Constraining snowmelt in a temperature-index model using simulated snow densities

Kathryn J. Bormann a,b,⇑, Jason P. Evans a, Matthew F. McCabe c

a Climate Change Research Centre and the ARC Centre of Excellence for Climate System Science, University of New South Wales, Sydney, Australia
b Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Drive, Pasadena, CA 91109, United States
c Water Desalination and Reuse Center, King Abdullah University of Science and Technology, Thuwal, Saudi Arabia

SUMMARY

Current snowmelt parameterisation schemes are largely untested in warmer maritime snowfields, where physical snow properties can differ substantially from the more common colder snow environments. Physical properties such as snow density influence the thermal properties of snow layers and are likely to be important for snowmelt rates. Existing methods for incorporating physical snow properties into temperature-index models (TIMs) require frequent snow density observations. These observations are often unavailable in less monitored snow environments. In this study, previous techniques for end-of-season snow density estimation (Bormann et al., 2013) were enhanced and used as a basis for generating daily snow density data from climate inputs. When evaluated against 2970 observations, the snow density model outperforms a regionalised density-time curve reducing biases from $\pm 0.027$ g cm$^{-3}$ to $\pm 0.004$ g cm$^{-3}$ (7%). The simulated daily densities were used at 13 sites in the warmer maritime snowfields of Australia to parameterise snowmelt estimation. With absolute snow water equivalent (SWE) errors between 100 and 136 mm, the snow model performance was generally lower in the study region than that reported for colder snow environments, which may be attributed to high annual variability. Model performance was strongly dependent on both calibration and the adjustment for precipitation undercatch errors, which influenced model calibration parameters by 150–200%. Comparison of the density-based snowmelt algorithm against a typical temperature-index model revealed only minor differences between the two snowmelt schemes for estimation of SWE. However, when the model was evaluated against snow depths, the new scheme reduced errors by up to 50%, largely due to improved SWE to depth conversions. While this study demonstrates the use of simulated snow density in snowmelt parameterisation, the snow density model may also be of broad interest for snow depth to SWE conversion. Overall, the study responds to recent calls for broader testing of TIMs across different snow environments, improves existing snow modelling in Australia and proposes a new method for introducing physically-based constraints on snowmelt rates in data-poor regions.

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1. Introduction

Understanding how snow water resources are distributed throughout snow-affected catchments is imperative for water resource planning in many regions worldwide. The snow water resources contained within small and isolated snowfields have been identified as particularly vulnerable in a warming climate (Bicknell and McManus, 2006). Regular observations of snow water equivalent (SWE) are currently unavailable at catchment scales (Dozier and Painter, 2004), and the available point-based observations are of limited use for snowmelt prediction (Rice and Bales, 2010). Snow models that estimate SWE distribution from more readily available climate observations are therefore essential for bridging the gap between available snow observations and information demand.

Temperature-index snow models (TIMs) have fewer static parameters and less complex data requirements than energy balance models, and despite their relative simplicity retain a somewhat physical basis (Ohmura, 2001). As such, TIMs are often selected over energy balance approaches in less monitored catchments, have demonstrated skill in snowmelt estimation (Jost et al., 2012) and continue to be used for catchment-scale studies (Shamir and Georgakakos, 2006). Unlike energy balance models,
TIMs require rigorous calibration with snow observations (Kumar et al., 2013). In these models, the melt factor (units of mm °C⁻¹ day⁻¹ or cm °C⁻¹ day⁻¹) directly relates daily snowmelt rates to near-surface air temperature. Sub-daily attribution of melt factors has also been used to introduce diurnal cycles in snowmelt rates (Tobin et al., 2013). During model calibration, the melt factor (often referred to as the degree-day factor) is the adjustable parameter that is tuned for optimum model performance. As such, the melt factor is not selected based on the physical characteristics that influence snowmelt rates, which include elevation, aspect, potential solar exposure, forest cover, physical snow properties and climate influences (Marsh et al., 2012; Musselman et al., 2012).

Many studies have demonstrated the benefits of incorporating physical influences such as solar radiation, cold content or landscape features into TIM based snowmelt algorithms (Brubaker et al., 1996; Rango and Martinec, 1995). These methods of modifying snowmelt estimation generally involve the modulation of melt factor values with potential solar radiation exposure, using landscape information such as aspect, slope or elevation. Few studies have explored the use of physical snow properties (such as snow density) for prescribing melt factors and melt behaviour (DeWalle et al., 2002; Rango and Martinec, 1995), particularly beyond the confines of point observation locations. The integration of physical snow properties into snowmelt parameterisation schemes in TIMs is appealing in small, marginal snowfields where snow properties (in particular snow densities) can differ substantially from most (cold) snowfields globally (Bormann et al., 2013). Methods for distributing existing density-based snowmelt parameterisations, such as that described in Rango and Martinec (1995), beyond point locations may be particularly useful in these snowfields.

The Australian snowfields are a good example of a marginal snowpack with unique snow properties (Bormann et al., 2013). With relatively long snow observation records in some areas, these snowfields provide an ideal region for the extension of existing snow modelling techniques to the less-studied warmer snow environments. In this study, an existing method for end-of-season snow density estimation (Bormann et al., 2013) has been extended to support a snow density model that generates daily snow densities from climate inputs. Many of the existing models that are used to statistically simulate snow densities from climate variables do not operate at daily time scales (McCready and Small, 2013). The density model development for daily estimations is one of the major contributions presented in this study. The simulated daily snow densities were used to apply the Rango and Martinec (1995) method for snowmelt parameterisation in TIMs. The models were tested at multiple point locations throughout the largest contiguous snowfield in Australia. The model performance was then compared to a typical air-temperature-based snowmelt estimation method that was developed for the region in previous studies (Schreider et al., 1997; Whetton et al., 1996). While this study is limited to point-based modelling, the objective was to provide a physically-based foundation to enable spatial distribution of the model beyond point locations and across the entire region. This study proposes a snow density algorithm that may be readily applied at catchment scales, extends the limited state of snow modelling in Australia and responds to recent calls for the testing of TIMs in different snow environments (Jost et al., 2012).

2. Data

2.1. The study region

Alpine catchments that are situated in southeast Australia (Fig. 1) contribute snowmelt to streamflows in the largely arid and agriculturally important Murray-Darling river system. The Murray-Darling basin is considered Australia’s “food bowl” and is currently the focus of much political debate due to over allocation of water resources and declining health of waterways (Kingsford, 2009). The snow-affected areas range from approximately 1400–2200 m in elevation, with around half of the terrain lying below 1550 m. The climatological mean freezing level during winter has been estimated at around 1500 m (Budin, 1985), which places large areas of snow in this region at or below the atmospheric freezing level. The largest contiguous snow-covered area in Australia is situated in the state of New South Wales (NSW) (Fig. 1) and is the focus region of this study. These maritime snowfields may be considered a typical example of relatively warm and marginal snowfields worldwide.

2.2. Snow data and model sites

Snow observations collected by Snowy Hydro Ltd. were obtained manually using Federal samplers (Snowy Hydro Ltd.,

Fig. 1. Study region in southeast Australia (left). The state borders mark the state of New South Wales (NSW), Victoria (VIC) and the Australian Capital Territory (ACT). The area above 1400 m (snowline, Ruddell et al., 1990) is shaded grey, the red boxes are in situ snow site locations, the open diamonds mark temperature observation sites and the crosses indicate precipitation gauge locations. The snow site numbers correspond with descriptions in Table 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
personal communication, March 17, 2014) for 16 snow courses throughout the NSW snowfields. One site was omitted due to a short record period of only three years leaving 15 snow observation sites with record periods exceeding 39 years (Table 1). The site locations are shown in Fig. 1. The data at these sites include snow water equivalent (SWE), snow density and snow depth, which have been retrieved at irregular sampling frequencies ranging from 6 to 60 day intervals during winter months. Typically measurements are retrieved every 7–14 days. For each observation, multiple measurements were obtained manually at 20 m spacings along snow course transects and the sample mean was recorded. Most of the site records extend back to the early 1960s and collectively sample the full elevation range of the snowfields (Table 1). The sites were categorised into three elevation bands: low elevation sites <1599 m (n = 5), mid elevation sites 1600–1799 m (n = 7), and high elevation sites >1800 m (n = 3). Four slope aspect categories were also classified, including NE (0–90°), SE (90–180°), SW (180–270°) and NW (270–360°). For reasons discussed in Section 3.1, the TIMs model could not be configured at two of the 15 sites listed in Table 1. However, these sites were used to evaluate the snow density model.

