Doctoral Dissertation Proposal

Improving our understanding of mountain surface temperatures with geostationary and low Earth orbiting satellite data

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General Examination

9:00 AM, Monday, November 8th, 2021

ECE Bldg. Rm. 303

University of Washington, Seattle, WA

Table of Contents

1. Background

a. Motivation

Satellite remote sensing in the thermal infrared can provide spatially contiguous maps of surface temperatures across wide areas, though these are constrained by the tradeoff between temporal resolution (the time interval between repeat observations), and spatial resolution. While several Earth imaging satellites can provide thermal infrared observations at moderate spatial resolutions (70 – 100 m ECOSTRESS, ASTER, Landsat TIRS; 750 – 1000 m VIIRS & MODIS) these have repeat observation intervals of 3-16 days for the higher resolution imagery, and at most four times daily for the lower resolution imagery. Only geostationary satellite imagers such as the new generation of Geostationary Operational Environmental Satellite (GOES) Advanced Baseline Imagers (ABI) can currently provide observations at sub-hourly high temporal resolutions, albeit at coarser spatial resolutions (≥2000 m) (Schmit et al., 2017).

Surface temperature observations of mountain snow environments can serve as a model evaluation tool for understanding the complex surface energy balance processes that drive snowmelt magnitude and timing (Lapo et al., 2015). This is especially important for diurnal processes like snow melt-freeze cycles (Niu et al., 2011) and snow grain metamorphism which in turn drive feedbacks in the surface energy balance through changes in emissivity and albedo (Warren, 1982; Flanner and Zender, 2006; Warren, 2019). Surface temperature controls upward longwave radiation (Marks and Dozier, 1992), serves as the lower boundary layer for land-atmosphere energy exchanges (Raleigh et al., 2013), and itself responds quickly to changes in the net radiative, turbulent, and conductive heat fluxes.

High temporal resolution observations of surface temperatures in mountains are needed to detect and correct biases in land surface models or their forcing data over snow-dominated basins in order to better simulate these surface temperatures (Lapo et al., 2015; Pepin et al., 2016; Xiang et al., 2017, Zink et al., 2018), near-surface diurnal air temperature ranges (Shamir & Georgakakos, 2014; Massey et al., 2016) and potentially for observing temperature lapse rates that vary in space and time (Lundquist & Cayan, 2007; Minder et al., 2010; Mizukami et al., 2014).

High spatial resolution observations of surface temperatures in mountains are needed to capture the spatial variations of the surface energy balance, which together with heterogeneous snow distribution exhibits control on snowmelt timing (Lundquist & Dettinger, 2005; Clark et al., 2011). Remote sensing imagery of mountain snow environments are subject to significant mixed pixel effects (Selkowitz et al., 2014), where each thermal infrared pixel blurs together the temperatures of sub-pixel scale surfaces (Gillespie et al., 1998). Surface temperature observations around the ~100 m hillslope scale will be important to observe temperature gradients with elevation, slope, aspect, vegetation cover, and topographic shading within individual watersheds, as these can have significant control on the snow surface energy balance (Elder et al 1998; Hock, 2003; Sicart et al., 2006; Anderson et al., 2014; Webster et al., 2016).

b. Objectives and dissertation outline

To answer our overarching question of: "<u>How does the surface energy balance, as measured by changes in snow-surface temperature, vary across mountain snow environments at the hillslope scale and over seasonal to diurnal time scales?</u>" this work will leverage geostationary and low Earth orbiting satellite imagery along with methods to extract sub-pixel temperature information to create high spatiotemporal resolution surface temperature maps for mountain study regions within the continental US. In this process we will address the following points in three chapters:

- Determine how the off-nadir views and coarse spatial resolutions of GOES-16 ABI bias surface temperature measurements over mountain terrain and how these biases change in space and over time.
- Apply a spectral separation method with GOES-16 and -17 ABI imagery to retrieve sub-pixel snow and vegetation temperatures, and evaluate how these observations represent the true temporal variability of surface temperatures from seasonal to diurnal time scales.
- Test methods of spatially downscaling GOES ABI imagery, in combination with low Earth orbiting satellite imagery and land surface features, to observe how mountain surface temperatures vary at both high spatial and temporal resolutions.

