Spatial and temporal variability in seasonal snow density

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1. Introduction

Snow density is an important physical feature that influences the thermal, mechanical and optical properties of snow layers. It is therefore a prominent variable in snow related research, including snow load estimation (Meløysund et al., 2007), slope stability calculations for avalanche prediction (Hirashima et al., 2009; Brun et al., 1989), assessment of snow traffiability (Lee and Wang, 2009), snow representation in land surface schemes and climate models (Pitman et al., 1991; Koren et al., 1999; Livneh et al., 2010), and snow hydrology (Rango and Martinec, 1995; Jonas et al., 2009; Sturm et al., 2010). These studies show that snow density is a complex parameter that can vary spatially, temporally and vertically within the snow pack profile.

Snow density has, therefore, been examined regionally in a variety of locations, most of which are in the large northern hemisphere snowfields (Bilello, 1984; Onuchin and Burenina, 1996; Sturm and Holmgren, 1998; Kershaw and McCulloch, 2007; Meløysund et al., 2007). In these studies, high snow densities are typically associated with high precipitation, warm air temperatures, strong winds and long season duration. These climate factors are well accepted influences for the spatial distribution of mean seasonal snow density however snow densities can increase considerably during individual seasons (Ruddell et al., 1990) at varying densification rates.

Seasonal densification of the snowpack over time may cause significant differences between early and late season snow densities which can deviate greatly from regional mid-season means. Linear density–time curves are commonly used to approximate seasonal snow densification (Jonas et al., 2009; Sturm et al., 2010) and although the density increases are relatively linear with time, these simple density–time relationships have limited spatial applicability, do not allow for interannual variability in densification rates nor provide links to physical processes or influences. Whilst the influences of climate on mid-season snow densities and regional density–time curves has been a focus for previous studies (Jonas et al., 2009; Sturm et al., 2010), less understood are seasonal densification rates themselves and their variability.
Seasonal densification of snow packs is caused by wind erosion, melt-refreeze events, compaction and snow metamorphisms acting in response to internal temperature and moisture gradients (Sommerfeld and LaChapelle, 1970; Colbeck, 1982). Wind erosion, for example, physically reshapes snow crystals to more sphere-like grains that can pack closer together. Similarly, the presence of liquid water (Brun, 1989a; Marshall et al., 1999) and destructive snow metamorphisms occurring when vertical temperature gradients are weak (Colbeck, 1982), also result in smaller, rounded grains. Conversely, strong vertical temperature gradients through dry snow layers result in the formation of larger faceted grains through constructive metamorphisms (Colbeck, 1982). These larger grains cannot pack closely together and consequently low densification rates are observed in cold regions where temperature gradients are prominent. Regardless of internal snow metamorphisms, the weight of new snow bears down on those below, densifying through compaction (Kojima, 1967; Anderson, 1976). Melt-freeze processes (Gray and Male, 2004) have long been implicated in snow densification, but no studies have established the link unequivocally. It is unclear which of these densification processes most influences densification rate and how dominant processes may differ between regions.

The relationship between snow densification processes and climate variability is not well understood. Limited studies in the US have linked air temperature, liquid water content and grain size to snow densification (Sturm and Holmgren, 1998), but report low interannual variability, perhaps due to the very cold climates in the study region, Alaska and Canada. Some correlation between densification rate and site characteristics such as elevation and proximity to the ocean has also been observed, with densification rate increasing during spring (Mizukami and Perica, 2008). Spatial variability in snow densification rate both regionally and between types of snow have been reported (Sturm et al., 2010) but interannual variability is generally considered negligible. As interannual climate variability is observed in snow affected regions, it is logical to also expect interannual variability in snow densification rates, particularly in highly variable climates.

Seasonal snowfields provide fresh water resources to large populations (Barnett et al., 2005) of which the accumulation and melt of snow in watersheds is critically important. Snow models show significant spread in simulations of snow water resources, even at sites with comprehensive observations (Essery et al., 2012), indicating that more research into understanding snow behaviour is required. Snow density may be used to parameterise energy flux and liquid water retention parameterisations in snow models (Essery et al., 2012), which are likely to affect runoff rates and late season SWE estimation (Dutra et al., 2010). Uncertainty in snow densification parameterisations is one of several potential sources of error contributing to snow model disagreement with SWE observations (Livneh et al., 2010; Fox et al., 2008). Snow density observations are somewhat limited even in well studied regions (Jonas et al., 2009), and often completely absent in less monitored locations. Snow research in these regions stands to benefit largely from methods of estimating important snow properties from more readily available data.

