b,c). For the higher elevation areas, the SCD period tended to be longer at the beginning of the study period than at

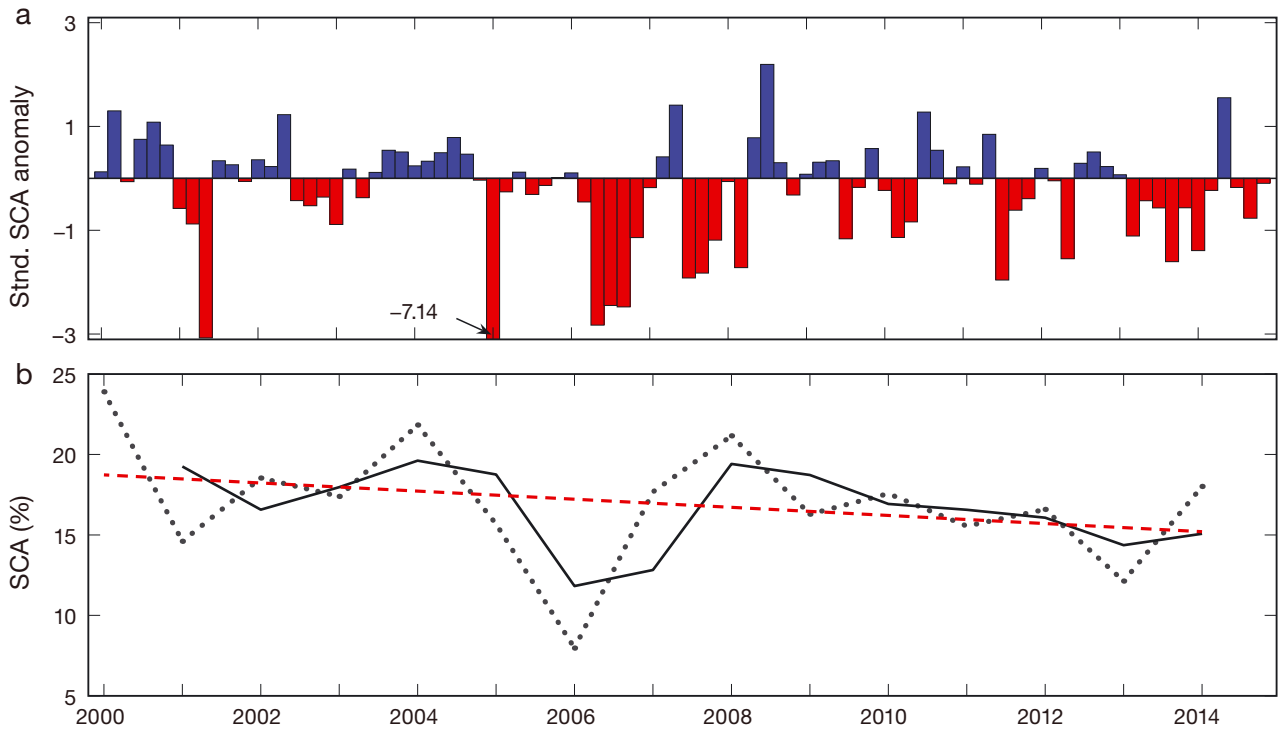

Fig. 6. (a) Standardised monthly anomalies (May–October, inclusive) of snow-covered area (SCA) and (b) yearly averaged SCA (June–September, inclusive). Dotted line: yearly averages; solid line: 1 yr running mean; dashed line: overall trend of the time-series

Table 1. Regression results of the snow-covered area trend analysis. ω_0: slope of the trend; ϕ: autocorrelation of the time series; σ: standard deviation of the residuals; n: number of years required to detect a statistically significant trend from the observations

ω_0	p-value	ϕ	σ	n
−0.252	0.268	−0.048	3.68	12.8

Table 2. ANOVA for snow-covered area and meteorological descriptor analyses, indicating degrees of freedom (df), amount of variation accounted for (η^2), *F*-value, significance (*p < 0.01) as well as overall R^2 and statistical significance for the model. P_m: total monthly precipitation; minT_m and maxT_m: average monthly minimum and maximum temperatures; minT_m:maxT_m: interaction between average monthly minimum and maximum temperatures

Variable	Model (n = 87; R^2 = 0.774*)		
	df	η^2	*F*
P_m	1	0.101	36.87*
minT_m	1	0.570	207.33*
maxT_m	1	0.001	0.19
minT_m:maxT_m	1	0.102	37.10*
Error	82	0.226	–

the end. Presumably, these differences can both be accounted for by differences in minimum temperatures, which will vary with elevation.