In Chapter 1 we evaluate off-nadir GOES-16 ABI thermal infrared imagery in comparison with coincident nadir-looking, moderate spatial resolution MODIS (1 km) and ASTER (90 m) thermal infrared imagery over three snow seasons in the central Sierra Nevada of California. We investigate: how GOES ABI surface temperature observations are biased due their view angle, the parallax effect, and large pixel sizes; how these biases vary across space in relation to terrain properties and forest cover; and how these biases vary over time in relation to changing snow cover.

In Chapter 2 we will assess how high temporal resolution GOES-16 and -17 ABI surface temperatures represent seasonal and diurnal temperature patterns. We will apply a spectral separation method, previously demonstrated with MODIS observations (Dozier 1981; Lundquist et al. 2018), to GOES ABI imagery to estimate separate snow and forest surface temperatures at 5-minute temporal resolution. These estimates will be compared against ground-based observations from Gaylor Pit and CUES (CRREL/UCSB Energy Site; Bair et al., 2015) in the Sierra Nevada of California, and from the NASA SnowEx 2020 campaign at Grand Mesa, Colorado.

In Chapter 3 we will test three methods of spatially downscaling GOES ABI imagery to the hillslope (~100 m) scale over the SnowEx 2020 Grand Mesa, Colorado study site. The first method (Kustas et al., 2003) relies on empirical relationships between GOES ABI imagery (visible through infrared), indices such as NDVI, and land surface properties such as terrain and fractional vegetation as explored in Chapter 1. The second is a "spatio-temporal fusion" method (Quan et al., 2018; Desai et al., 2021) that combines geostationary and low Earth orbiting satellite imagery to create empirical relationships between these observations for downscaling GOES ABI imagery. The third method combines either prior method with spectral separation from Chapter 2, downscaling surface temperature maps of snow and forest temperatures separately.

2. Chapter I: Evaluating GOES-16 ABI thermal infrared observation biases over the central Sierra Nevada of California

Co-authors: Jessica D. Lundquist

Status: Paper in preparation for submission to *Remote Sensing of Environment* (December 2021)

Abstract: Thermal infrared imagery from the latest generation of NOAA's Geostationary Operational Environmental Satellites (GOES) presents an opportunity to observe mountain surface temperatures over the full diurnal cycle, to better understand the surface energy balance, and in turn water fluxes through evapotranspiration, the timing and magnitude of snowmelt, or near-surface air temperatures. However, imagery from the GOES Advanced Baseline Imager (ABI) instrument are subject to off-nadir view angles, and coarse resolution pixels (≥2 km) that blur together the different surface temperatures of heterogeneous mountain landscapes such as snow and forests. We investigate how GOES-16 ABI thermal

infrared brightness temperatures are biased with respect to 90 m spatial resolution ASTER and 1 km spatial resolution MODIS imagery, and how these biases change over space and time for a study region in the central Sierra Nevada of California for the 2017-2020 snow seasons. We demonstrate the necessity of orthorectifying ABI imagery of mountain terrain to correct for the parallax effect in off-nadir imagery, which reduced the mean and standard deviation of temperature biases in this study by 0.6 and 1.5 °C respectively. How these biases vary across space are investigated with elevation, slope, aspect, and fractional vegetated area, while variations over time are investigated with changes in fractional snow cover. Understanding the controls on these biases will aid interpretation of the full high temporal resolution (5-minute) timeseries of ABI imagery for observing the diurnal cycles of mountain surface temperatures. This work provides a first look at using the latest GOES satellites for observing surface temperatures of forested mountain environments with seasonal snow.