The present study therefore aims to capture the full range of snow densification variability across a large number of sites by (1) characterising interannual and spatial variability in snow densification rates; (2) identifying the dominant climatological drivers for snow densification rates; and (3) developing relationships between spring snow densities and climate variables. The study examines a wider range of sites, snow types and geographical conditions than previous work, including the southern hemisphere, using data from approximately 1700 snow years across 96 locations throughout the US, the former Soviet Union and Australia.

### 2. Data

#### 2.1. Sourcing the data

Snow depth, snow water equivalent (SWE), air temperature (minimum, maximum) and precipitation observations were collected for sites in the US, Australia and the former Soviet Union. The three main sources of data are outlined below.

- Daily data from the US for all variables listed above were obtained from the SNOwpack TELemetry (SNOTEL) network via the National Water and Climate Center website ([www.wcc.nrcs.usda.gov/snow/](http://www.wcc.nrcs.usda.gov/snow/)). Snow depth measurements from the SNOTEL network are typically available from the mid 1990s to present.
- Data from Australia of snow density, snow depth and SWE, at weekly to twice monthly intervals, were collected from the hydro-electric scheme operators, Snowy Hydro Pty Ltd. and Southern Hydro Pty Ltd. Snow data are available from the late 1950s to present.
- Former Soviet Union snow depth and SWE data, available at 5 day intervals, were obtained from the former Soviet Union Hydrological Snow Surveys (FSUHSS) dataset. This dataset is archived at the National Snow and Ice Data Center website ([NSIDC www.nsidc.org/](http://www.nsidc.org/)) and contains data from the mid 1960s to the 1990s. Corresponding climate data were sourced from the Daily Temperature and Precipitation Data from 223 former-USSR Stations dataset ([Razuvaev et al., 1993](http://www.azusa.vc/)) held at the Carbon Dioxide Information Analysis Center (CDIAC [http://www.cdiac.ornl.gov/ndps/ndp040.html](http://www.cdiac.ornl.gov/ndps/ndp040.html)).

#### 2.2. Criteria for site selection

Suitable sites for study were selected based on the following data. A minimum record of 10 years was required with a sampling frequency that captured the seasonal evolution of the snowpack. The time span was allowed to vary between sites to maximise the number of snow seasons in the data pool. Whilst all eligible sites in the US and Australia were included, the large number of eligible sites throughout the former Soviet Union required further screening. The FSUHSS dataset provided 618 sites that satisfied the criteria, of which the 40 with the highest number of snow observations over the longest period were selected as possible study sites. From these 40 sites, three were rejected due to poor or missing collocated temperature and precipitation data. The resulting 37 sites throughout the former Soviet Union are spatially distributed across the region and were considered representative of the full dataset. From the available data, four sites in Australia, 55 sites in the western US and 37 sites throughout the former Soviet Union were selected.

Fig. 1 shows the locations of the 96 observation sites across two hemispheres and three continental zones. The marker colour and type represents snow type classification. The Australian snowfields cover the smallest area of those investigated, but represent sites with demonstrated high interannual variability (Bormann et al., 2012).
2.3. Ensuring data quality

Data from the SNOTEL observation sites in the US are fully automated and are not quality controlled. Obvious instrument errors can affect snow depths from these stations, therefore the screening of outliers is required. Snow depth observations that significantly exceeded the expected maximum values at each site and those occurring during summer months were removed. The expected maximum values were based on manual inspection of snow depths for each US site and ranged from 2 m at low depth sites to 7 m at high accumulation sites.

Snow data for Australia and the former Soviet Union are both collected manually through field surveys, are much less prone to errors that require removal and were subject to similar pre-processing measures. Linear interpolations between irregular weekly or twice-monthly snow observations at Australian sites, and the 5 day measurement intervals at former Soviet Union sites were used to obtain daily values. The BoM climate data for the Australian sites are subject to quality checks and suspect values are removed from the data prior to release. Likewise, both the snow and climate observations for the former Soviet Union sites contain data quality flags.