### Table 1
Snow observation site inventory.

<table>
<thead>
<tr>
<th>Site</th>
<th>Elevation (m)</th>
<th>Aspect</th>
<th>Period of record (years)</th>
<th>F50</th>
<th>L50</th>
<th>Solar exposure</th>
<th>Wind exposure</th>
<th>General</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1585</td>
<td>SE</td>
<td>50 1960-1984</td>
<td>1985-2009</td>
<td>High</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>1463</td>
<td>NE</td>
<td>40 1960-1984</td>
<td>1985-2009</td>
<td>High</td>
<td>Moderate</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1798</td>
<td>NW</td>
<td>40 1970-1989</td>
<td>1990-2009</td>
<td>High</td>
<td>Moderate</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1798</td>
<td>SE</td>
<td>40 1970-1989</td>
<td>1990-2009</td>
<td>-</td>
<td>High</td>
<td>High accumulation, potential wind deposition</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>2012</td>
<td>NW</td>
<td>39 1971-1989</td>
<td>1990-2009</td>
<td>-</td>
<td>High</td>
<td>High accumulation, potential wind deposition</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>1615</td>
<td>NW</td>
<td>50 1960-1984</td>
<td>1985-2009</td>
<td>Moderate</td>
<td>Moderate</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>1737</td>
<td>NW</td>
<td>46 1964-1985</td>
<td>1985-2009</td>
<td>Low</td>
<td>Low</td>
<td>W/NW facing slope, trees present</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>1740</td>
<td>SW</td>
<td>44 1964-1985</td>
<td>1985-2009</td>
<td>-</td>
<td>-</td>
<td>Insufficient precipitation data for TIMs setup</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>1585</td>
<td>NW</td>
<td>46 1964-1985</td>
<td>1985-2009</td>
<td>High</td>
<td>High</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>1524</td>
<td>SE</td>
<td>50 1960-1984</td>
<td>1985-2009</td>
<td>High</td>
<td>Moderate</td>
<td>-</td>
<td>Snow course partly shaded and exposed</td>
</tr>
<tr>
<td>11</td>
<td>1676</td>
<td>NW</td>
<td>46 1964-1985</td>
<td>1986-2009</td>
<td>Moderate</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>1463</td>
<td>NW</td>
<td>53 1957-1982</td>
<td>1983-2009</td>
<td>High</td>
<td>-</td>
<td>Low accumulation site, part swamp</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>1676</td>
<td>SW</td>
<td>44 1966-1984</td>
<td>1985-2009</td>
<td>High</td>
<td>Low</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>2012</td>
<td>SW</td>
<td>40 1970-1989</td>
<td>1990-2009</td>
<td>-</td>
<td>High</td>
<td>High accumulation, potential wind deposition</td>
<td></td>
</tr>
</tbody>
</table>

Note: Shaded rows highlight the sites that were used to evaluate the snow density model only.

2.3. Meteorological data

Daily precipitation and temperature data for the region were obtained from both the Bureau of Meteorology (BoM) and Snowy Hydro Ltd. There were limited climate observations at altitudes above the snowline (Fig. 1) and spatially consistent climate observations at each of the snow sites were not always available. Daily temperature and precipitation time series were prepared at each of the 15 snow sites from the point-based meteorological observations to match the snow data period of record at each site. Gaps and missing data were filled by merging records from nearby stations when required, favouring sites at higher altitude for the precipitation data. A lapse rate of 5.5 °C km⁻¹ (Appendix 4 in Ruddell et al. (1990)) was used to adjust air temperature observations to
account for elevation differences between climate stations and snow observation sites. The daily precipitation observations were adjusted for undercatch biases using a mass balance technique, further details of which are provided in the Method section.

Small-scale orographic effects were detected at several high elevation precipitation gauges, where very low winter precipitation totals were observed at sites near the summit (>2000 m). The accumulated winter precipitation at these sites did not correlate well with neighbouring sites (<5 km away) or observed snow accumulation profiles. The data from these precipitation sites (n = 3) were not representative of the winter precipitation totals experienced at other high elevation snow sites near the summit or observed on-ground accumulations and as such were omitted.

2.4. Landscape data

Potential relative radiation (PRR) was obtained following the GIS-based method developed by Pierce et al. (2005) using elevation data obtained from the Shuttle Radar Topographic Mission (SRTM) (Farr et al., 2007). The Pierce method accounts for local terrain shading but does not account for canopy shading in forested areas. The SRTM elevation data were first regridded from ~90 m to ~500 m spatial resolution to allow processing across the entire NSW and VIC region (~10,000 km²). The elevation data were degraded prior to calculating PRR to match the Moderate Resolution Imaging Spectroradiometer (MODIS) pixel scale, in preparation for a future spatially distributed model. The Pierce method integrates solar exposure throughout the day (at hourly intervals) for each winter month from geospatial and terrain information. The PRR therefore reflects the potential solar radiation exposure at each 500 m pixel whilst considering elevation, aspect, slope and local terrain shading. While spatial coarsening of elevation data has been shown to reduce the spatial variability of potential solar radiation estimates, much of the fine-scale variability is present at scales less than 100 m (Liu et al., 2012) and largely beyond the capabilities of the original data. The PRR is therefore considered a broad-scale estimate of solar exposure at each 500 m pixel in the resampled SRTM grid.

The 250 m resolution Dynamic Land Cover Dataset (Lymburner et al., 2011), derived from Landsat and MODIS remote-sensing data, was used to identify forested and exposed snow sites. Three of the snow observation sites lie within open forest, while the remainder of the sites lie within low-lying vegetation such as alpine grass, sedges or pasture landscapes (Table 1). A binary vegetation classification derived from the land cover data (forest/ exposed) was used to discriminate sites to improve the performance of the snow density model.

In this study, snow density, meteorological and landscape (PRR and vegetation) data were used to develop the snow density model. The snow density algorithm requires seasonal metrics derived from the daily temperature and precipitation data in conjunction with landscape metrics including vegetation cover, elevation, latitude and PRR. The SWE data were used for snow model calibration and evaluation, and the snow depth data were retained for model evaluation. The daily temperature and precipitation data were also used as inputs to the snow models (TIMs) to produce long-term daily snow density, SWE and snow depth estimates at each of the snow observation locations.

3. Method

While the application and evaluation of TIMs in the Australian snowfields generally follow common methods used in cooler snow environments, the technique used to correct for snowfall undercatch biases, the snow density model and its subsequent application for snowmelt parameterisation in TIMs are all unique features to this study and are introduced in this section.

3.1. Adjustments for snowfall undercatch biases

Precipitation gauges in snow-affected environments generally underestimate total precipitation as a result of systematic undercatch during winter (Legates, 1993). The degree of undercatch increases with wind speed and can exceed 20–50% (Rasmussen et al., 2012). The standard precipitation gauges installed throughout the Australian alpine region do not have sufficient wind diffusion structures to minimise these errors and large undercatch biases are likely in the precipitation data.