Similarly, the per-pixel annual deviations from the long-term mean SCD (Fig. 4) also exhibited considerable variability. In some years (such as 2005 and 2006), the spatial results mirrored the aggregated results, in that the SCD was clearly lower across most of the study area. In some instances, the mapped results provided additional insights that were masked by data aggregation (Fig. 3). For example, although the SCD was shorter in 2006, it was considerably shorter along the western edge of the main range in that year. In contrast, the eastern edges of the main range experienced a shorter SCD in 2003. This is interesting, as most snow-bearing storms are associated with westerly airflow (Davis 1998). In some years (such as 2008 and 2014), lower elevation pixels experienced longer SCD relative to their long-term mean, while the higher elevation areas experienced shorter durations.

Like the snow seasonality descriptors, the results of the SCA analysis also exhibited considerable intra- and interannual variability. Intra-annual variability is evident in Fig. S2 in the Supplement at www.int-res.com/articles/suppl/c068p025_supp.pdf, which indi-

cates that the percentage of SCA often varied over relatively short time frames, and is likely a reflection of the diurnal variability in minimum and maximum temperatures. Although the overall trend in SCA was negative, decreasing at a rate of 2.52% decade^{-1} across the study period, there was considerable variability in the data (σ = 3.68) with little interannual autocorrelation ($\phi = -0.048$; Table 1). This latter result is consistent with the findings of Budin (1985), who also found that maximum snow-depths were generally not correlated between successive years.

Statistical analysis indicated that average minimum monthly temperature was the most significant factor influencing variability in SCA during the study period. This contrasts the results presented by Nicholls (2005), who reported that yearly maximum snow depths were strongly correlated with maximum temperatures, although Nicholls (2005) did not investigate the influence of minimum temperatures. Monthly minimum temperatures were correlated with average maximum temperatures in this study; however, statistical analysis indicated that monthly minimum temperature was the most significant factor influencing the amount of SCA, although there was an interaction between minimum and maximum average temperatures in relation to the quantity of SCA. Whereas low temperatures are a necessary condition for snow formation and thus positively contribute to SCA, high temperatures during the day will generally only impact snow-cover when temperatures during the night are also high, thus preventing melted snow from refreezing.

The lack of statistical significance in the temporal trends is consistent with other studies (e.g. Ruddell et al. 1990, Nicholls 2005, Hennessy et al. 2008) but was not consistent with the finding of Bormann et al. (2012). These inconsistencies may be a result of the fact that the latter characterised trends in maximum snow extent, which were likely influenced by anomalously large snow-fall events. This is supported by Fig. 10 in Bormann et al. (2012), where the observed trends closely track with the highest values for maximum snow-cover extent. It is further corroborated by our Fig. S2 in the Supplement, where peaks in SCA were observed that were relatively short-lived.

In addition to highlighting the variability in both snow seasonality and SCA, the results of this study also provide additional context for previous studies of Australian snow-cover. For example, Davis (1998) noted that the Australian Alps were generally considered as a single entity when it came to snow-bearing weather systems. This is somewhat supported by Fig. 2a, in which some uniformity is apparent in the SCOD, particularly for lower elevation pixels. While there was a relatively homogenous start to the snow-covered period at lower elevations, the results presented in Fig. 2a also demonstrate the ameliorating influence of elevation, as higher elevation areas exhibited earlier SCOD relative to lower elevations. While the study area may be relatively homogenous from the perspective of storms, whether or not precipitation fell as snow during the study period was presumably a function of minimum temperature, with higher elevations supporting an earlier start to the snow-covered period due to their lower temperatures. The elevation at which snow-cover can persist within an area defines the regional snow line for that time period. With climate change, the regional snow line is expected to shift to progressively higher elevations in Australia, and the methods employed in this paper could potentially be used to quantify changes in the regional snow line through time. Considering the relationship between SCA and minimum temperature, these methods could also help improve regional climate models.

As previously noted, early studies of Australian snow observed both biennial and 4 yr patterns in ground-based snow depth observations (Colquhoun 1978). Discussion of these patterns has not appeared in more recent studies (e.g. Nicholls 2005, 2009, Green & Pickering 2009). The 3 yr lag observed in the ANOVA residuals is within the 2–4 yr range reported in those early studies. An attempt was made to relate the lagged residuals to the SOI, Antarctic Oscillation Index and the IOD, however this investigation did not find a meaningful relationship between the residuals and the climate phenomena. A broader analysis of the SCA data and climatological indices was also conduced, but also failed to identify meaningful relationships and was not included in the results. This lack of correlations to climate indices is consistent with the results of Gallant et al. (2013), who reported little correlation between local meteorological observations and broader climate indices.