Snow data quality flag 5 was used to remove suspect values from the former Soviet Union dataset. The flag, assigned by NSIDC as a quality control measure, marks “suspect data with unknown error” for snow depth, SWE and snow densities. Further details on the quality control measures applied to the snow data may be found on the NSIDC website (nsidc.org/data/g01170.html). For the associated former Soviet Union climate data, quality flag 9, assigned by CDIAC marks “rejected values” and was used to remove suspect temperature and precipitation values. A detailed description of the quality flags provided for the former Soviet Union climate data may be found at the CDIAC website (cdiac.ornl.gov/ftp/ndp040/data_format.html).

In addition to erroneous data, in situ data often contain missing values that can be problematic when seasonal means or cumulative metrics are required. The analysis undertaken in the current study was conducted over seasonal timescales and winter precipitation totals and mean winter temperatures were required. To avoid underestimation errors in total winter precipitation due to data gaps, if winter records were missing precipitation values from 10% of the calendar days, the whole winter was omitted from the analysis. While missing temperature observations were less common, seasons that were missing temperature data for more than 25% of the calendar days were also omitted. A higher tolerance for missing temperature data was allowed than for precipitation because the missing temperature values were less likely to affect seasonal means since temperature fluctuated less from day-to-day. The additional screening process removed snow seasons with prolonged periods of missing data during winter from the analysis at sites for all three regions, without affecting site selection.

Snow densities (g/cm$^3$) were derived from snow depth (cm) and SWE (cm) data pairs following the well-known formula reproduced in Sturm et al. (2010), at the SNOTEL and former Soviet Union sites. Errors in observed snow or SWE depths may lead to snow density errors and sometimes physical inconsistencies when values are low. Snow density estimates that exceeded the physical range of 0–1 g/cm$^3$ were masked at all sites. Only ~0.5% of all snow density observations for the US and former Soviet Union combined exceeded the physical range. To ensure the seasonal evolution of snow densities was adequately described, seasons at all sites with less than six individual snow density values (roughly less than two observations every month) were also omitted.

The quality assurance and data checking process reduced the number of suitable snow seasons from almost 1900 seasons to ~1690 seasons across 96 sites. Table 1 shows the typical periods for analysis and the breakdown of data for each of the three regions.

<table>
<thead>
<tr>
<th>Region</th>
<th>Earliest start year</th>
<th>Latest end year</th>
<th>Mean data period length (year)</th>
<th>Number of analysis seasons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>1957</td>
<td>2009</td>
<td>53</td>
<td>192</td>
</tr>
<tr>
<td>US</td>
<td>1994</td>
<td>2009</td>
<td>12</td>
<td>667</td>
</tr>
<tr>
<td>Former Soviet Union</td>
<td>1966</td>
<td>1990</td>
<td>25</td>
<td>831</td>
</tr>
</tbody>
</table>

2.4. Using snow type as a classification

Sites examined in this study were grouped into the following six snow types: alpine, maritime, prairie, taiga, tundra and Australian following the snow classification maps developed by Sturm et al. (1995) and subsequent research conducted by Sanecki et al. (2006). The scheme discriminates snow types using snow properties such as depth, mean bulk density, crystal morphology, grain size and the sequencing of snow layers. Climate characteristics including precipitation, air temperature, snow-ground interface temperature and wind speeds have also been used to distinguish these classes. Sanecki et al. (2006) observed unique snow condi-
tions at the Australian sites, noting that mean snow densities, winter air temperatures, snow/ground interface temperatures and vertical temperature gradients all fell outside the ranges established for the Sturm et al. (1995) classification scheme, requiring a separate classification category for Australian snow.

3. Method

Annual climate indicators and snow metrics were developed for each site individually, then the results were collated across all sites and analysed both together and for each snow type classification.

3.1. Decomposition of variability in densification rate

Following the analysis of variance methods (ANOVA) described in Yip et al. (2011) the total variance in snow densification was divided into two main components: the within-site variability (interannual) and the between-site variability (spatial) for each site, as shown in following equations:

\[
\text{VAR}_{\text{WITHIN-SITE}_i} = \frac{1}{n} \sum_{j=0}^{n} (x_{ij} - \bar{x}_i)^2 \\
\text{VAR}_{\text{BETWEEN-SITE}_i} = (\bar{x}_i - \bar{x})^2
\]

where \(x_{ij}\) is the snow densification rate at site \(i\) and year \(j\); \(\bar{x}_i\) is the climatological mean densification rate at site \(i\) and \(\bar{x}\) is the mean densification rate for all sites combined. The total variance may be approximated by the sum of within-site and between-site variance components.

