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

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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 -0.027 g cm^{-3} to -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.

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,

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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; Hock, 1999; Jost et al., 2012). 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 (McCreight 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.,

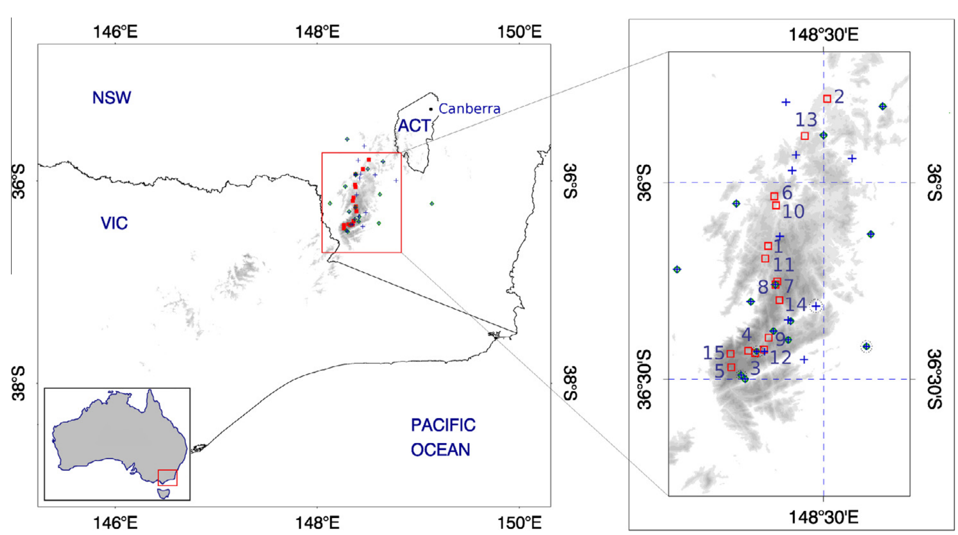

Fig. 1. Study region in southeast Australia (left). The state borders mark the state of New South Wales (NSW), Victoria (VIC) and the Australian Capital Territory (ACT). The area above 1400 m (snowline, Ruddell et al., 1990) is shaded grey, the red boxes are in situ snow site locations, the open diamonds 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.)