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Separating snow and forest temperatures with thermal infrared remote sensing

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ABSTRACT

Thermal infrared sensing from space is a well-developed field, but mixed pixels pose a problem for many applications. We present a field study in Dana Meadows, Yosemite National Park, California to scale from point (~2-m resolution) to aerial (~5-m resolution gridded, 1 km × 6 km extent) to satellite (MODIS, ~1000-m resolution, global extent) observations. We demonstrate how multiple thermal bands on MODIS can be used to separate snow and forest temperatures and determine the fractional snow-covered area (f_{SCA}) over a 3 km × 3 km array of 9 MODIS grid cells. During the day, visible, near-infrared, and shortwave-infrared bands provide a first guess of f_{SCA} and help to constrain the solution. This technique, which has estimated errors < 2 °C and 10% f_{SCA} for many expected conditions, enables better understanding of the snowpack energy balance, atmospheric inversions and cold air pools, and forest health.

1. Introduction

Remote sensing of surface temperatures using infrared wavelengths has seen extensive development and applications over land (Kalma et al., 2008; Li et al., 2013) and oceans (Kilpatrick et al., 2015), providing insight on global fluxes of energy and moisture. Satellite thermal infrared radiation (TIR) images—available from such sensors as Landsat TM, ETM+, and TIRS, ASTER, NOAA AVHRR, GOES, MODIS, and VIIRS—provide comprehensive spatial and temporal data (see Tomlinson et al., 2011 for history and IR specifications). Applications cover a wide range of topics, including surface heat flux (Norman et al., 1995), evapotranspiration (Wang and Dickinson, 2012), stream temperatures (Handcock et al., 2006, 2012), a surrogate for air temperature (Shamir and Georgakakos, 2014; Pepin et al., 2016), urban heat island studies (Rizwan et al., 2008), and snow surface temperature (Fily et al., 1999; Westermann et al., 2012; Pérez Díaz et al., 2015).

MODIS land surface temperature (LST) and emissivity products have proven reliable over homogeneous terrain (Wang and Liang, 2009) but have greater biases and uncertainty in mountain areas (Lipton and Ward, 1997; Liu et al., 2006). A common issue in heterogeneous terrain is the mixture of different components at very different temperatures within a single pixel. Prior work has successfully separated fire temperatures (and their sizes) from the rest of the pixel (Dozier, 1981) and vegetation and soil temperatures in arid regions (Norman et al., 1995). Although the mixed-pixel temperature problem has not been previously addressed in snow-covered areas, at all but the finest spatial resolutions, most pixels are mixed. Approximately 40% of the North American snow zone is forest-covered (Klein et al., 1998), with most of this area covered with forest densities ranging between 20% and 90%, resulting in large areas where satellite grid cells contain a mix of both forest and snow (or in the summer, soil or underbrush).

Current LST products provide one temperature for a blend of all components in a grid cell, but practically and scientifically, temperatures of the individual end-members are much more valuable. Forest surface temperature (T_{forest}) may be used as a proxy for air temperature and/or as an indication of forest health and transpiration (Wang and Dickinson, 2012). Snow surface temperature (T_{SS}) depends on energy-balance forcing and provides a spatially explicit measure of how energy is distributed over terrain. In the snow sciences, comparing modeled and measured T_{SS} has proven a key tool to evaluate model ensembles (Rutter et al., 2009; Essery et al., 2013; Raleigh et al., 2013; Pomeroy et al., 2016) and has enabled identification of fundamental errors in modeling the energy balance, including downwelling longwave radiation (Lundquist et al., 2015) and model turbulence schemes (Lapo et al.,

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2015).

Impediments to using satellite-measured snow surface temperatures that Dozier and Painter (2004) identify include: (1) lack of validation work to quantify errors at various scales; (2) the mixed-pixel problem, where a single pixel seen by the satellite contains more than just snow; (3) thermal path radiance from the atmosphere in between the sensor and the snow surface; and (4) imprecisely quantified emissivity of the snow surface. Of these, the mixed-pixel problem (Pérez Díaz et al., 2015) and clouds in between the sensor and the surface (Fily et al., 1999; Westermann et al., 2012) have been mentioned most frequently. Although snow emissivity varies with grain structure and viewing angle, it is generally thermally dark, with an average longwave emissivity of 0.985–0.990 for all grain sizes (Dozier and Warren, 1982), which makes problems with incorrect emissivity a second-order effect (Raleigh et al., 2013), with variations < 0.5 °C.

Here, we address the first and second issues listed above, exploring error sources in T_{forest} and T_{SS} signals at various scales and presenting a solution to the mixed-pixel problem.

To address the issue of validation, we present data from a February 2016 field campaign to quantify differences in brightness temperatures measured at a plot (radiometer with ~2-m footprint), from an aircraft (IR camera plus radiometer with ~5-m gridded pixel resolution), and from satellite (MODIS, ~1000-m footprint), over Dana Meadows in the Tuolumne River Watershed, Sierra Nevada, California. With these data, we focus specifically on a high elevation (2897 m) subalpine region during clear weather, with a dry atmosphere with limited atmospheric influence. We focus on fairly flat terrain locally, with grid cells comprised of snow and forest (lodgepole and whitebark pine).

Section 2 outlines our approach to solving the mixed pixel problem; Section 3 describes the field campaign, location, and measurements. Section 4 details results; Section 5 discusses caveats and implications. We conclude in Section 6.