3.2. Identification of dominant climatic factors

When selecting possible factors that influence interannual variability in snow densification rate, only climate variables are considered, as static site information such as elevation and latitude can only contribute to spatial variability. Annual fluctuations of many climate metrics are highly correlated, for example seasonal mean and minimum temperatures, and to avoid collinearity, three major climate metrics with links to snow density processes were sourced from previous investigations (Svoma, 2011; Ruddell et al., 1990; Bilello, 1984). The selected climate predictors include mean winter temperature (\(t_{\text{ave}}\) in °C); mean daily winter precipitation (\(P\) in cm/day); and mean daily melt-refreeze events (MRF in mean total events/days in season). A melt-refreeze event (MRF) occurs if daily melt conditions precede an overnight freeze such that \(t_{\text{max}} > 0\) and \(t_{\text{min}} + 1 < 0\). The mean daily MRF is determined by dividing the number of melt-refreeze events by the season length.

Predictors were all derived from winter months: June–September for Australian sites (JJAS) and December–March in the US and the former Soviet Union (DJFM). The exception was for MRF events, which were counted during the period at each site when snow was present for all years in the record. There is not always snow present at the very beginning and end of the snow season and this definition of MRF events ensured that the metric reflected the events that were directly experienced by the snowpack.

The dominant climatological drivers of annual snow densification variability were extracted by establishing single linear regressions between each of the three climate predictor terms and snow densification rates at all of the 96 sites. A natural log transformation was applied to the \(P\) data to ensure a more linear relationship with snow densification rate. The single predictor with the strongest relationship with annual snow densification rate, as determined by the coefficient of determination (\(R^2\)), was identified at each site as the dominant predictor.

3.3. The challenge of estimating snow densification rate

Annual snow density observations often display a great deal of variance at both the start and the end of each season, where abrupt spikes are observed at the boundaries of otherwise relatively stable snow density periods. These periods of high instability pose challenges for the estimation of snow densification rates using linear methods as the abrupt spikes can significantly influence the regressions. Annual snow density progressions for 12 years at the Galena Summit SNOTEL site in Idaho are presented in Fig. 2 as a
data example, where annual snow density profiles (thin grey lines) diverge at the start and end of each season. The sub-panel in Fig. 2 (the variance subplot) highlights the significant variance in snow density observations at the beginning and end of each season. The mid-season linearity of the density-time curves are common across the majority of sites examined and allows for the estimation of snow densification rates using linear methods, provided the high variance periods are objectively treated.

Weighted least squares regression may be used to apply individual point weightings to snow density observations when determining the line of best fit. Low weights are used at the start and end of each season and high weights are used during the mid-season stable density period. Like simple linear regression, weighted least squares seeks to optimise the line of best fit by minimising the residual sum of squares (RSS). As a result, low weighted points will have less influence in the optimisation process, as per following equation:

\[
\text{WeightedRSS} = \sum_{i=1}^{n} W_i (y_i - \bar{y}_s)^2
\]

where \( W_i \) are the point weightings; \( y_i \) are observed snow densities (g/cm³); and \( \bar{y}_s \) are expected snow densities along the regression line.

Two methods for assigning point weightings at each site were explored. The first was based on the observed variance for each day of the year (VW method) and the second used mean air temperatures (TW method). Weighting the points using the observed variance at each day of the season provides an accurate description of the periods of high variance however multiple years of snow density data are required to obtain a good estimate of these periods. As snow density is likely to be variable at times of the season when temperatures are high, the mean air temperature is also tested to confirm whether it may be used to describe the periods of high variance, in the absence of snow density data. Derivation of point weightings for both VW and TW methods are shown in following equations:

\[
W_{i}[\text{VW}] = \frac{\text{var}(y_i) - \text{var}(y_i)_{\text{max}}}{\text{var}(y_i),\text{min} - \text{var}(y_i)_{\text{max}}}
\]

\[
W_{i}[\text{TW}] = \frac{T_{\text{ave}}_i - T_{\text{ave}}_{\text{max}}}{T_{\text{ave}}_{\text{min}} - T_{\text{ave}}_{\text{max}}}
\]

where \( T_{\text{ave}}_i \) is the mean air temperature (°C) at day of year \( i \).