Empirical relationships between precipitation undercatch at snow-affected gauges and climate variables such as air temperature and wind speed are commonly used to correct precipitation biases (Fassnacht, 2004). While a near-surface wind-speed dataset has become available for Australia (McVicar et al., 2008), these data have not been evaluated in the complex terrain of the alpine regions, where few direct wind-speed observations are available. Instead, the precipitation undercatch errors were estimated using a mass balance approach that uses concurrent in situ precipitation and snow accumulation observations to estimate precipitation gauge capture efficiency (CE) at each site. A CE of 0.5 indicates that only 50% of the accumulated snow observed on the ground was recorded by the precipitation gauge and a CE of 1 reflects a total absence of undercatch error. The mass balance technique is detailed in Appendix A. The estimated CE’s were used to adjust the snowfall component of the precipitation forcing data using Eq. (1).

$$P_{ADJUSTED} = P_{RAIN} + P_{SNOW}$$

$$= (1 - P_{SN}[T_{MIN}]) \cdot P_{OBS} + \frac{P_{SN}[T_{MIN}] \cdot P_{OBS}}{CE}$$

(1)

where $P_{OBS}$ is the observed daily precipitation time series, $P_{ADJUSTED}$ is the corrected precipitation time series, $T_{MIN}$ is the daily minimum air temperature, $P_{SN}$ is the probability of snowfall and CE is the estimated catch efficiency (defined as $1 - \text{undercatch}$) as determined from Eq. (A1) in Appendix A. The method for estimating the probability of snow for each precipitation event is presented in Section 3.2.1. Previous work has found that undercatch estimates obtained from mass balance approaches compare relatively well to those obtained from precipitation correction models that consider wind effects (Carturan et al., 2012).

The sub-sample of SWE estimates that were used to estimate CE were selected according to the limitations of the mass balance technique (Appendix A). These data requirements prevented CE estimation at two of the snow sites (9 and 10), reducing the number of temperature-index model sites to 13, and ultimately represented only a small fraction of the total SWE observations (<15% at any one site). The SWE data that were used to inform precipitation adjustments were excluded from the model evaluation calculations to avoid circularity issues. As a result, the presented model evaluation and calibration statistics do not consider model performance during large SWE accumulation events. To avoid skewing the data used for model calibration simulations to favour the melt season, all SWE data were used to inform model calibrations.

3.2. Temperature-index model (TIMs)

A temperature-index model was set up at each of the 13 snow model sites with long observational records and adjusted precipitation data (Fig. 1). Each model requires only daily temperature (both minimum and maximum) and precipitation input data and operates on a daily time step for the entire snow record period at each site (Table 1). The model uses both precipitation and
minimum air temperature data to generate snowfall accumulation. The Rango and Martinec (1995) snowmelt parameterisation scheme was selected as it incorporates the physical state of the snow in melt estimation. The model was compared to a snowmelt scheme used previously in the study region, which employs only air temperatures to estimate snowmelt (Schneider et al., 1997). Each of the two snowmelt schemes use a single melt parameter to constrain the sensitivity of the snow pack. Snowmelt is generated as soon as air temperatures rise above 0 °C, without consideration of cold content or snowpack ripening. Mean observed temperatures at the soil-snow interface in the study region rarely fall below 0.4 °C (Sanecki et al., 2006). The melt factors for both snowmelt schemes were calibrated and evaluated at each site using a split-sample calibration and evaluation process. The model configuration and calibration process are detailed in the following sections.

3.2.1. Snow accumulation

Following Schneider et al. (1997), daily snow accumulation A (in mm), is a function of daily precipitation (mm), P_{OBS} and the temperature-dependent probability of precipitation falling as snow \( P_r [T_{\text{min}}] \), where \( T_{\text{min}} \) is the daily minimum surface temperature (Eq. (2)).

\[
A = P_r [T_{\text{min}}] \cdot P_{\text{OBS}} \tag{2}
\]

The probability of snow (\( P_r \)) for each day was approximated from daily minimum temperature using the curve developed for the region by Ruddell et al. (1990), who used over 16,000 observation days. From the non-linear probability curve, the probability of snowfall reaches a maximum of 1 when daily minimum air temperatures are below -3.0 °C, provides equal parts rain and snow (\( P_r = 0.5 \)) at 1.5 °C and rapidly declines after minimum air temperatures exceed 2.0 °C from a probability of 0.2 to near-zero probability of snow at 4.0 °C. The non-linear probability curve was also used to separate the total daily precipitation into rain and snow components for the undercatch adjustment (Section 3.1). The probability-based method of estimating snowfall from total precipitation data is considered a more sophisticated method of estimating snow accumulation than adopting a single temperature threshold (for example, 0 °C), and may be an important distinction in regions that experience a prevalence of mixed rain/snow precipitation, although this is not examined in this study.

3.2.2. Snowmelt parameterisation schemes

TILMs snowmelt schemes use air temperature as a proxy for constraining snowmelt and may be expressed generally by Eq. (3).

\[
M_p = M_F \cdot (T_{\text{mean}} - T_{\text{ref}}) \tag{3}
\]

where \( M_p \) is the potential snowmelt (mm day^{-1}), \( T_{\text{mean}} \) is the mean daily air temperature, \( M_F \) is the melt parameter (mm °C^{-1} day^{-1}) and \( T_{\text{ref}} \) is a reference temperature above which melt starts to occur. In this study \( T_{\text{ref}} \) is set to 0 °C. The melt parameter is a crucial element that constrains snowmelt rates and must be rigorously calibrated. Therefore, two alternative schemes for prescribing the melt parameter both spatially and temporally are provided.

Scheme 1: Melt factor based on simulated snow density. The Rango and Martinec (1995) method of melt parameter estimation (Eq. (4)) draws on observed relationships between melt parameter values and snow densities (DeWalle et al., 2002), and provides a technique for incorporating the spatial and temporal influence of snow properties on snowmelt dynamics. By allowing the melt factor to increase proportionally with snow density, the simple model provides some representation of the increasing thermal conductivity and decreasing albedo that also occurs as snow ages. The temporal representation captures the time-based correlation between snow densification and snow albedo decay processes, although the authors acknowledge that these processes are not physically linked. These factors may be particularly important in maritime snowfields with relatively high snow densities, snow densification rates and interannual variability (Bormann et al., 2013). The melt factor is described as:

\[
M_F = k \cdot \frac{\rho_s}{\rho_w} \tag{4}
\]

where the calibration coefficient \( k \) is set to 1.1 (mm °C^{-1} day^{-1}) in the source reference, \( \rho_s \) is snow density (in g cm^{-3}) and \( \rho_w \) is the density of water (assumed to be 1 g cm^{-3}). To account for regional differences, the parameter \( k \) is treated as a calibration constant in the present study.

One of the major drawbacks with the Rango and Martinec method of melt factor parameterisation is the reliance on regular snow density observations. These observations are only available at in situ point measurement sites and are not always recorded variables. Density-time curves are commonly used to approximate snow densities at catchment scales or in data poor regions (Mizukami and Perica, 2008; Sturm et al., 2010). However, in marginal maritime snowfields the interannual variability in snow densities can be significant, and mean density-time curves may not capture important year-to-year variance (Bormann et al., 2013). As such, a snow density model was developed to estimate daily snow densities from climate-based variables. These density estimates may be used to inform the Rango and Martinec method for melt factor estimation in lieu of observations. The snow density model predictions were compared to values from a density-time curve that was obtained by applying a linear regression to the full set of snow density observations, from all sites in the region (\( n = 2970 \)). The resulting density-time curve is expressed in Eq. (5).

\[
\rho_{\text{obs}} - \tau = 0.001369 \cdot \text{day} + 0.1095 \tag{5}
\]

where \( \rho_{\text{obs}} \) is the estimated snow density (g cm^{-3}) and \( \text{day} \) is the day of year.

