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Applying object-based segmentation in the temporal domain to characterise snow seasonality

Jeffery A. Thompson *, Brian G. Lees

School of Physical, Environmental and Mathematical Sciences, University of New South Wales, Canberra Campus, PO Box 7916, Canberra, ACT 2600, Australia

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ABSTRACT

In the context of a changing climate it is important to be able to monitor and map descriptors of snow seasonality. Because of its relatively low elevation range, Australia's alpine bioregion is a marginal area for seasonal snow-cover with high inter-annual variability. It has been predicted that snow-cover will become increasingly ephemeral within the alpine bioregion as warming continues. To assist the monitoring of snow seasonality and ephemeral snow-cover, a remote sensing method is proposed. The method adapted principles of object-based image analysis that have traditionally be used in the spatial domain and applied them in the temporal domain. The method allows for a more comprehensive characterisation of snow seasonality relative to other methods. Using high-temporal resolution (daily) MODIS image time-series, remotely sensed descriptors were derived and validated using *in situ* observations. Overall, moderate to strong relationships were observed between the remotely sensed descriptors of the persistent snow-covered period (start $r = 0.70$, $p < 0.001$; end $r = 0.88$, $p < 0.001$ and duration $r = 0.88$, $p < 0.001$) and their *in situ* counterparts. Although only weak correspondence ($r = 0.39$, $p < 0.05$) was observed for the number of ephemeral events detected using remote sensing, this was thought to be related to differences in the sampling frequency of the *in situ* observations relative to the remotely sense observations. For 2009, the mapped results for the number of snow-cover events suggested that snow-cover between 1400 and 1799 m was characterised by a high numbers of ephemeral events.

1. Introduction

Snow-cover is an important land cover type that both influences, and is influenced by, the energy balance at the Earth's surface (Déry and Brown, 2007; Groisman et al., 1994). Remote sensing has played a central role in highlighting changes in snow-covered area (Vaughan et al., 2013). While most of these studies have examined changes in the areal extent of seasonal snow-cover (*e.g.* Brown et al., 1995; Frei and Robinson, 1999; Groisman et al., 1994; Robinson and Frei, 2000), other studies have recently begun exploring changes in the seasonal timings of the snow-covered period (*e.g.* Bormann et al., 2012; Choi et al., 2010; Dietz et al., 2013; Dye, 2002; Stone et al., 2002). This is important, as a full appreciation of how climate change will impact upon seasonally snow-covered environments requires the consideration of both the spatial and temporal aspects of snow-cover responses to warming. From an ecological perspective, winter snow cover plays an important role in dormancy and hibernation of small animals (Aitchison, 2001). Within Australia's alpine areas, persistent snow cover provides an important buffer against winter temperatures for the endangered Mountain Pygmy Possum (*Burramys parvus* – Shi, 2013), and changes in snow seasonality has serious implications for the survival of these animals.

One issue with some of the previous studies of the seasonal timings of the snow-covered period is that they have often been overly simplistic in their derivation of descriptor dates for the start and end of the snow-covered period (Choi et al., 2010). In some cases (*e.g.* Bormann et al., 2012; Dye, 2002; Kimball et al., 2004; McDonald et al., 2004; Narasimhan and Stow, 2010), the start and end of the snow-covered period was defined in relation to either the first or last remotely sensed observation of snow-cover that occurred within specific months. This approach tends to over-estimate the length of the snow-covered period. It does not account for the fact that snow-cover can be ephemeral during transition periods into and out of the winter months, when snow-cover becomes persistent. The failure to account for the ephemeral nature of snow-cover during transition periods skews trend analysis derived from image time-series (Choi et al., 2010). This limitation

* Corresponding author. Tel.: +61 262 688 890.
E-mail address: jeff_thompson@netspace.net.au (J.A. Thompson).

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has been acknowledged by some authors (*e.g.* Kimball et al., 2004; McDonald et al., 2004; Narasimhan and Stow, 2010), but not by others (*e.g.* Bormann et al., 2012).

One way of overcoming the bias introduced by ephemeral snow-cover events has been to define the start and end of the snow-covered period using a series of arbitrary snow persistence thresholds. For example, Karlsen et al. (2007) defined the end of the snow-covered period as the date when snow disappeared and did not subsequently reappear within 5 days. Working with remotely sensed observations, Gao et al. (2011) defined the start of the snow-covered period as the first date with snow observations followed by 13 days of either snow or cloud observations. Gao et al. (2011) also used a similar 13-day threshold to define the end of the snow-covered period. Other alternatives have been proposed (*e.g.* Farmer et al., 2010; Gamon et al., 2013; Kimball et al., 2004; Koskinen et al., 1999; McDonald et al., 2004; Narasimhan and Stow, 2010; Zhao and Fernandes, 2009), though many of these have been dependent on the type of remotely sensed data (*i.e.* optical, synthetic aperture radar), the temporal resolution of the data (*i.e.* daily, weekly), and whether or not the data were image composites. Table 1 presents a summary of studies that have used remote sensing to characterise aspects of snow seasonality.