The point weightings presented in Eqs. (3a) and (3b) are high when observed variance in snow density is low (VW method) and when mean daily air temperature is low (TW method). The two methods are used to estimate snow densification rates for each season at each site in the present study, i.e. 1690 snow seasons across 96 sites. An example of the resulting weighted linear approximations on a subset of the data and then tested on the remaining 1/10th. The process was repeated 10 times, testing on each of the 10 data chunks, from which the resulting model coefficients were obtained by averaging coefficient values across all 10 models.

Australian snow density observations are recorded at irregular intervals towards the end of each season, and the closest snow density observation may have occurred up to 1 week from the official spring date. Furthermore, during unusually short snow seasons, the beginning of spring may coincide with an end of season density spike. To better gauge the mean state of snow pack density at the beginning of spring the linear regressions that were developed to estimate annual snow densification rates were used to approximate annual spring snow densities at each site. The regression method was less sensitive to highly variable end of season observations, density spikes and interannual variability in snow season timing. A comparison of actual spring snow densities and those estimated by the weighted linear approximations on a subset of the data (3 sites only) provided a mean difference of less than 15% between the methods, with a negligible difference in most years.

4. Results

In this section, the variability in snow densification rates is characterised, and decomposed into spatial and interannual components, and extended to identify dominant climatological drivers. The results from the MLR models for spring snow density estimation are compared to observations. The results presented use the VW point weighting method for densification rate estimation and are grouped using snow type classification.

4.1. Interannual and spatial variability in snow densification rates

Low densification rates throughout the former Soviet Union were generally observed with low interannual variability, refer to Fig. 3a. Conversely, densification rates and spring snow densities
at Australian sites were generally higher with high interannual variability, refer to Table 2. The densification rates at the US sites were between these two extremes. Densification rates and associated variability observed at maritime sites in the US were lower than those observed in Australia, this is highlighted in Fig. 3b. While regionally these results were not surprising, they demonstrate the variability observed at marginal snowfields and further characterise snow density variability for each region and snow type. Increasing densification rates were observed during mid-late spring at approximately 35% of sites in the US, 36% of the former Soviet Union sites and were not observed at Australian sites, suggesting a non-linear relationship between snow density and densification rate and an intensification of densification processes with melting.

The total variability in densification rate was explored by decomposing the total variance into between-site (spatial) and within-site variability (interannual). The decomposition of variance is presented in Fig. 4 which shows that interannual variability explains around 65–70% of the variance in snow densification rate observed at Australian, alpine, prairie and maritime sites while the remaining 30–35% of the variance may be attributed to spatial differences. As can be seen from Fig. 4a the total variance observed at Australian sites is very high compared to other snow types. The proportion of the total variance that may be explained by spatial variability at taiga and tundra sites, found throughout the former Soviet Union in this study, was comparatively high (Fig. 4c).

4.2. Dominant climatological drivers for snow densification rate

Single predictors were collectively able to explain the variability at 39 sites (or 41% of all sites) to at least the 90% significance level, refer to Fig. 5. From these 39 sites, precipitation (Prec.) was the dominant climate variable at 45% of sites, mean temperature ($T_{ave}$) at 35% of sites and melt-refreeze events (MRF) at 20% of the sites. Generally, these results highlight slightly greater importance of precipitation related processes in snow densification rate than temperature related processes, and that the MRF signal can be locally significant.

For the 18 sites (19% of total sites) at which precipitation is the single dominant driver at the 90% significance level, a positive correlation between the coefficient of variance (Zar, 2010) for annual precipitation and that for snow densification rate was observed ($R^2 = 0.28$ at 95% level – not shown).

Densification rates were positively correlated with spring snow densities ($R^2 = 0.56$ at 95% significance level) and given this link, similar regional variability was observed in spring snow densities, refer to Fig. 6. Fig. 7 shows distinct differences in mean spring density between three main snow type groups taiga/tundra; alpine/
prairie; and maritime/Australian. The pattern in mean values is regionally similar, but more pronounced, to that observed for snow densification rates in Fig. 3b. Spring densities experienced in Australia significantly exceeded those observed elsewhere, and the mean spring snow density was well outside the full range experienced at all taiga, tundra and alpine sites. The spring snow densities observed at taiga and tundra sites were very low compared to other regions.

