

LINKING SURFACE TEMPERATURES TO PAST ENVIRONMENTS ON MARS
THROUGH REMOTE SENSING, MODELING, AND ANALOG STUDY

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ABSTRACT

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Infrared imagers orbiting Mars have collected an astoundingly complete record of surface temperatures spanning over five decades. Because the physical nature of different rocks and sediment affect how quickly they can heat up or cool down, temperature measurements provide a valuable tool for studying geology in areas where ground measurements are limited or absent. Inferred sedimentary features can be used to help interpret past environmental processes, which for Mars inform us as to whether habitable conditions might have once existed at the surface. However, the task of directly quantifying how a given temperature response aligns with a sediment type, and thus past environmental setting, faces numerous challenges. Combinations of surface materials lead to nonunique thermal signals, and uncertainties associated with orbital remote sensing add to the difficulty. This dissertation is an effort to expand the limits of thermophysical interpretation of Martian sedimentary deposits. Progress is achieved through three distinct projects that incorporate remote sensing observations, thermophysical modeling, and experiments at Mars analog sites on Earth. The result is both a new approach to conducting thermophysical studies on Earth as well as new insights into the nature and formation of materials on the Martian surface. These advances build on decades of research into thermophysical processes and take an innovative step that opens the door to a new generation of investigations to come.

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Thinking back on the past five years since starting work as a Ph.D. student at NAU, I can truly say I have undergone a transformation both in how I think about and approach science and in how I think about and approach my life. It was a turbulent, but ultimately triumphant journey, and if I know anything for certain after reaching this point in my career, it's that I couldn't have made it here without the assistance, advice, friendship, love, and support of many individuals.

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CHAPTER 1

INTRODUCTION

Satellite-derived surface temperature measurements of Earth and Mars date back to the 1960s, when the Television InfraRed Observation Satellites (TIROS) and Mariner probes first began collecting infrared radiometer data from orbit (Astheimer et al., 1961; Neugebauer et al., 1971). Since then, numerous instruments, including the Thermal Emission Imaging System (THEMIS) (Christensen et al., 2002) and Thermal Emission Spectrometer (TES) (Christensen et al., 2001) for Mars and the Landsat Thermal Infrared Sensors 1 and 2 (TIRS/TIRS-2) (Reuter et al., 2015) for Earth, have relied on thermal infrared imaging spectroscopy ($\sim 7\text{-}25\text{ }\mu\text{m}$) to map out temperatures over multiple seasons and times of day. These efforts have yielded pivotal insights into the nature of the Martian crust and atmosphere and into climate dynamics and ecological processes on Earth (Prata et al., 1995; Golombek et al., 2008; Rangarajan et al., 2018; Good et al., 2022).

Sedimentary deposits on Mars have been a major focus of imaging campaigns because of their potential to have recorded past climates and surface environments. Surface conditions are thought to be strong indicators as to whether Mars was once habitable for water-based life and yield insights into similarities with early Earth, at the time when life first arose (Bandfield et al., 2013; Cabrol et al., 1999; Carter et al., 2015; McKay, 2010). *In situ* observations Mars' surface have provided extraordinary details that lay a framework for the types of deposits that might exist across the rest of the planet (Table A-1). The Opportunity rover has observed bedded eolian deposits in Meridiani Planum (Edgar et al., 2012; Grotzinger et al., 2005; Squyres et al., 2006), the Curiosity rover has analyzed mudstones (Grotzinger et al., 2015; Hurowitz et al., 2017), fluvial sandstones (Edgar et al., 2018), and conglomerates (Mangold et al., 2016; Williams et al.,

2013) in Gale crater (Rampe et al., 2020), and the Perseverance rover is investigating a large fluvial delta (Goudge et al., 2017; Williford et al., 2018). These Martian deposits, which have gone largely unchanged in the last 2 billion years, provide a window into the types of sedimentary processes that were possible, given the inner solar system dynamics, around the time that complex life was forming on Earth.