The foundations of the snow density model are the climate-based multiple linear regressions (MLR) that have been used to estimate spring snow densities in the study region in previous work (Bormann et al., 2013). These MLR’s exploit relationships between seasonal climate variables and the highly metamorphosed end-of-season snow pack properties, and are capable of capturing some of the high interannual variability observed in spring snow densities within maritime environments. The end-of-season snow densities obtained from these existing MLR’s must then be extrapolated at daily timesteps to the start of each season to adequately inform the Rango and Martinec melt parameterisation. The current work presents a model to leverage daily snow density estimates from the end-of-season values that may be obtained from the MLR’s.

Early season snow density may be considered similar to “fresh” or “newly settled” snow density. In the study region, the snow density observations are typically obtained at 7–14 day intervals. Therefore the observations correspond to “newly settled” snow (with settling times ~7 days on average) rather than true “fresh” snow. Chen et al. (2010) observed short-term densification rates of fresh snow of 0.004 g cm^{-3} h^{-1} from 5th hour after deposition to the 291st hour (or 12.1 days). During 7 days (between measurement dates), fresh densities are expected to increase from 0.01–0.26 g cm^{-3} (Judson and Doesken, 2000) to 0.08–0.32 g cm^{-3}. As there was relatively low variability observed in “newly settled” snow densities in the region, a constant density of 0.26 g cm^{-3} at June 1 (the start of the Austral winter) was adopted. The adopted density for “newly settled” snow of 0.26 g cm^{-3} lies within the expected range after initial settling.

The late and early snow density estimates provide two constraints on the seasonal snow density profile, for which a linear
The snow density model (which uses the climate-based MLR's as a foundation) was then applied to each of the snow model sites individually, to generate daily snow density estimates at each of the 15 sites for the full simulation periods. As both the climate and landscape inputs differ between sites, the model produces different density profiles for each year at each site. These snow density time series allow melt factors in the Rango and Martinec scheme to vary both spatially and temporally.

Scheme 2: Melt factor based on air temperature.

In previous studies, Schreider et al. (1997) introduced an albedo-related factor ($A_f$) into the temperature-index model structure to account for the increasing melt rates that occur as snow albedo reduces with snow age (Baker et al., 1990). The albedo-related factor is determined from empirical relationships between mean monthly temperatures and melt factors and were developed specifically for the Australian snowfield region (Eq. (5)).

$$M_f(i) = MF \cdot T_{mean} \cdot A_f(month, T_{month})$$

where the albedo-related factor $A_f(month, T_{month})$ is determined from the mean monthly temperature.

$$A_f = \frac{T_{month}}{12} + \frac{7}{6}$$

for March, April and May;

$$A_f = \frac{T_{month}}{24} + \frac{12}{13}$$

for June, July and August;

$$A_f = \frac{T_{month}}{8} + \frac{5}{4}$$

for remaining months.

$A_f$ defaults to a value of 1 if $T_{month} < -2 \, ^\circ C$, and MF is used as a calibration factor.

Snowmelt Scheme 2 has been adopted in previous snow modeling studies in Australia (Hennessy et al., 2003; Schreider et al., 1997; Whetton et al., 1996) and was included in the present study for comparison and benchmarking purposes.

3.3. Model calibration and evaluation

The calibration and evaluation of model parameters was undertaken using a split-sample technique, which involved dividing the simulation periods at each site into two. The model calibration and evaluation were conducted in two stages with: (a) the first half used to calibrate or train the model parameters and the last half reserved for model testing; and (b) the model calibration conducted using the last half of the data and evaluation using the first half of the sample. Observed variability in the Australian snowfields is relatively high and therefore a relatively long minimum training period of 20 years was adopted to obtain a reasonable calibration at each site. There were sufficient data periods at all 13 NSW snow model sites (those with CE estimates) to use the split-sample approach. The split-sample method results in different training periods for each site, as the periods of record differ slightly. Generally, the first half sample (hereby known as FS0) covers the period from the 1960s to the mid-1980s and the last half sample (known as LS0) starts in the mid to late 1980s and extends to 2009. Actual periods for each site are included in Table 1.

Four evaluation statistics, including bias, mean absolute error (MAE), root mean squared error (RMSE) and the coefficient of efficiency (NSE), were used to determine optimum model parameters (MF and k) through calibration at each site for each split-sample period. The bias, MAE and RMSE were calculated following Willmott and Matsuura (2005) and the NSE was calculated following Nash and Sutcliffe (1970). During calibration, the evaluation statistics were determined for a range of possible model parameter values using all available SWE observations in each period (FS0 or LS0). For each snowmelt scheme, the MF or k parameter that
resulted in the lowest model error was extracted for each evaluation statistic, providing four potential melt parameter values for each snowmelt scheme. A graphical representation of the calibration results (Fig. 3) shows the error profiles for each evaluation statistic over the parameter ranges tested, where the potential parameter values for each statistic occur at cost function global minima or maxima (vertical green lines in Fig. 3). The optimised calibration parameter that considers all four statistics, is obtained by averaging the four potential melt factor values. Consequently, the calibration factors vary between sites. In Scheme 1, the calibration parameter ($k$) physically represents the overall effect of landscape characteristics such as elevation, aspect, solar exposure and forest cover on snowmelt rates. In Scheme 2 the calibration parameter (MF in mm°C$^{-1}$ day$^{-1}$) physically represents the same landscape characteristics as well as snow pack properties. Model evaluation using multiple cost-functions avoids limitations of single evaluation statistics (Willmott and Matsuura, 2005) and therefore provides more robust model calibration (Ritter and Muñoz-Carpena, 2013).

4. Results

To assess the full benefit of the snow density model in informing snowmelt estimation, the model must first be evaluated against the full set of density observations. The TIMs were then evaluated for SWE and snow depth estimation, and finally the spatial distribution of calibrated melt factor values was examined.

4.1. Snow density estimation

The updated MLR’s for snow density estimation on October 1 (mid spring) provided slightly different relationships for exposed and forested sites (Eq. (7)) than previous work (Bormann et al., 2013). The simulated snow densities were still predominately influenced by the previously identified predictors including elevation, seasonal precipitation and MRF events, although the new MLR’s include the solar radiation exposure term PRR on exposed sites.

$$
\rho_s^{\text{EXPOSED}} = 0.01095 T_{\text{max}} + 0.0401 \log \text{Prec} - 0.1759 \text{MRF} + 0.007145 \text{PRR} + 0.19263
$$

$$
\rho_s^{\text{FOREST}} = 0.0374 \log \text{Prec} - 0.5471 \text{Elev} + 0.3767 \text{Lat} - 0.08750 \text{MRF} - 12.1566
$$

When the revised MLR models were evaluated against available spring snow densities in September ($n = 722$), mean errors of 0.048 g cm$^{-3}$ and an $R^2$ of 0.22 were obtained. The MLR’s presented in Bormann et al. (2013) produced a mean error between 0.029 and 0.043 g cm$^{-3}$ (depending on snow type), and an $R^2$ of 0.38 ($n = 192$). The updated MLR’s (Eq. (7)) produce similar mean errors.
to the previously published MLR’s for spring density estimation, while incorporating over three times as many data points from a much broader range of sites to the previous work. The increased site variability represented in the present study may contribute to the observed correlation reduction. The absolute errors indicate that the revised MLR’s are comparable to those presented previously (Bormann et al., 2013) and are considered to be within acceptable error limits.