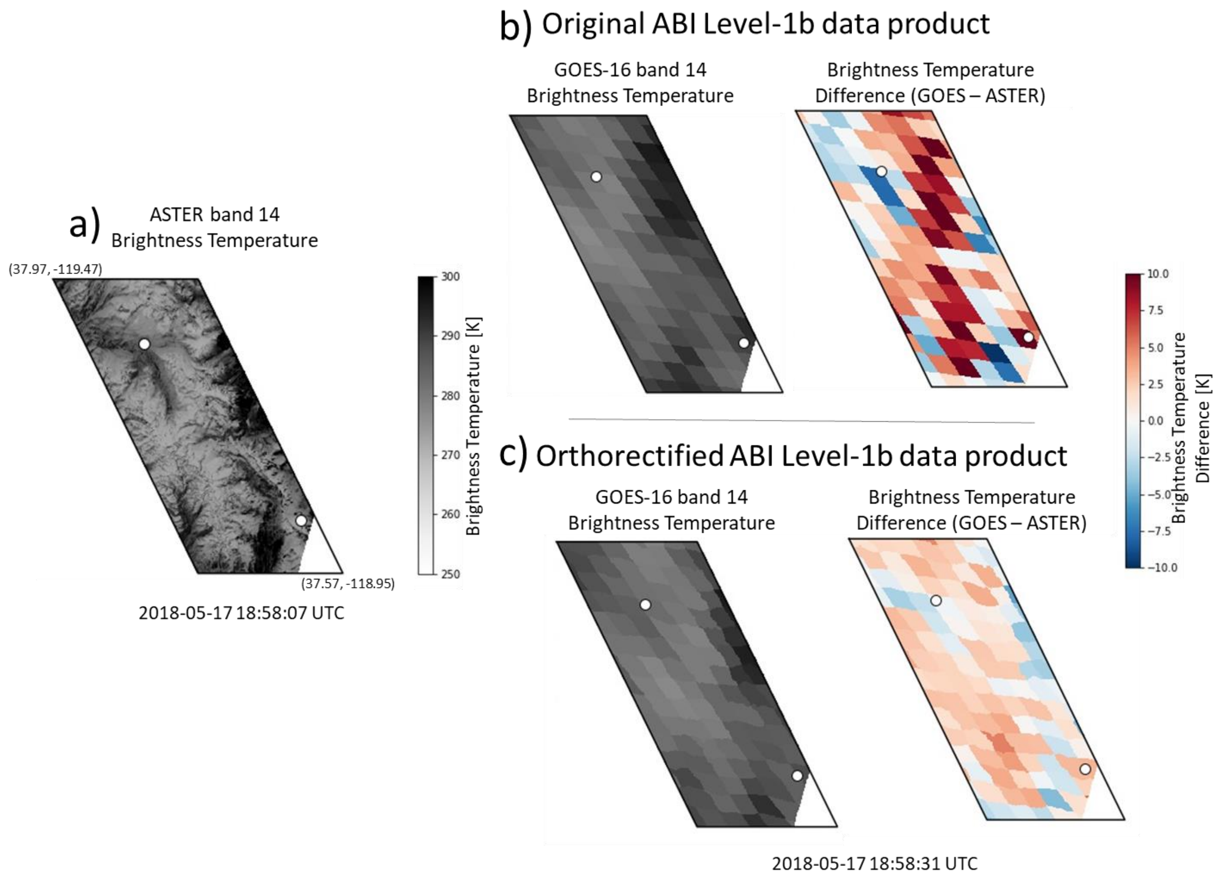

Figure 1. a) ASTER thermal infrared imagery used to evaluate the spatial distribution of biases in GOES-16 ABI thermal infrared imagery b) before, and c) after orthorectifying to correct for terrain parallax.