The physical, textural, mineralogical, geochemical, and isotopic properties of sediments and sedimentary rocks on Earth have painted detailed pictures of the diverse biological, structural, and climatological history of our planet (Hutton, 1795; Leeder, 2011) (for a list of prominent methods, see *Leeder, 2011* and *McLennan et al., 2019*); and our relatively small collection of Martian samples have begun to do the same (Kite, 2019; McLennan et al., 2019). Despite the increasing number of rovers, however, on Mars our interpretations of the vast majority of the surface are still limited primarily to what we can decipher from orbit. For this reason, orbitally derived measurements like surface temperature have become important proxies for deciphering the rock record (M. T. Mellon et al., 2009).

Ground heat flux and surface temperature are controlled by a material property called thermal inertia (TI), which is a function of thermal conductivity (k), density (ρ), and specific heat capacity (c_p) as follows $TI = \sqrt{k\rho c_p}$ typically in units of $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$. Because TI is controlled by the physical structure of a rock, sediment, or soil, estimating its value using temperature data can be a valuable tool for interpreting geology and surface features remotely in a manner that complements other remote sensing tools.

For Mars, TI is usually derived from nighttime thermal infrared imagery, which is less influenced by slope and albedo effects than daytime imagery (Edwards et al., 2018; Fergason et al., 2006b; Kieffer, 2013). From emission-derived temperatures, numerical thermal models, such as

KRC (Edwards et al., 2018; Fergason et al., 2006b; Kieffer, 2013), fit TI by considering the energy flux in the system and observing conditions (controlled by, for example, solar irradiance and azimuth, atmospheric opacity and radiance, surface albedo, elevation, slope, and aspect). For geologic materials, higher TIs are traditionally associated with coarser-grained deposits, indurated surfaces, liquids, and bedrock. Thermal Emission Imaging System (THEMIS) observations of bedrock materials yield TI values from ~ 500 to $>1200 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ (Christensen et al., 2013; Edwards et al., 2009; Rogers et al., 2018). Cohesionless dust (grain size approximately $< 40 \text{ }\mu\text{m}$) generally shows TIs of $40\text{-}150 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ (Fergason et al., 2006b). Much of Mars' sedimentary deposits show surface TIs lying in the intermediate range of $200\text{-}450 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$. Due to the multitude of factors that cause bulk TI to vary across this range, interpretations of modeled TIs in this range also vary broadly (Figure 1-1).

A critical gap remains in our knowledge of the magnitude and extent of deposition and alteration processes likely to have been active on ancient Mars. A detailed mathematical understanding of how thermophysical properties relate to the morphological, textural, and compositional signatures of weathering for sedimentary deposits offers a means to address that missing information. Filling the knowledge gap over what intermediate TI values represent for the histories of sedimentary deposits on Mars and uncovering new insights into Mars' geologic past were the primary motivators for the research objectives in this dissertation.

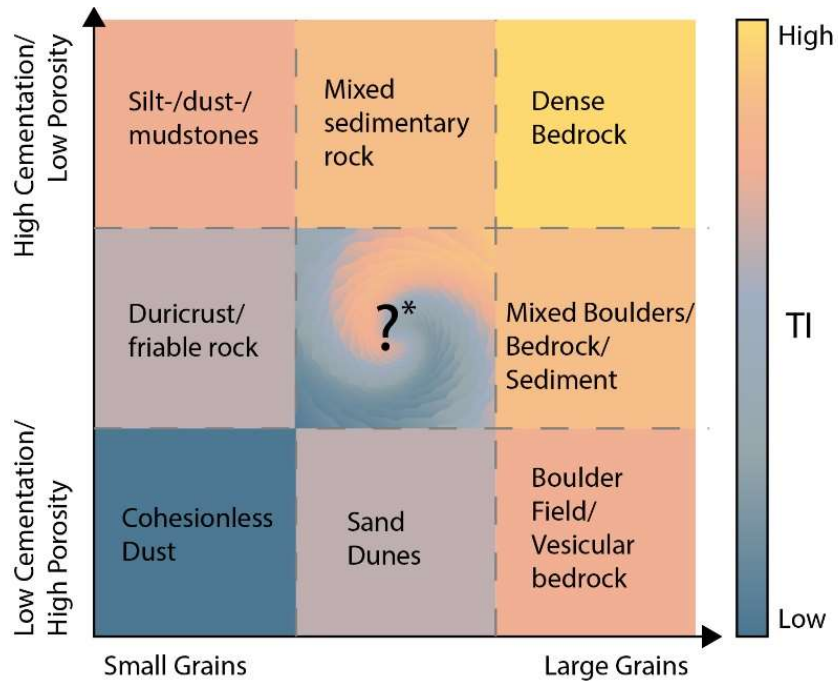


Figure 1-1. Conceptual depiction of the thermal inertia trends on Mars with the knowledge gap at the center. *Center square appears to include many of the environment-informing sedimentary deposits on Mars, as viewed from orbit.