An assumption of the snow density model (Fig. 2) was that the seasonal profiles were relatively linear from June 1 to October 1 (start of winter to mid spring). While this assumption is reasonable in most seasons, complex snow density profiles were observed at low elevation sites, which violated the assumption of linearity. At these sites, mid-season snow disappearance that was immediately followed by low snow densities when the pack was reformed with new snow was observed. The mid-season low snow densities that are associated with intermittent snow packs were partially captured with a simple “reset” of the snow density model back to the “newly settled snow” density constant (0.26 g cm⁻³) when the snow depth reached zero. The “reset” feature also allowed the snow density model to delay snow densification until the snow pack actually formed, which may be well after the arbitrary start date (June 1) in low snow years and at low elevation sites as highlighted in Fig. 4a. The difference in seasonal densification rates between the two sites is apparent in Fig. 4 and is one of the strengths of the snow density model.

With overall biases of −0.004 g cm⁻³ and mean absolute errors of 14%, the snow density algorithm performed relatively well compared to the full set of snow density observations (during June – September, inclusive) as shown in Fig. 5a. The model performance increased linearly with elevation ($R^2 = 0.45$ at the 95% significance level, not shown). The poorer performance of the model at low elevation sites is clear when the evaluation is confined to the three elevation bands (Table 2). Snow densities are best estimated at high elevations (>1800 m), in forested areas rather than exposed slopes and at sites with low solar exposure (Table 2), which

---

**Table 2**

Snow density model performance for three elevation bands.

<table>
<thead>
<tr>
<th></th>
<th>Snow density model</th>
<th>Density-time curve</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of observations</td>
<td>$R^2$</td>
</tr>
<tr>
<td>All</td>
<td>2970</td>
<td>0.37</td>
</tr>
<tr>
<td>Low elevation</td>
<td>867</td>
<td>0.22</td>
</tr>
<tr>
<td>Mid elevation</td>
<td>1301</td>
<td>0.35</td>
</tr>
<tr>
<td>High elevation</td>
<td>802</td>
<td>0.50</td>
</tr>
<tr>
<td>Forest sites</td>
<td>748</td>
<td>0.44</td>
</tr>
<tr>
<td>Exposed sites</td>
<td>2256</td>
<td>0.34</td>
</tr>
<tr>
<td>High solar exposure</td>
<td>1101</td>
<td>0.26</td>
</tr>
<tr>
<td>Low solar exposure</td>
<td>1865</td>
<td>0.41</td>
</tr>
<tr>
<td>High wind exposure</td>
<td>321</td>
<td>0.46</td>
</tr>
<tr>
<td>Low wind exposure</td>
<td>2649</td>
<td>0.34</td>
</tr>
</tbody>
</table>

*Indicates statistical significance at the 95% level.
suggests that the precipitation term in the MLR has considerable influence. The snow density model provides improved snow density estimates with overall bias values that are an order of magnitude lower than those obtained from a regionalised density-time curve (Fig. 5b and Table 2).

The density-time curve does not account for interannual variability, which contributes to the broader scatter in Fig. 5b as well as the ‘capped’ spring snow density at \( \sim 0.49 \) g cm\(^{-3}\) (correlating to the last observation date of each season in mid-spring near October 4). The annual variability in seasonal density error statistics is reduced by 36% when interannual variability is considered, from 0.0038 g cm\(^{-3}\) for the density-time curve to 0.0028 g cm\(^{-3}\) for the density model. The reduced variance in interannual error suggests that the ability of the snow density model to respond to annual variability is important. The further reduced skill of the density-time curve at low elevation sites is clear in Fig. 5b. Overall, the snow density algorithm is considered capable of providing realistic snow density estimates, beyond the capability of regionalised density-time curves, to the Scheme 1 within the TIMs.

### 4.2. SWE estimation

The snow model generally captures the SWE depth variability across the region (13 sites) with model biases between -3.5 and Table 3

**Simulated SWE (mm) calibration and evaluation statistics.**

<table>
<thead>
<tr>
<th>Snowmelt scheme</th>
<th>Statistic (mm)</th>
<th>All sites (n=13)</th>
<th>F50 Calibration</th>
<th>L50 Evaluation</th>
<th>L50 Evaluation</th>
<th>F50 Evaluation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bias</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>-26.2</td>
<td>-27.5</td>
<td>-34.1</td>
<td>-3.5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Accum.</td>
<td>-7.6%</td>
<td>-8.3%</td>
<td>-10.3%</td>
<td>-1.0%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Melt</td>
<td>-4.9%</td>
<td>3.7%</td>
<td>0.2%</td>
<td>0.3%</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>-16.3%</td>
<td>-22.8%</td>
<td>-24.7%</td>
<td>-7.1%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MAE</td>
<td>113.2</td>
<td>115.5</td>
<td>100.4</td>
<td>135.7</td>
<td></td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>32.8%</td>
<td>34.7%</td>
<td>30.2%</td>
<td>39.3%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Accum.</td>
<td>37.1%</td>
<td>42.7%</td>
<td>36.0%</td>
<td>42.4%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Melt</td>
<td>42.7%</td>
<td>42.7%</td>
<td>36.1%</td>
<td>51.1%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>206.5</td>
<td>183.2</td>
<td>158.1</td>
<td>249.6</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.71</td>
<td>0.71</td>
<td>0.77</td>
<td>0.63</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MAE</td>
<td>110.7</td>
<td>117.5</td>
<td>103.8</td>
<td>129.9</td>
<td></td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>32.1%</td>
<td>35.3%</td>
<td>31.2%</td>
<td>37.6%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Accum.</td>
<td>35.7%</td>
<td>42.9%</td>
<td>38.1%</td>
<td>40.8%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Melt</td>
<td>42.8%</td>
<td>44.3%</td>
<td>39.1%</td>
<td>50.3%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>206.5</td>
<td>188.5</td>
<td>164.9</td>
<td>241.7</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.72</td>
<td>0.70</td>
<td>0.76</td>
<td>0.64</td>
<td></td>
</tr>
</tbody>
</table>

*a* The table shading groups the simulations by melt parameter values, where calibration parameters determined during the F50 period were used to evaluate the model in the L50 period. The values in bold represent absolute values of bias or MAE (in mm) for all data, which includes both the accumulation and the melt phases.

*b* Evaluation statistics exclude SWE data that was used to estimate snowfall undercatch.

Fig. 6. SWE evaluation at all sites (L50 evaluation results). The results for Scheme 2 were omitted as there was little difference between the two snowmelt schemes for SWE estimation. The marker styles reflect elevation (a) of which are described in Fig. 5 and aspect (b). In (b) the blue crosses represent north east facing slopes (NE), the grey circles represent south east facing slopes (SE), the black asterisks mark south west facing slopes (SW) and the orange squares identify north west facing slopes (NW). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
–27.5 mm (or –1% to –8%) and MAE’s between 100.4 and 135.7 mm, with little difference between the two snowmelt schemes (Table 3). Model performance was generally better during the snow accumulation phase (i.e. June – August) with mean evaluation biases of 2% compared to values of 15% during melting (Scheme 1). The model biases were generally low during the F50 period in both calibration and evaluation simulations (1960s to mid to late 1980s). Across the entire region, the modelled SWE estimates are generally centred about the observations for all values of SWE providing an $R^2 = 0.71$ (the L50 evaluation plots are shown for example in Fig. 6a). At SWE depths less than 800 mm, the model may provide significant underestimates. Many of these underestimates are observed on equator-facing slopes that receive afternoon sun (NW), as can be seen in Fig. 6b. In contrast, slopes facing southwest (SW) are less exposed to direct solar radiation and show very low SWE biases (1%).