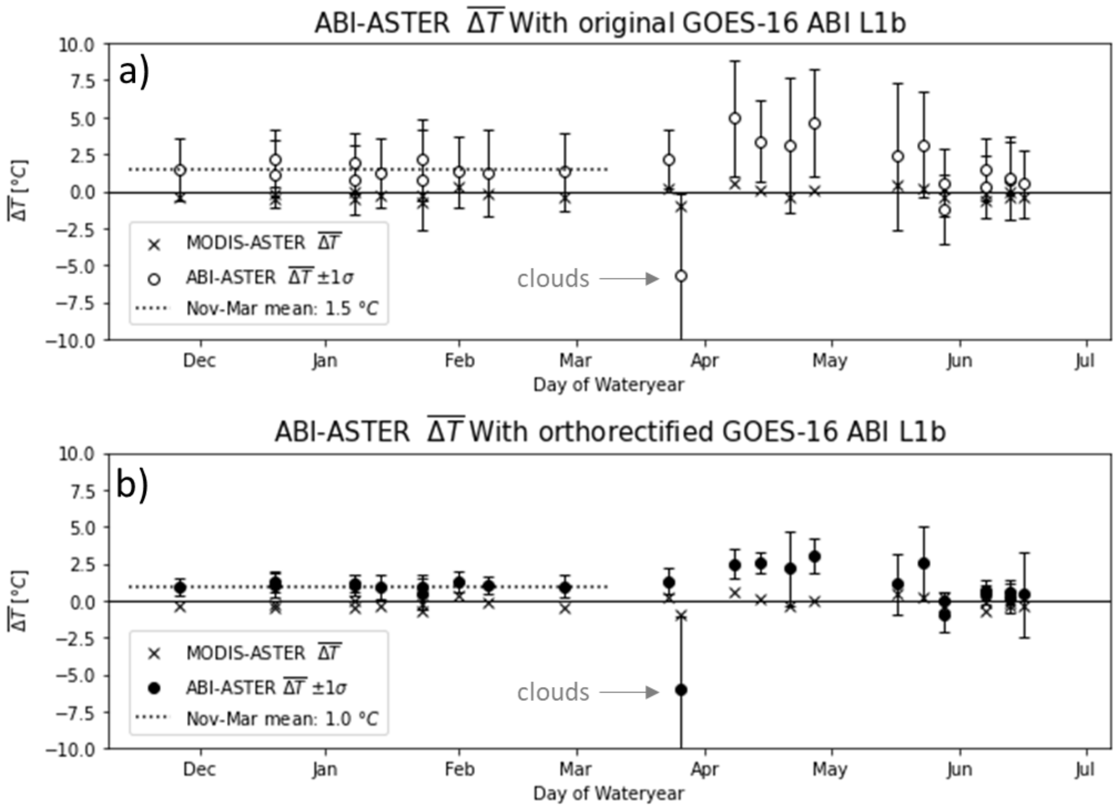

Figure 2. Mean and standard deviation of differences between GOES-16 ABI and ASTER thermal infrared brightness temperatures over the course of the snow season is compared a) before (○), and b) after (●) orthorectifying the ABI images. Results are presented alongside the mean bias between nadir-pointing MODIS and ASTER thermal infrared brightness temperatures (×).

3. Chapter II: Spectral separation of snow and forest temperatures from high temporal resolution GOES-16 and -17 ABI observations

Co-authors: Edward H. Bair*, Jessica D. Lundquist
* Earth Research Institute, University of California, Santa Barbara, CA, USA

Status: Work in progress; paper to be submitted by Spring 2022

a. High temporal resolution GOES ABI and ground validation data

Orthorectified GOES-16 and -17 ABI thermal infrared images at high temporal (5-minute) resolution from the 2017-2020 snow seasons will be compared against timeseries of ground-based observations at: Gaylor Pit within the upper Tuolumne River Basin (Figure 3a), the CUES study site at Mammoth Mountain (Figure 3b), both in California's Sierra Nevada, and the Grand Mesa study site from the SnowEx 2020 field campaign in Colorado (Figure 3c). How the coarse spatial resolution ABI images represent the diurnal temperature cycle and range, and how that varies over the course of the snow season at the three different sites will be investigated.