4.3. Predicting spring snow density from climate variables

Following the multiple linear regression (MLR) methods for predicting spring snow density, nine separate models were created, each using a different number of model predictor terms, spanning from a single predictor model through to a complex nine term model. Model performance, as determined by the AIC and $R^2$, improved rapidly from the single predictor model as more variables were included, until the number of terms reached around 6, from which only marginal improvements in model performance was achieved with additional predictor terms. As such, subsequent MLR model development were limited to six terms: five predictor variables with an intercept term.

The resulting MLR models for each snow type group are presented in Table 3. The most common model predictors for spring snow density were winter precipitation, latitude and the interactive term $D_{\text{max}} T_{\text{ave}}$. This correlated well with the dominant
climatological driver analysis where precipitation was an influential driver of snow densification variability. Maximum snow depth, which is closely related to precipitation, was another common variable where either the maximum depth or the interactive variable \((\text{D}_{\text{max}} \times \text{T}_{\text{ave}})\) was selected for all models. The optimum six-predictor MLR models were used to make spring snow density predictions from climate variables for all years at all sites \((n = 1690)\). Ten-fold cross validation of the optimum MLR model to obtain robust model coefficients was undertaken, with results presented in Fig. 8a. The figure identifies larger model error at maritime, prairie and Australian sites, with the structure of deviations from the 1:1 reference line differing between snow types. The variation in response indicated that a global model may not be appropriate and that a unique MLR model for each snow type may be more informative. To address this problem, the six-predictor MLR process with 10-fold cross validation was repeated for each snow type group individually. By developing a unique MLR model for each snow type, the \(R^2\) of the fit when compared to observations increased from 0.74 to 0.81, as shown in Fig. 8b.

The coefficient values in Table 3 infer that minimum temperatures are generally more useful than maximum temperatures, melt-refreeze events are significant at Australian sites and that the models with the least predictive strength (as determined by the \(R^2\) value) coincide with the most variable sites of Australian, prairie and maritime snow types. From the six snow type models the two with the poorest fit were those developed for maritime and Australian snow types.

### Table 3

<table>
<thead>
<tr>
<th>Snow type</th>
<th>(t_{\text{min}} \times 10^{-3})</th>
<th>(t_{\text{max}} \times 10^{-3})</th>
<th>MRF (\times 10^{-3})</th>
<th>(P \times 10^{-3})</th>
<th>(D_{\text{max}} \times 10^{-3})</th>
<th>(D_{\text{max}} \times \text{T}_{\text{ave}} \times 10^{-3})</th>
<th>(\text{CDD} \times 10^{-3})</th>
<th>(\text{Lat} \times 10^{-3})</th>
<th>(E \times 10^{-3})</th>
<th>Int.</th>
<th>(R^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>–</td>
<td>–</td>
<td>47.95</td>
<td>32.67</td>
<td>22.44</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>0.566</td>
</tr>
<tr>
<td>Aust.</td>
<td>–</td>
<td>–</td>
<td>84.94</td>
<td>50.51</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>0.39</td>
</tr>
<tr>
<td>Alpine</td>
<td>–</td>
<td>–</td>
<td>31.96</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>0.33</td>
</tr>
<tr>
<td>Mari.</td>
<td>–3.88</td>
<td>–</td>
<td>69.67</td>
<td>–17.85</td>
<td>2.06</td>
<td>–</td>
<td>0.0392</td>
<td>–</td>
<td>–</td>
<td>–</td>
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<tr>
<td>Prairie</td>
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<td>32.58</td>
<td>25.48</td>
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<td>–</td>
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<td>1.99</td>
<td>–</td>
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<tr>
<td>Taiga</td>
<td>4.35</td>
<td>–5.99</td>
<td>–</td>
<td>31.75</td>
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<td>–</td>
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<td>0.365</td>
</tr>
<tr>
<td>Tundra</td>
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<td>–</td>
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</tr>
</tbody>
</table>

5. Discussion

Unique challenges arise when dealing with snow density time-series for seasonal snow covers. Density spikes and the high inter-annual variability in snow density values observed at the start or end of each season, and the source of these high variance periods warrants further discussion. Firstly, it must be remembered that...
snow density is a derived metric based on the ratio of SWE to snow depth (two separate observations) and the value of the ratio is sensitive to both measures, particularly when either value is low. This may explain the abrupt density spikes that are often observed in the annual snow density data at the start or end of each season. The difficulty of obtaining a sensible density value for wet slushy snow that has a high liquid water content may also give rise to these density spikes. Secondly, these annual spikes, combined with the interannual variability in snow season timing (i.e. beginning and end of each season), collectively produce periods of high variance when many seasons are considered.