### 4.3. Snow depth estimation

In contrast to the previous section, the evaluation of simulated snow depths at all sites highlight important differences between the two snowmelt schemes (Table 4). While the snow model tends to overestimate snow depths for both snowmelt schemes, Scheme 1 biases of 37–90 mm were at least 7–50% lower than values for Scheme 2. The largest errors in Scheme 2 were observed at large snow depths and maximum seasonal SWE (at low elevation sites) (Fig. 7), where snow density errors from the assumed constant density of 0.4 g cm$^{-3}$ had the greatest impact during conversion from SWE. With negative SWE biases for both schemes, the general overestimation in snow depth reflects the general underestimation of snow density (negative snow density biases, Table 2). These results confirm the expected benefits of the snow density model for SWE to depth.
conversion. Scheme 1 tends to overestimate snow depths during the accumulation phase and underestimate snow depths during snowmelt, which suggests that the underestimation of snow densities from the density model occurs mostly during snow accumulation. The differences between the snowmelt schemes for snow depth estimation are most prominent when the pack experiences intermittent snowmelt throughout the season, rather than at the end of the season when snowmelt is rapid and the schemes converge.

4.4. Spatial and temporal variability in model performance

Quite different annual SWE profiles were observed between model sites, from the patchy and intermittent snow cover at sites near the snowline (1, 2 and 13), to the more consistent seasonal snow profiles at high accumulation sites at the top of the range (4, 5 and 15). On a site-by-site basis, a range of performances were observed with $R^2$ values ranging from 0.56 to 0.84 at 10 of the evaluation sites. Reduced performance at the remaining sites (1, 2 and 13) was observed with $R^2$ values of 0.24–0.52. These three sites experience low SWE accumulation (generally < 400 mm maximum), high solar exposure and intermittent snow cover and are responsible for the reduced snow model performance at low SWE depths.

The annual performance of the snow models for SWE estimation for the full data record (F50 and L50) is presented in Fig. 8. The maximum deviation in model performance from the mean occurred in years 1968, 1973, 1975, 1977, 1998 and 2004. The larger deviations in model performance during these years highlight the interannual variability experienced in the Australian snowfields and the challenges of snow modelling in the region. A weak

---

### Table 5

<table>
<thead>
<tr>
<th>Snowmelt scheme</th>
<th>Melt factor</th>
<th>% Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First half training period (F50)</td>
<td>Last half training period (L50)</td>
</tr>
<tr>
<td>Scheme 1 ($k$)</td>
<td>2.73</td>
<td>2.57</td>
</tr>
<tr>
<td>Scheme 2 (MF)</td>
<td>10.45</td>
<td>9.66</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td>7</td>
</tr>
</tbody>
</table>

---

**Fig. 8.** Temporal variability in the annual mean model bias (SWE – relative to maximum annual observed SWE) for all sites for both snowmelt schemes (solid lines – Scheme 1 = blue and Scheme 2 = orange). The horizontal dashed lines show the mean annual biases. For reference, the maximum annual observed SWE is included (thin dashed line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Fig. 9.** Relationship between calibrated melt factors at each site (averaged between F50 and L50 calibration periods) and elevation for both snowmelt schemes. The bold linear regressions shown calculated using all data for each site and are significant to the 95% level. The thin linear regression lines represent each leave-one-out realisation.
negative correlation was observed between annual model biases and SWE depth, as the model tended to overestimate SWE during low snow years and underestimate SWE during high snow years.

4.5. Physical representation of calibrated melt factors

When the snow models were calibrated during the first half of the observations (FO50), the mean melt factor values were ~7% higher than those obtained when the model was calibrated on the second half of the observations (LO50) (Table 5). The relatively small shift in optimum model parameters between calibration periods indicates that optimum model parameters are not completely stable through time.

Statistically significant negative correlations were observed between calibrated melt factors and elevation for both snowmelt schemes and precipitation forcing data ($R^2 = 0.80$ and $R^2 = 0.39$ for $P_{OBSERVED}$ and $P_{ADJUSTED}$, respectively at a 95% significance level, with p values <0.043). The regression correlations are shown in bold in Fig. 9. Weaker correlations ($R^2 < 0.34$) were observed between two of the other physical landscape features: transformed aspect (as defined by Jost et al. (2012)) and potential relative radiation. The relationships between melt factors and elevation were stronger when precipitation undercatch biases were uncorrected ($P_{OBSERVED}$), with $R^2 = 0.78–0.83$ compared to $R^2 = 0.35–0.43$ ($P_{ADJUSTED}$), which may reflect the increased spatial variability in calibrated melt factor values when terrain influences on snowfall undercatch are incorporated across highly variable terrain. The precipitation adjustment also addresses the structural elevation-dependent biases that are associated with higher snow to rain ratios and the likelihood of stronger wind speeds with increasing elevation. The robustness of these relationships was examined using leave-one-out cross validation (as shown by the thin linear regressions shown in Fig. 9) in order to estimate the error in calibration factor that might occur at locations beyond calibration sites. The mean error in calibration factor ranges from $-5.9\%$ to $20.0\%$ for Scheme 1 and $-2.1\%$ to $22.6\%$ for Scheme 2, with the largest errors observed for the $P_{ADJUSTED}$ relationships due to increased scatter and the removal of structural biases in the precipitation data. For both schemes, the calibrated melt factor values from the $P_{ADJUSTED}$ simulations were 150–200% higher than those from the $P_{OBSERVED}$ simulations (Fig. 9), which highlights the significant influence of precipitation data errors on snow model calibrations.

5. Discussion

5.1. Snow density modelling

The climate-based snow density algorithm presented here extends previous methods for spring snow density estimation to provide an alternative to the compaction-based methods that appear in many models (Anderson, 1976; Essery et al., 2013; De Michele et al., 2013) for the simulation of daily snow densities. These existing compaction-based methods are routinely based on spatially limited observational data (Essery et al., 2013). As the snow density algorithm developed in this paper is capable of responding to climate variability, resilient estimates are expected in regions where conditions differ from calibration data or those with high climate variability. The snow density model outperforms the regionalised density-time curve that was generated for the study area, which despite omission of interannual variability, have successfully been used in other regions (Sturm et al., 2010). The model does not consider short timescale variability associated with fresh snowfall (McCready and Small, 2013), and instead focuses on the long-term evolution of the pack. Periods of high variability in snow density, such as those observed during the start and end of each season (Bormann et al., 2013) or during intermittent snow cover, along with variability at fine temporal scales (McCready and Small, 2013) may explain much of the scatter that is observed in Fig. 5. These periods are more prevalent at low elevation sites and sites with high solar exposure, which can explain the reduced performance of the snow density model in these situations (Table 2).

With mean absolute errors of 0.055 g cm$^{-3}$ (14%) the snow density model compares well to alternative statistical methods of snow density estimation reporting errors of 0.045 g cm$^{-3}$ (Jonas et al., 2009). The model performs best at forested sites and sites with low solar exposure (Table 2), which suggests that solar radiation may be important for snowpack densification processes along with precipitation, snow depth and melt-refreeze. As the snow density model requires only landscape and meteorological inputs, the model may be applied spatially to produce daily snow density fields. An important advantage of the snow density model is that snow observations are not required. The present study demonstrates the use of simulated snow densities for snow model parameterisation and highlights the benefits of improved density estimates in SWE/snow depth conversions. However, these types of snow density estimates may also be useful for those looking to improve SWE estimates from remotely sensed snow depth observations.

5.2. Snow modelling challenges in maritime snow environments

Model evaluations of TIMs are often made using runoff hydrographs rather than direct comparisons with SWE observations (Butt and Bilal, 2011; Debele et al., 2010). From the limited number of studies for which direct comparisons may be made, the SWE MAE errors of 115–138 mm obtained in this study are considerably larger than those obtained for other applications of the temperature-index model in Canada of 33–48 mm (Jost et al., 2012), and 25 mm across multiple sites in the US (Todd-Walter et al., 2005). Likewise, the NSE statistics at the three well-monitored sites (6, 12 and 13) of 0.42 on average are considerably lower than those generally obtained in northern hemisphere regions of 0.83 (Jost et al., 2012). Mean bias errors of $-15$ mm fall slightly outside the range of previously reported biases in these studies of $-1.2$ to $+7.8$ mm, indicating that the increased errors are not from systematic biases and are likely from the interannual deviations.