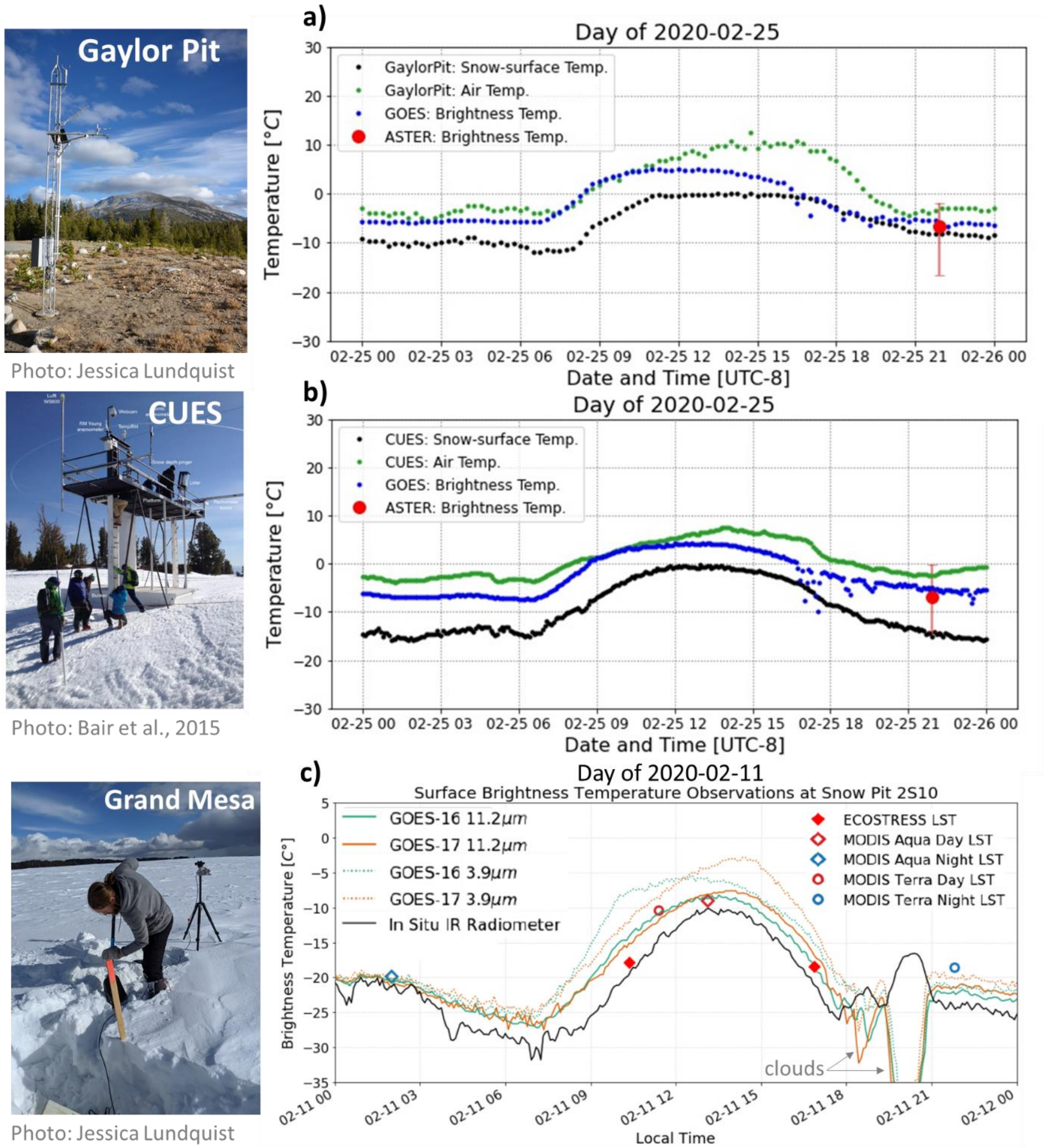

Figure 3. Examples of the high temporal resolution GOES ABI surface brightness temperature and ground-based surface temperature observations from February 2020 at a) Gaylor Pit and b) CUES in the Sierra Nevada of California, and at c) Grand Mesa in Colorado (which also shows GOES ABI midwave infrared, 3.9 µm, bands in dotted lines). (CUES photo from Bair et al., 2015)

b. Spectral separation of forest and snow temperatures with GOES ABI imagery

A spectral separation method for estimating sub-pixel snow and vegetation temperatures, previously applied with MODIS imagery (Lundquist et al., 2018), will be tested with these high temporal resolution GOES ABI observations to determine the method's efficacy at each of the three study sites with their differing topography, forest cover, climatology, and snow types. This method (Dozier, 1981) uses observations of the radiance emitted in midwave and longwave infrared bands (Figure 3c) to solve for sub-pixel temperatures, modeling each pixel as a linear combination of these sub-pixel temperatures weighted by their fractional areas (Figure 4). We will investigate which combination of bands provides sub-pixel snow and forest temperatures that match best with in situ observations at each site (ABI midwave IR band 7 (3.9 μm), in combination with longwave bands 13 (10.3 μm), 14 (11.2 μm), or 15 (12.3 μm)).