These periods of high variance must be addressed when estimating snow densification rates from raw data. The weighted least squares regressions (TW and VW) allow the use of all observations, including those obtained within the high variance period. The development of weights based on observed variance (VW) rather than the proxy, mean temperature (TW), is a more direct method for describing the variance in snow density observations however the TW method requires less snow density data. The results presented use the VW method for densification rate estimation, however as both methods of densification rate estimation are similar (with a mean difference of 2.65 × 10⁻³ g/cm³/day between the methods), the analysis remains robust for both methods of estimating densification rate. This suggests that the high variance periods at the beginning and end of each snow season, caused by interannual differences in season length and snow persistence are temperature related.

The densification rates compare well with those reported previously for maritime (1.3 × 10⁻³ g/cm³/day), taiga (0.6 × 10⁻³ g/cm³/day) and tundra (0.2 × 10⁻³ g/cm³/day) snow types throughout Alaska and Canada (Sturm and Holmgren, 1998). Increased rates of densification have been observed at sites in the western US, where the spring densification slopes of 2.0 × 10⁻³ g/cm³/day (Mizukami and Perica, 2008) are very similar to the mean densification slopes of 1.77 × 10⁻³ g/cm³/day observed mid-season in Australia. Marked densification rate increases in spring were observed at around 1/3 of the sites throughout the US and the former Soviet Union. Despite this notable change in densification rate at some of the sites, the linear approximations still achieved an overall average R² of 0.83 at the 95% significance level. The high R² value achieved by the simple linear regression indicates that despite the potential for improved representation with a non-linear method for seasonal densification, or a separate linear representation during mid-late spring, a single linear regression provides a reasonable fit to the observations. Thus for the estimation of densification rate, it was difficult to justify adding complexity beyond the single weighted linear regression.

The characterisation of snow densification variability highlighted unique features of Australian snow properties. In contrast to other locations high densification rates with significant interannual variability are observed at Australian sites. It is well known that Australian precipitation is highly variable compared to other similar climates (Nicholls et al, 1997) and that this manifests as high variability in annual snowfalls (Budin, 1985). Therefore, it is not surprising that high variability is also observed in snow pack properties. The high densification rates indicate dominance of destructive metamorphisms where snow grains evolve quickly towards the sphere-like equilibrium. Sanecki et al. (2006) measured ground-snow interface temperatures of around +0.6 °C across a number of persistent snow patches in Australia and reported a distinct lack of temperature gradient. The absence of a vertical temperature gradient allows destructive metamorphisms to prevail through the snow pack profile in this region. Conversely, constructive metamorphisms dominate when strong temperature gradients are present resulting in very slow densification rates. In this study we observe these conditions at many of the sites throughout the former Soviet Union and at some of the cold continental sites in the US.

A number of studies based in the US, Canada and Switzerland have reported very low interannual variability of snow density and snow densification rates, and report similar snow densities for each day of the year (Kershaw and McCulloch, 2007; Mizukami and Perica, 2008; Jonas et al., 2009; Sturm and Holmgren, 1998). This low variability allowed the development of generalised snow density–time curves to enable SWE estimation from snow depths. Interannual variability in snow densification rates was observed at many, if not all sites. However, in agreement with previous studies, the magnitude of this variability was very low at sites where daily temperature was always well below zero, and low daily winter precipitation rates were experienced, such as throughout the former Soviet Union.

These results support the importance of precipitation variability in observed snow pack properties relative to other climate related influences. While precipitation was a useful explanatory term for almost 50% of sites, the lack of a common dominant variable for all sites or within each snow type group suggests that snow densification processes are also sensitive to local conditions beyond the climate metrics tested. The results presented here confirm previous observations of low interannual variability in snow densification rates at taiga and tundra sites (Sturm et al., 2010), although this finding is not maintained at many of the prairie, alpine and maritime sites within the US. The observed interannual variability has implications for the use of density–time curves in these regions.

As found by previous studies (Kay, 2006; Dingman et al., 1978) the grouping of dominant climate predictors for snow densification rates were not associated with elevation, snow type or latitude. Indicating that climatic drivers may combine with site specific characteristics such as solar radiation exposure, aspect, slope, vegetation or exposure to wind to influence local dominant processes. Previous authors have discussed the potential importance of melt refreeze processes on snow densification in seasonal snow packs in general (Sommerfeld and LaChapelle, 1970) and specifically for Australian snow (Ruddell et al., 1990). The results here confirm this for Australian sites however at other sites, different predictors are more influential.