The larger model errors may arise from: (a) high variability in energy balance components and dominant snowmelt processes; (b) remaining uncertainty in the adjusted precipitation data; or (c) skewed SWE evaluations to the melt phase of the season caused by excluding the accumulation events that were used to estimate catch efficiency. Firstly, the TIMs rely on the information content of near surface air temperatures to constrain snowmelt rates, and therefore imply a constant relative contribution of energy balance components (sensible and latent heat fluxes) (Lang and Braun, 1990). In the highly variable maritime snow environment characteristic of Australian snowfields, dominant snowmelt processes may vary intra- and inter-annually and contribute to unsystematic variability and reduced skill in these regions (Debele et al., 2010). The poorer performance of the TIMs on NW slopes, equator-facing slopes with afternoon solar exposure, and conversely the higher performance of the TIMs on SW slopes, may vary intra- and inter-annually and contribute to unsystematic variability and reduced skill in these regions (Debele et al., 2010). The poorer performance of the TIMs on NW slopes, equator-facing slopes with afternoon solar exposure, and conversely the higher performance of the TIMs on SW slopes may be important for snowpack densification processes along with precipitation, snow depth and melt-refreeze. As the snow density model requires only landscape and meteorological inputs, the model may be applied spatially to produce daily snow density fields. An important advantage of the snow density model is that snow observations are not required. The present study demonstrates the use of simulated snow densities for snow model parameterisation and highlights the benefits of improved density estimates in SWE/snow depth conversions. However, these types of snow density estimates may also be useful for those looking to improve SWE estimates from remotely sensed snow depth observations.

Secondly, the results presented in Fig. 9 show that model calibrations are sensitive to changes in precipitation forcing. Raleigh and Lundquist (2012) also highlight the importance of precipitation errors at low-lying snow sites near the snow-rain transition line, which confirm the challenges of snow modelling in warmer maritime environments. Finally, the model generally performs...
better during the accumulation period (Table 3). By excluding 15% of the available SWE observations during accumulation events >50 mm (see Appendix A), the overall SWE evaluation is conducted using an increased proportion of observations taken during the melt phase. Therefore, the values presented in Table 3 may be considered conservative estimates of actual model performance.

5.3. Choice of snowmelt scheme in warm maritime environments

For SWE estimation, the differences between the two schemes were small. The sites with least discrepancy between the snowmelt schemes were at low elevations, where snow accumulation was low and the snow disappeared very quickly once melting started to occur. Over such short time scales the choice of snowmelt scheme becomes far less important than other factors. Previous studies that compare snowmelt schemes in TIMs have found larger differences between schemes for SWE estimation, which have largely been attributed to melt factor discrepancies (Hock, 1999). In this study the melt factors provided by the air-temperature based method (Schreider et al., 1997) differ from those obtained through the density-based method (Rango and Martinec, 1995). The difference in melt factors was largest during snow accumulation months (June and July) where far less variability in melt factors was obtained from the air-temperature based method. Much smaller differences in melt factors between the two schemes were observed during spring (September) when the snowpack is losing mass rapidly.

The introduction of a more physically-based snowmelt parameterisation into the TIMs using Scheme 1 was expected to improve snow model performance by appropriately enhancing daily melt rates during warmer years, where the snowpack is more likely to be ‘ripe’ for melting throughout the season despite cold content not explicitly being considered by the model. Instead, SWE profiles for the two schemes were very similar and did not reflect the observed discrepancies in melt factors between the schemes. While the details of the snowmelt schemes in the present study differ from previous work, the results suggest that the choice of snowmelt scheme in warm maritime environments is much less important for SWE estimation than other factors, such as the quality of meteorological inputs and regional calibration. These results do not support future efforts to improve snowmelt estimation in TIMs for maritime environments with melt algorithm modifications.

5.4. The impact of precipitation and climate forcing on model parameters

The problem of snowfall deficiencies in precipitation data is not uncommon (Rasmussen et al., 2012) and was observed in the station precipitation data from the NSW alpine region. The precipitation errors due to undercatch were estimated to be as much as 56% at the high elevation sites and ~20–30% at mid-elevation sites. The magnitude of these precipitation errors is within the range of previously documented undercatch errors in general (Rasmussen et al., 2012), and across an elevation gradient (Fassnacht, 2004). A simple multiplication factor applied to the probability-based snowfall component \( P_{\text{snow}} \) of the precipitation observations (based on \( T_{\text{mtn}} \)) proved useful in correcting these precipitation undercatch errors, reducing SWE biases in the snow model from ~12% to 2% (or ~50 to +9 mm for \( P_{\text{Obs}} \) and \( P_{\text{ADJ}} \), respectively). Precipitation undercatch corrections based on mass balance techniques have previously demonstrated agreement with aerodynamic precipitation correction models and have been used to improve modelling in glacial catchments in Italy (Carturan et al., 2012).

The present study shows that precipitation undercatch biases also significantly influence calibrated melt factor parameters. During model calibration, melt factors are generally optimised for model performance and resulting calibration parameters may partially compensate for all sources of model error, including forcing data biases and model structural errors (Stisen et al., 2012). Results from this study suggest that broad-scale climate factors may also influence model calibrations, with a shift in optimum model parameters of 7% between the split-sample periods. Climatologically, the F50 calibration period was more likely to be ‘wetter’ than the L50 period due to a higher prevalence of La-Niña-like conditions, negative phase of the Southern Annular Mode (which brings the westerly storm track closer to the mountains) and prevailing drought conditions during the 2000s (Chubb et al., 2011; Van Dijk et al., 2013). These large-scale climatological features may have contributed to the slightly higher melt factor values obtained for the F50 period, where more winter precipitation resulting in deeper snowpacks and increased cloudiness during the F50 period would require increased snowmelt rates to deplete the snow pack rapidly during the spring melt, particularly at higher elevation sites. With increased cloudiness, the solar radiation component of the energy balance would be reduced. These results confirm previous suggestions that wet and dry years have a role in TIMs calibrations (Kumar et al., 2013) and may be a response to energy balance components and dominant snowmelt processes.

After appropriate snowfall adjustments, the mean calibrated melt factor values for the region, generally exceed the typical values previously obtained in northern hemisphere studies by ~6 mm °C⁻¹ day⁻¹ (Scheme 2) and 1.5 (Scheme 1). Previous studies for the region using snowmelt Scheme 2 employ a spatially and temporally constant melt factor of 2.9 mm °C⁻¹ day⁻¹ that was generated at a single site in NSW (the mid-high elevation well-monitored Site 12) (Schreider et al., 1997; Whetton et al., 1996). The results presented here suggest that the previously adopted value at this site was too low and a melt factor closer to 8.4 mm °C⁻¹ day⁻¹ would be more appropriate. The reason for the melt factor underestimated in the previous studies may be attributed to the unaccounted precipitation undercatch. A lower melt factor of 2.2 mm °C⁻¹ day⁻¹, which is much closer to the value adopted by these previous studies, was obtained through calibration in the present study when the unadjusted precipitation input data were used (\( P_{\text{OBSERVED}} \)). The spatial variability in melt factors presented here also indicate that the previously adopted spatially constant melt factor of 2.9 mm °C⁻¹ day⁻¹ may be improved to better represent spatial variability in snowmelt, as acknowledged by the previous authors.