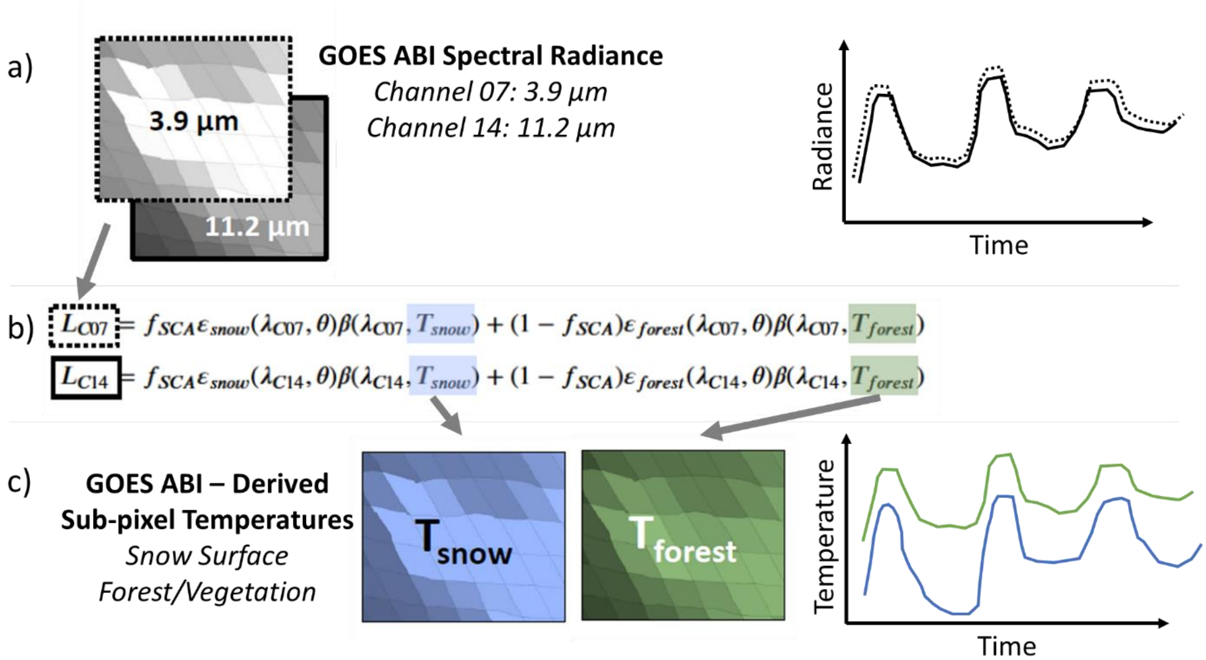

Figure 4. Conceptual flow-chart illustrating the spectral separation workflow with a) input midwave and longwave infrared spectral radiance from GOES ABI, b) the system of equations to be solved for each sub-pixel surface temperature over time, and c) the resulting sub-pixel temperatures for snow and forest/vegetation. (Equations and parts of figure adapted from Lundquist et al., 2018)

4. Chapter III: Downscaling GOES ABI observations for high spatio-temporal surface temperature maps during the SnowEx 2020 field campaign

Co-authors: C. Chris Chickadel*, Jessica D. Lundquist
* Applied Physics Laboratory, University of Washington, Seattle, WA, USA

Status: Ideation

a. Validation data from SnowEx 2020

In Chapter 3 we will test three methods of spatially downscaling GOES ABI imagery to the hillslope (~100 m) scale over the SnowEx 2020 Grand Mesa, Colorado study site. During the SnowEx 2020 field campaign, in addition to ground validation temperature data (Figure 3c), ~5m spatial resolution airborne infrared imagery was collected coincident with GOES ABI, ASTER, MODIS, and ECOSTRESS observations on two days (Figure 5). These very high spatial resolution surface temperature maps, along with the timeseries of point temperature measurements, will serve as our ground truth for testing three methods of downscaling GOES ABI thermal infrared imagery.