The suite of MLR models used to estimate spring snow density for each snow type confirms the importance of precipitation on spring snow density and snow densification processes. Others have identified precipitation as an important factor for spring snow densities in the western US (Swoma, 2011). Results from the current analysis demonstrate this interaction is also observed for snow densification rates and extends to regions beyond the US. At both global and regional scales, the latitude predictor term that appears in almost all of the models. Latitude directly influences solar radiation exposure thus implicating solar radiation as a potentially important factor. Aspect was investigated as a potential model predictor however it did not improve results and the elevation term was only removed due to the cross-validation process. Pierce et al. (2005) suggests that aspect is not a good proxy for incoming solar radiation exposure in complex terrain and additional research is required to confirm links between snow density and solar radiation.

The coefficient values for each of the model terms were generally within the same order of magnitude, which indicates that minor or adjustment of model parameters is sufficient to customise the model for each snow type. The exception here was the model for Australian sites, where the estimated model parameters for latitude, elevation and the intercept deviate significantly from corresponding parameter values in other snow type models. This may be due to the limited elevation difference between the four sites (1470–1820 m), limited spatial separation of sites (latitudinal
ranges from 36.4° to 36.9°), the highly variable conditions or omitted factors such as solar radiation exposure.

There is also some disagreement in the sign of the coefficients for minimum winter temperature and the interactive depth term between models. It is expected that higher minimum winter temperatures would induce to higher spring snow densities. However, this is not reflected by the corresponding coefficients at maritime and prairie sites. Additionally, we expect spring snow densities to be positively related to the interactive depth term, where larger spring snow depths increase compaction to produce higher snow densities—again, this is not reflected by the corresponding coefficient value at tundra and alpine sites. The occurrence of counter-intuitive regression coefficients is a common result from complex multiple regressions and is often due to predictor interactions and/or multi-collinearity. While the unexpected coefficient signs may appear concerning it reflects predictor interactions rather than an incorrect statistical model. Methods have been proposed to force multiple regression coefficients to maintain the sign of their direct relationship with the response variable during the model fitting process. However, the motivations for this are purely to enhance model credibility and often result in poorer model fits (Pazzani and Bay, 1999).

Density–time curves have been used for the conversion of snow depth measurements to SWE estimates in relatively high northern latitude regions (>45°N) with mean SWE errors of 22 mm across all sites down to only 3 mm at taiga sites (Sturm et al., 2010). The value of the present study for informing this type of SWE conversion from snow depths in is clear and the results support the previous use of such density–time curves (Sturm et al., 2010; Jonas et al., 2009) to be most useful at taiga/tundra sites or at high latitude alpine sites. The present study however also suggests there is a regional limitation to density–time curves, as they are not well suited to the lower latitude alpine, prairie, maritime and Australian sites examined, due to interannual variability in densification rates.

At these lower latitude sites, the MLR models presented for spring snow density provide an independent method to density–time curves for estimating SWE from snow depths in spring. Although the MLR models are limited to estimating spring snow densities in hindsight due to the use of predictor variables such as total winter precipitation, and are not suitable for real-time prediction or assimilation with forecasting tools. The present study may also be useful for improving snow densification expressions in snow models, and regionalising snow detection algorithms in remote sensing techniques.

6. Conclusions

Snow densification rates over seasonal timescales are often overlooked in studies considering snow pack dynamics. The present study addresses the current knowledge gap and draws from a unique dataset that extends across three continents, six snow types and a wide range of climatic conditions including less known snowfields in the southern hemisphere. Total winter precipitation was identified as the most prevalent driver of annual snow densification variability. The interannual variability in snow densification is largest in Australia’s marginal snowfields where mid-season densification rates are equivalent to those observed in the US during spring. Interannual variability is the predominant source of variance observed at sites throughout the US and Australia, and is a much lower component of the variance throughout the former Soviet Union. A useful method for predicting spring snow density from climate and site-based data is presented and may be useful when snow density data is unavailable. Finally, interannual variability in snow densification may be considerable at marginal snowfields or regions with maritime, alpine or prairie snow types, thus caution must be taken when using density–time curves at these sites, particularly when precipitation variability is high.

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