2. Approach to solving the mixed pixel problem in forest and snow

2.1. General theory and background

Satellite thermal infrared (IR) imagery is generally coarser resolution than the features we hope to observe, particularly in mountainous and/or forested terrain. However, most satellite sensors that observe in the thermal infrared wavelengths use two or more bands, usually to enable atmospheric correction of the signal (Wan and Dozier, 1996). When the sensor's bands include both the midwave IR (~4 µm) and the longwave IR (~11 µm), multispectral un-mixing is possible (Dozier, 1981; Zhan et al., 2013). The basis of this approach lies in the Planck equation and Wien's displacement law, wherein warmer objects emit more thermal radiation at all wavelengths, with peaks at shorter wavelengths, than cooler objects. Therefore, a grid-cell area that emits at a mix of warmer and cooler brightness temperatures, compared to a uniform grid cell of the mean temperature, will appear warmer at all wavelengths, with a greater increase in the midwave IR than the longwave IR (Fig. 1). For example, given a 1 km × 1 km grid cell comprised of forest and snow, with a bimodal temperature distribution peaking near −10 °C and −3 °C, the brightness temperature of the pixel as a whole would be about 0.3 °C warmer in the midwave IR than the longwave IR (Fig. 1). Note that for simplicity, this example (Fig. 1) considers an image taken before sunrise (no reflected radiation) and only brightness temperatures (which assumes the emissivity of all elements is 1).

The radiance sensed is the integration across the full range of temperatures in the pixel, which, neglecting reflected radiation for the moment, can be written in discretized form as

$$L_j = \sum_{k=1}^{N} f_k \varepsilon_{jk} \beta(\lambda_j, T_k) \tag{1}$$

where L_j is the radiance at wavelength λ_j, f_k is the fraction of the pixel area at temperature T_k, ε_{jk} is the emissivity of the k^{th} fraction of the pixel at wavelength j, and β represents the Planck equation

$$\beta(\lambda, T) = \frac{2hc^2}{\lambda^5 (e^{hc/(k\lambda T)} - 1)} \tag{2}$$

where c is the speed of light, k is the Boltzmann constant, and h is the Planck constant. Conceptually, the radiance sensed at each pixel by each sensor band can be modeled as a mixture of that emitted from two endmembers, snow and forest, each weighted by the fraction of area of the pixel they cover, plus any reflected radiance in that wavelength:

$$\begin{aligned} L_j = {} & f_{SCA}\, \varepsilon_{snow}(\lambda_j, \theta) \beta(\lambda_j, T_{SS}) + (1 - f_{SCA}) \varepsilon_{forest}(\lambda_j) \beta(\lambda_j, T_{forest}) \\ & + f_{SCA} [1 - \varepsilon_{snow}(\lambda_j, \theta)] R_\downarrow(\lambda_j) + (1 - f_{SCA}) [1 - \varepsilon_{forest}(\lambda_j)] R_\downarrow(\lambda_j) \end{aligned} \tag{3}$$

where f_{SCA} is the fractional snow-covered area of the pixel, $\varepsilon_{snow}$is the emissivity of snow at wavelength λ_j and viewing angle θ, T_{SS} is the mean temperature of the snow, $\varepsilon_{forest}$is the emissivity of the forest as a function of wavelength, T_{forest} is the mean temperature of the forest cover, and $R_\downarrow$ is the wavelength specific radiance reaching the surface. We presume sky radiance is negligible; therefore we neglect $R_\downarrow$ at night and solve for it as a function of incoming solar radiation during the day (described further in Section 2.5). Note that we consider f_{SCA} to be the viewable fraction of snow cover; this does not include snow underneath forest cover.

Using nonlinear optimization methods (Coleman and Li, 1996), we can simultaneously solve for the two temperatures. If f_{SCA} is measured independently, for example by spectral un-mixing in the visible through shortwave-infrared wavelengths (Painter et al., 2009), and emissivity is calculated using theoretical methods (Dozier and Warren, 1982) or laboratory measurements (Salisbury et al., 1994), then the two temperatures are the only unknowns, so only two brightness temperature measurements—one in the midwave IR and one in the longwave IR—are needed. Extra temperatures (more than one band in the 4 µm and/or 11 µm regions) enable a least-squares solution rather than an exact one. If independent estimates of f_{SCA} are not available, for example at night, then assuming that T_{ss} and T_{forest} are the same in adjacent pixels whose f_{SCA} values are different also leads to the solution by determining values that would produce the set of radiances that best match those measured in each of the sensor's observational bands. Note that each radiance can be converted to a brightness temperature by algebraically inverting the Planck Equation (Eq. (2)), and so we minimize the difference between observed and calculated brightness temperatures across all observed wavelengths (Fig. 1c). Details related to this methodology are outlined below and tested in Section 4.

2.2. Application of general theory to MODIS

For MODIS, five bands are sensitive to land surface temperatures and are minimally impacted by the atmosphere (Berk et al., 2014) or by noise issues that plague photovoltaic sensors (Sun et al., 2015; Xiong et al., 2015; Sun et al., 2016). These useful bands (marked in Fig. 1) include 20 (3.66–3.84 µm), 22 (3.929–3.989 µm), 23 (4.02–4.08 µm), 31 (10.78–11.28 µm), and 32 (11.77–12.17 µm) and are used together for various remote sensing applications, including the split-window atmospheric correction and operational sea-surface temperature retrieval (Wan and Dozier, 1996; Kilpatrick et al., 2015). With regards to Eq. (3), radiances in 5 bands generate 5 equations and 3 unknowns, which should be easily solved. While they are among the best performing bands on the satellite, bands 31 and 32 have an uncertainty of about 0.1% (Xiong et al., 2015), which, for a blackbody at 0 °C, leads to uncertainty of up to ± 0.05 °C in the retrieved brightness temperature. For typical snow and forest surface temperatures (e.g., −10 °C and 0 °C) with a near-even mix of covered area, the difference in sensed brightness temperatures between the three midwave bands (20, 22, 23) and