Links to possible changes in temperature regimes may also be inferred from Fig. 5. From his time-series analysis of long-term data from the Spencer's Creek snow-coarse, Nicholls (2005) reported decreased snow-depths during both the start and end of the austral snow-covered period; similar responses were also observed in the SCA results from this study (Fig. 5). Fig. 5 indicates that the SCA generally encompasses <5% of the study area in both May and October during the study period. In the first month of the austral winter, the median SCA for the time-series was <10%. Given the strong relationship between SCA

and average minimum temperature observed in this study, this suggests that changes in minimum temperatures associated with climate change may already be impacting the Australian Alps. With the exception of Bormann et al. (2012), most studies of Australian winter snow-cover and snow seasonality have almost exclusively used *in situ* observations from Spencer's Creek in their time-series analysis. The results presented here constitute independent verification of the results of Nicholls (2005, 2009), and also corroborate some of the findings of Bormann et al. (2012), thereby providing additional confidence in the latter's experimental snow-detection algorithm.

The influence of both elevation and intra-regional variability on snow seasonality has been noted by many (e.g. Budin 1985, Ruddell et al. 1990, Duus 1992, Davis 1998, Nicholls 2005). To date, these studies have primarily characterised both snow seasonality and intra-regional variability as resulting from the aforementioned elevation gradient across the study area. In contrast, the results in Fig. 3b indicate that, on average, the eastern areas of the main range exhibit an earlier than average SCMD relative to other areas with comparable elevations. As such, this characterisation of, and identification of geographic differences between, snow-seasonality descriptors is a novel aspect of this study.

Previous studies have predicted that the SCA will substantially decrease in response to the changing climate (e.g. Whetton et al. 1996, Hennessy et al. 2008). The models used in previous studies were constructed using *in situ* observations, in which elevation and average temperatures were the primary governing factors of SCD. Because *in situ* snow-cover measurements are only made at a limited number of locations in the Australian Alps, it has been difficult to derive independent datasets that could be used for validating both the models and their predictions. The results presented here indicate that minimum temperatures govern the quantity of SCA, and previous studies of Australian snow-cover have generally not adequately considered the influence of minimum temperatures on snow cover. It is also worth noting that global climate models are generally unable to predict localised impacts resulting from mountain topography, though this has improved with the use of various downscaling techniques (Whetton et al. 1996). As such, the data and methods described in this study could be used to provide insights into climate-related changes in Australia's alpine areas, and can be used to improve future modelling efforts.

Although the results presented in this study are thought to be reasonable, there are some limitations associated with the methodology used. In particular, there is some question as to how successful the gap-filling algorithm was, as the percentage of SCA often varied over very short periods of time (Fig. S2 in the Supplement). Given that the ICLM algorithm is not a clear-sky conservative algorithm (Thompson et al. 2015a), it is possible that some of the snow-cover associated with unusually high SCA was a result of snow/cloud misclassification. In contrast, given that much of the Australian Alps are comprised of lower elevation areas where snow-cover is ephemeral, it is also conceivable that temporal spikes in SCA (Fig. S2a,b) indicated the presence of low elevation snowfalls that simply did not persist for long. On average, below 1500 m, snow-cover was relatively short-lived in this study period (Fig. S3c).

Given the lack of a dense network of ground-based monitoring sites in Australia's alpine region, distinguishing between these 2 alternatives is currently not possible. As Thompson et al. (2015a) noted, problems with the standard MODIS snow-product are likely a function of scale-related misclassification issues in the MODIS cloud-masking algorithm. Were these issues to be addressed in the standard MODIS processing chain, it would then be possible to analyse the SCA using the standard MODIS snow products. This could provide an indication of the reliability of the SCA results presented here, as the MODIS cloud-masking algorithm is a clear-sky conservative algorithm. Although this is currently not possible, since the SCA data were averaged by month, the impacts of the uncertainties associated with gap-filling and the ILCM were thought to be minimal.

7. CONCLUSIONS

Overall, the aims of this study were to generate an automated and consistently processed snow-cover image time-series for the Australian Alps, to use the time-series to characterise spatio-temporal variability in snow-cover, and to understand the meteorological factors that influence variability in SCA. The results confirmed the findings of previous studies, mainly that elevation is a significant driver of both snow-cover and snow seasonality in the Australian Alps. Unlike previous Australian studies, however, average monthly minimum temperature was found to be the significant driver of SCA. This study provides new insights into the spatial aspects of snow seasonality, which are likely linked to changes in monthly minimum temperatures.

Importantly, this is the first study to have quantified a decadal rate of change in areal snow-cover in Australia using a remotely sensed time-series. Because snow seasonality is a significant driver of vegetative processes in alpine areas generally, understanding spatio-temporal dynamics of snow-cover in areas like Australia is also important globally, as it can potentially provide insights into the effects of atmospheric changes associated with climate change. Given the general lack of snow studies from the Southern Hemisphere (Vaughan et al. 2013), the results of this study also represent an important contribution to climate science. It is important to note that snow-cover influences vegetative processes in the biosphere, and a better understanding of the links between changes in snow-cover and associated vegetation may provide additional insights into potential climate-related interactions in other alpine areas. This represents an area for further research.

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