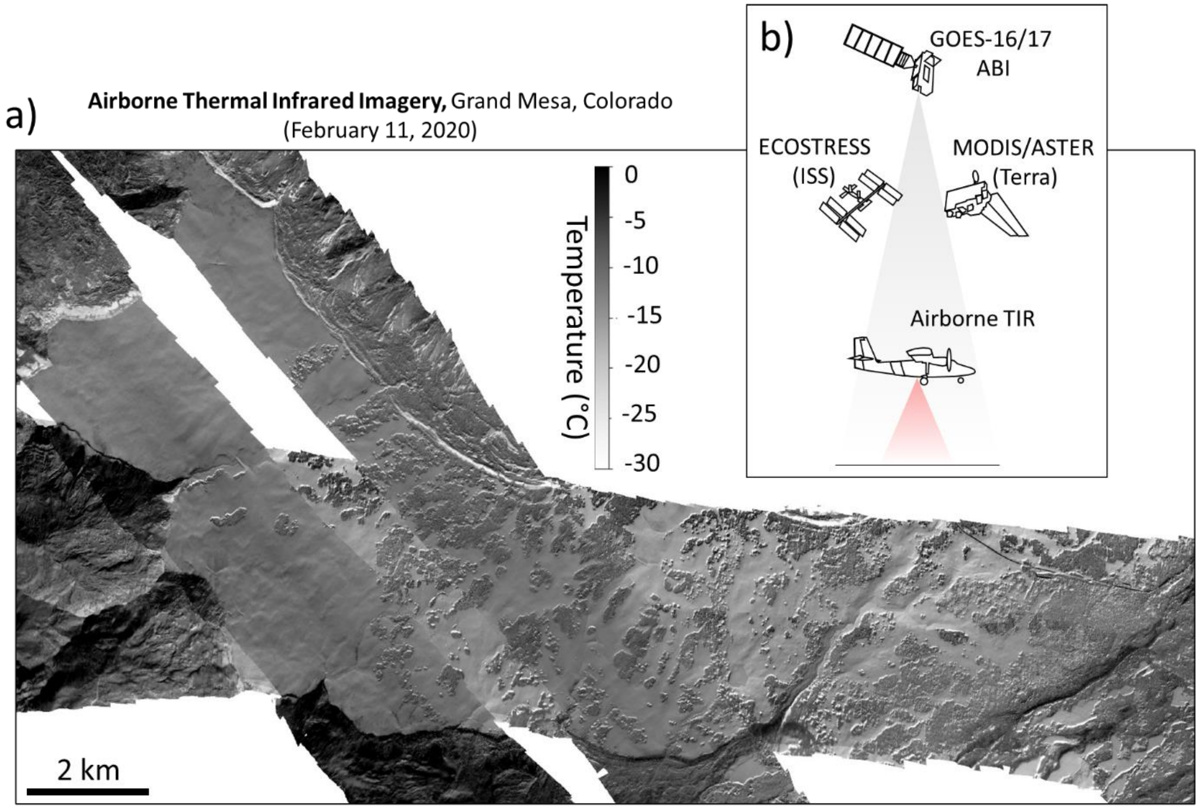

Figure 5. a) Mosaic of airborne thermal infrared imagery collected over Grand Mesa, Colorado on February 11, 2020 as part of the SnowEx 2020 field campaign. b) Conceptual diagram of the airborne and satellite thermal infrared imagery collected simultaneously during SnowEx 2020.

b. Summary of potential downscaling methods

Method 1: We will first test a downscaling method that requires only the high temporal resolution GOES ABI thermal infrared observations. We will test downscaling ABI images using empirical relationships between the thermal infrared, finer resolution VSWIR observations from GOES ABI, indices derived from these VSWIR images (e.g. NDVI), or other land surface properties (such as elevation, slope, aspect, fractional vegetation, or snow cover investigated in Chapter 1). These empirical relationships for downscaling thermal infrared imagery have been modeled using multilinear regressions (Kustas et al., 2003; Inamdar et al., 2008; Weng et al., 2014), random forest regressions (Walters et al., 2013), support vector machines (Keramitsoglou et al., 2013), or principle component analysis (Zakšek et al., 2012). We will investigate which, if any, empirical relationships allow us to downscale GOES ABI imagery to the ~100 m spatial scale, as well as the functional form of those relationships.

Method 2: This “spatio-temporal fusion” downscaling method uses empirical relationships between coincident surface temperature observations from two or more satellites at different spatial and temporal scales. We will use thermal infrared observations from ECOSTRESS, and/or ASTER (Figure 6a), to provide the finer “hillslope” (~100 m) scale spatial patterns of surface temperatures at 3-16 day repeat intervals, to downscale GOES ABI thermal infrared imagery (Figure 6c). The inclusion of moderate spatial resolution imagery (1000 m) from MODIS Aqua and Terra will also be tested (Figure 6b). We will also test how frequent these empirical downscaling models needs updating, especially during the late snow season as the fractional snow covered area decreases. These downscaling methods have been demonstrated over semi-arid vegetation and mountains (Zhu et al., 2010; Yang et al. 2016; Wu et al.

2015), and flat agricultural or forest regions (Quan et al., 2018; Desai et al., 2021), but not yet over mountain forests and snow.