In recent years, object-based image analysis (OBIA) and its geospatial counterpart (GEOBIA) have featured prominently in the literature (Aplin and Smith, 2011; Benz et al., 2004; Blaschke, 2010). The increased popularity of object-based analyses has in part been a result of the increased availability of multispectral data obtained from high spatial resolution sensors, such as IKONOS, QuickBird, and WorldView2. An important aim of object-based image analyses is to better understand the implications and complexities of real world phenomena (Lang, 2008; Lang et al., 2010). Typically, this is achieved through the inclusion of spatial information in the classification process for remotely sensed imagery with very high spatial resolution (Aplin and Smith, 2011; Benz et al., 2004; Blaschke et al., 2014). Whereas early image segmentation algorithms incorporated spatial information to identify regions of spectral similarity of contiguous pixels within an image associated with particular land surface features (Kettig and Landgrebe, 1976), the increased availability of high resolution imagery has allowed analysts to focus on the identification of objects within particular scenes (Benz et al., 2004). Blaschke et al. (2014) recently suggested that the use of GIS-type procedures in the classification process for remotely sensed imagery was a defining characteristic of the object-based analysis and represented a new paradigm within remote sensing. Aplin and Smith (2011) have suggested that object-based methods have matured to the point where they are eminently suited for landscape analysis.

Historically, image segmentation algorithms have tended to be ad hoc, with differences between algorithms often reflecting authors' emphasis on specific characteristics and the computational trade-offs associated with their use in a particular scene (Haralick and Shapiro, 1985). In spite of their ad hoc nature, Blaschke (2010) has suggested a typology for object-based algorithms, whereby they are categorised as point-based, edge-based, region-based or mixed approaches. Edge-based algorithms typically emphasise the contrast between objects within image space. In contrast, region-based approaches utilise internal characteristics of objects within images in the segmentation process (Kettig and Landgrebe, 1976). Mixed approaches combine aspects of edge-, point- and/or region-based approaches to partition an image into constituent objects (Blaschke, 2010). Irrespective of their categorisation and methodological underpinnings, it is the inclusion of GIS-type methods and information from the spatial domain that has been a defining characteristic of object-based image analytical approaches (Blaschke et al., 2014; Lang, 2008).

Because segmentation approaches employed in object-based analysis have typically focused on high spatial resolution imagery, to date there have been few studies that have adapted object-based methods for application in the temporal domain. Where object-based image analysis has been employed in multi-temporal studies, it has generally been used to characterise the relative changes in objects between discrete dates for the purposes of land-use/land-cover change detection (*e.g.* De Chant and Kelly, 2009; Duro et al., 2013; Gomez et al., 2011; Im et al., 2008; Wulder et al., 2008). As such, these studies typically characterised the results of transitions between two distinctly different land-cover types or land-use states (Blaschke et al., 2014). Early typologies for basic object-based change analysis were proposed by both Blaschke (2005) and Niemeyer et al. (2008) which have been further extended by Duro et al. (2013). In these typologies, three basic

Table 1
Summary of remote sensing studies that explored aspects of snow seasonality, highlighting the senor used in the study, the temporal resolution of the sensor platform (T. Res.), whether the data were composited (Comp.), the descriptor of the snow season, and the threshold used to determine the relevant descriptor dates (Date threshold).

Study	Sensor	T. Res.	Comp.	Descriptor	Date threshold(s)
Farmer et al. (2010)	SSM/I	Daily	N	Start of accumulation Start of melt End of melt Duration	1st inversion of second derivative Global max. of second derivative Global min. of second derivative End melt – Start melt
Gamon et al. (2013)	MODIS	16-day	Y	Start of melt End of melt	1st positive NDVI value NDVI $\geqslant$ 0.3
Gao et al. (2011)	AMSR-E & MODIS	Daily	N	Start of persistent snow End of persistent snow Duration	$\geqslant$14 days consecutive snow $\geqslant$14 days consecutive no-snow End persistent – Start persistent
Karlsen et al. (2007)	AVHRR	14-day	Y	End of persistent snow	$\geqslant$5 days consecutive no-snow
Koskinen et al. (1999)	ERS-2 AVHRR	3–16 days 1–30 days	N N	End of melt End of melt	Snow fraction = 0% (Ch1 – Ch2) > 0
Kimball et al. (2004)	NSCAT	Daily	N	Start/End spring thaw	(Averaged backscatter – daily backscatter) < –2.9 dB
McDonald et al. (2004)	SSM/I	Daily	N	Start of spring thaw	Max. value of first derivative
Narasimhan and Stow (2010)	MODIS	Daily	N	Complete melt	Snow fraction = 0%
Wang and Xie (2009)	MODIS	8-Day	Y	Start of persistent snow End of persistent snow Duration	Dec. 1 – Duration before date Dec. 1 + Duration before date Sum of snow days (Sep–Aug)
Zhao and Fernandes (2009)	AVHRR	Daily	N	Snowmelt date	$\geqslant$3 days no snow (Apr–Aug)