Recent studies have highlighted the importance of spatial variability in melt factors in TIMs (Kumar et al., 2013). These studies strongly support the development of methods for spatial distribution of melt parameters beyond calibration points as an essential component of catchment-scale snow models. The negative relationship between elevation and calibrated melt factors (Fig. 9) is crucial for parameterising spatially-distributed TIMs. Interestingly, the negative relationship derived from the model calibrations disagrees with the conceptual model provided in Hock (2003), which indicates higher melt factor values with elevation. Hock (2003) provides a large table of documented melt factors across a range of glacial and non-glacial sites. Using this data, we have plotted melt factor against elevation and confirmed that the relationship is positive (as the conceptual model indicates). However, for non-glacial sites the relationship is negative and is consistent with the results presented in our manuscript. Since Hock (2003) only provides non-glacial information for two sites, we extended this test analysis to include results from several other non-glacial studies (Lang and Braun, 1990; Hodgkins et al., 2012; DeWalle et al., 2002 and Rango and Martinec, 1995). When all the data from these studies were collated, we confirm that the relationship remains
negative between melt factor values and elevations at non-glacial sites ($R^2 = 0.30, p = 0.02$ not shown). Bare ice has a much lower albedo than snow and will therefore absorb more solar energy. As solar radiation absorption is the primary driver for snow/ice melt, it is reasonable to expect different melt dynamics at glacial and non-glacial sites.

Reported melt parameters from previous studies should be interpreted with caution as input data biases and model structural errors are not commonly reported, and substantial changes in melt factors obtained through calibration may be obtained for relatively small input data errors. The results presented here show that the relationship between elevation and calibrated melt factors is robust and errors in melt factors of $-5.9\%$ to $22.6\%$ may be expected beyond calibration locations. The impact of this magnitude of errors on simulated SWE may, in part, be inferred from the split-sample calibration results, where a difference of $11\%$–$14\%$ in calibration factor between F50 and L50 (Table 5) yields TIMs SWE biases of up to 29.8 mm (Table 3). The results also provide an indication of the magnitude of melt factor changes that may occur with typical precipitation undercatch errors.

It is important to note that while precipitation undercatch can have a significant influence on SWE simulations, air temperature measurements in snow-affected areas can incur mean daily biases of $+0.6$ to $+2.2\degree C$ due to radiative heating (estimated from information presented in Huwald et al., 2009). Measurement biases from typical air temperature sensors over snow packs vary with wind speed and solar radiation exposure and as such can vary considerably throughout the day. Adjusting daily air temperature data to account for these biases is desirable, but opportunities are limited in data-sparse regions without independent measurements that are unaffected by radiative heating. If air temperature biases were considered, the calibrated melt factor values would likely reduce to account for the increased melt forcing, while optimising model performance. Note that Raleigh and Lundquist (2012) find that in the maritime snowfields of the western US, forward-type models (such as the TIMs presented in the present study) are more sensitive to snowfall forcing, which is a combination of both precipitation and temperature inputs.

6. Conclusions

With point-based models operating for at least 39 years at 13 sites that were located throughout the NSW snowfields in Australia, this study provides one of the most comprehensive modelling efforts for the region and contributes towards snow model testing in warm maritime environments. The present study builds on existing techniques for end-of-season snow density estimation to provide a method for obtaining daily snow density estimates that outperform density-time curves in the Australian region. One of the main advantages of the enhanced snow density model is the capability to incorporate important interannual variability and improve SWE to depth conversions. The climate based snow density technique may therefore be of use in maritime snowfields in other regions where interannual variability in snow properties can also be high or where snow observations are limited. Model parameters would likely require recalibration in areas outside NSW.

The choice of snowmelt scheme was found to be less important than other factors for SWE estimation in the warm maritime environment due to rapid snowmelt. However, improved snow depth estimates were obtained when the daily snow density model was used to inform SWE to depth conversion compared to using regional climatologies. The extension of the model evaluation metric from SWE to snow depth is an important aspect of rigorous model testing in the region that allows model development to be expanded to areas with only snow depth measurements. Considerable spatial distribution of melt factors was also observed, reflecting the variability of snowmelt sensitivities when overall solar radiation is high. The calibrated melt factors show a large sensitivity to precipitation forcing and a correlation with elevation and to a lesser extent potential solar exposure. These types of relationships are essential for spatial application of such models. While the present study demonstrates the use of the snow density model for parameterisation of a temperature-index snow model, the model may be useful to those interested in other aspects of snow research such as SWE/snow depth conversions.

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Appendix A

The mass balance approach estimates precipitation undercatch by assuming that observed SWE accumulation depths should reconcile with observed total precipitation, if all falling precipitation is captured by the gauge and air temperatures are below freezing. Therefore any precipitation deficit during these conditions may be attributed to undercatch error as presented in Fig. A1. The ratio of
observed total precipitation and SWE accumulation depths over a common time period provides an estimate of the undercatch, expressed as gauge catch efficiency ratio (CE) (Eq. (A1)).

$$\text{CE} = \frac{\sum P_{\text{observed}}}{\text{SWE}_{t1} - \text{SWE}_{t0}}$$

where $\sum P_{\text{observed}}$ is the sum of daily precipitation observed at dates $t_0$ and $t_1$ (where $t_0$ is the date at which snow accumulation commenced and $t_1$ is when the snow accumulation ceased) and $\text{SWE}_{t1} - \text{SWE}_{t0}$ is the observed SWE change between these dates. A CE value of 0.5 indicates that 50% of the total precipitation observed on the ground (as SWE) was uncollected by the precipitation gauge, and a CE of 1.0 indicates complete precipitation collection. Fig. A1 provides a schematic of the mass balance correction technique.

The mass balance technique estimates the CE achieved at the precipitation gauges during snowfall days (i.e. when mean air temperatures were below freezing). The SWE observations were collected at irregular intervals during winter (measurements obtained at 7–14 day intervals) and as such the mass balance was applied at irregular time steps. The SWE accumulation observed between two observation dates may be the cumulative result of several precipitation events or days. To account for multi-day time steps, the daily precipitation was summed over the entire interval between SWE observation dates. At low SWE depths or when SWE accumulations between measurements were small and $\text{SWE}_{t1} - \text{SWE}_{t0} < 0$, the signal to noise ratio for SWE accumulations is expected to be high. Similarly, as the time interval between SWE observations increases, the cumulative impact of factors such as sublimation, evaporation and mid-period snowmelt occurring between SWE measurements increases. To minimise these two potential sources of error, the CE calculations were only performed for events where SWE accumulation between the two observation dates was between greater than 50 mm and the interval between observations was shorter than 14 days. These limitations both increased the signal to noise ratio and reduced potential sources of error, and were optimised during an iterative sensitivity analysis.

After the SWE accumulation and time thresholds were used to mask the data, any CE values that were calculated for single snow accumulation events ($t_0$–$t_1$) that were greater than 1.0 (~20% of all events) were omitted, as this suggests that other processes (other than undercatch) were also influencing the mass balance. The sub-sample of SWE estimates based on these criteria resulted in the mass balance analysis using only a small fraction of the total SWE observations (~15% at any one site) to inform precipitation adjustments. The estimated CE values ranged between sites from SWE observations (<15% at any one site) to inform precipitation accumulation events ($t_0$–$t_1$) that were greater than 1.0 (e.g. low air temperatures were below freezing). The SWE observations were obtained at 7–14 day intervals) and as such the mass balance was applied at irregular time steps. The SWE accumulation observed between two observation dates may be the cumulative result of several precipitation events or days. To account for multi-day time steps, the daily precipitation was summed over the entire interval between SWE observation dates. At low SWE depths or when SWE accumulations between measurements were small and $\text{SWE}_{t1} - \text{SWE}_{t0} < 0$, the signal to noise ratio for SWE accumulations is expected to be high. Similarly, as the time interval between SWE observations increases, the cumulative impact of factors such as sublimation, evaporation and mid-period snowmelt occurring between SWE measurements increases. To minimise these two potential sources of error, the CE calculations were only performed for events where SWE accumulation between the two observation dates was greater than 50 mm and the interval between observations was shorter than 14 days. These limitations both increased the signal to noise ratio and reduced potential sources of error, and were optimised during an iterative sensitivity analysis.

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