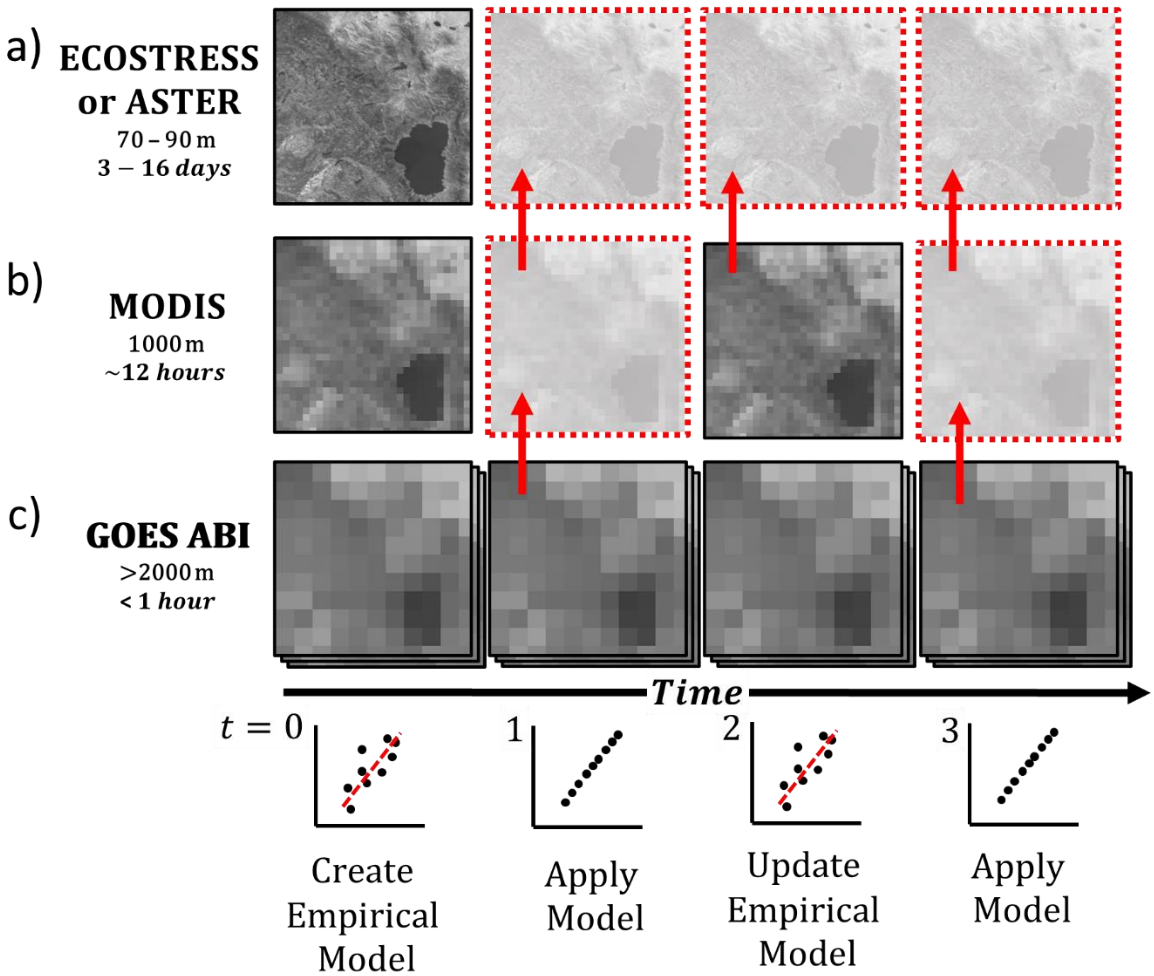

Figure 6. Conceptual diagram of a spatio-temporal fusion model using three resolutions of satellite observations (a, b, and c) at four steps in time (0-3). The resulting downscaled imagery fills the temporal and spatial resolution gaps outlined in red. (Thermal infrared image shown for illustrative purposes is from ECOSTRESS over Lake Tahoe, California)

Method 3: The third method would apply one of the prior methods to snow and forest temperature maps derived through spectral separation. We will first use GOES ABI midwave and longwave observations to spectrally separate snow and forest temperatures, but rather than for single pixels as in Chapter 2, for the entire Grand Mesa study area. These separate snow and forest temperature images will then be used to train empirical downscaling models with either VSWIR or land surface properties (as in the first method), or with higher spatial resolution surface temperature maps (as in the second method).

5. Research Timeline

Milestone	*Date*
General Examination	November 8, 2021
Submit Ch. 1 paper to RSE	Fall Qtr. 2021
AGU presentation on Ch. 1	December 14, 2021
Submit Ch. 2 paper	Spring 2022
Conference presentation on Ch. 2	Summer or Fall Qtr. 2022
Submit Ch. 3 paper	Winter or Spring Qtr. 2023
Final Examination	Spring Qtr. 2023
Graduation	Spring Qtr. 2023

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