This dissertation’s next three chapters aim to address some of the outstanding challenges for thermophysical data interpretation. Each chapter is written to be a stand-alone scientific manuscript. In Chapter 2, the current state-of-the-art in Mars remote sensing datasets were used to study the intriguing, but notably obscured-by-dust, layered sedimentary deposits that proliferate Mars’ Arabia Terra region. There, I disentangle the relationships between thermal inertia, mineralogy, and erosion susceptibility by quantifying cohesion for layered deposits in the Arabia Terra region. I demonstrate that variations in dust cover associated with relative erodibility and aeolian abrasion can be inconspicuous controls on apparent thermal inertia, and I ultimately find that these deposits are not as cohesive as would be expected from a high water-to-rock ratio setting either during or after deposition.

In addition to the scientific interpretations, one of the major outcomes of that project was a realization of the potential for TI to pick out nuanced trends in surface materials and processes that were previously considered too complex to address. How we interpret apparent TI values in the $200\text{--}450\text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ range appears to depend largely on context. Although we have a decent understanding of the individual controls on TI, a comprehensive model that incorporates context into our understanding of TI for heterogeneous surface environments has been missing. These insights led to the formulation of an experimental procedure that is explored in Chapters 3 and 4.

In Chapter 3, I provide an original approach for deriving thermal inertia on Earth. I address the challenge of deriving a quantitatively precise TI using nadir imagery and without causing surface disturbance – an achievement previously considered too complicated by Earth’s atmosphere and hydrologic cycle to attempt. That achievement was made possible by new advances in high cadence weather instruments paired with elements from numerous models, including ones that had previously only been applied to other worlds. The outcomes of that effort have wide ranging utility on both Earth and Mars, at the surface and from orbit.

The success of the work in Chapter 3 enabled a robust multivariate study that is detailed in Chapter 4. In that section, the model and field methods are extended to a total of eight field sites in order generate an unprecedented dataset of thermal inertia, and spectral and physical properties for a diverse range of sediments relevant to Mars’ surface. A multivariate analysis approach was employed to uncover the relationships between thermal, spectral, and physical traits, reinforcing known understandings and revealing new interpretations of controls on thermal inertia relevant to Mars. Those results provide updated insight into which observations to use in tandem with TI to estimate the formation and alteration histories of sediments on Mars, and we demonstrate the utility of that model in tests using data from sites on Mars and Earth.

Together, these three works demonstrate a five-year thought process on how our understanding of the physics of heat transfer can be used to study geology on Mars. The effort has employed theory, observations, and modeling that build on decades of thermophysical studies from Mars and Earth. The result is a functional roadmap to potentially reshaping our understanding of the conditions that have formed and altered large swaths of the Martian surface.

CHAPTER 2

MANUSCRIPT I: A FRAGILE RECORD OF FLEETING WATER ON MARS

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2.1. ABSTRACT

The light-toned sedimentary layers that outcrop widely throughout Mars' Southern Highlands have long been an enigma in uncovering the climatic history of Mars. Although these units seem to contain unique records of fluctuating surface conditions, the role of water in their formation is debated. A distinctive property of many such deposits is their elevated thermal inertia relative to that of surrounding materials. This temperature-controlling trait is often interpreted to indicate induration resulting from aqueous processes. However, prevalent erosional landforms suggest that the deposits host much weaker materials than neighboring units. We address this apparent contradiction by disentangling the relationships between thermal inertia, mineralogy, and erosion susceptibility and by quantifying the cohesion of layered deposits in the Arabia Terra region. We demonstrate that variations in dust cover associated with relative erodibility and eolian abrasion can be inconspicuous controls on apparent thermal inertia. We ultimately find that these deposits are not as cohesive as would be expected from a high water-to-rock ratio setting either during or after deposition. If water-rich surface conditions existed in the region after the Noachian, these deposits suggest they may have only been intermittent and fleeting.

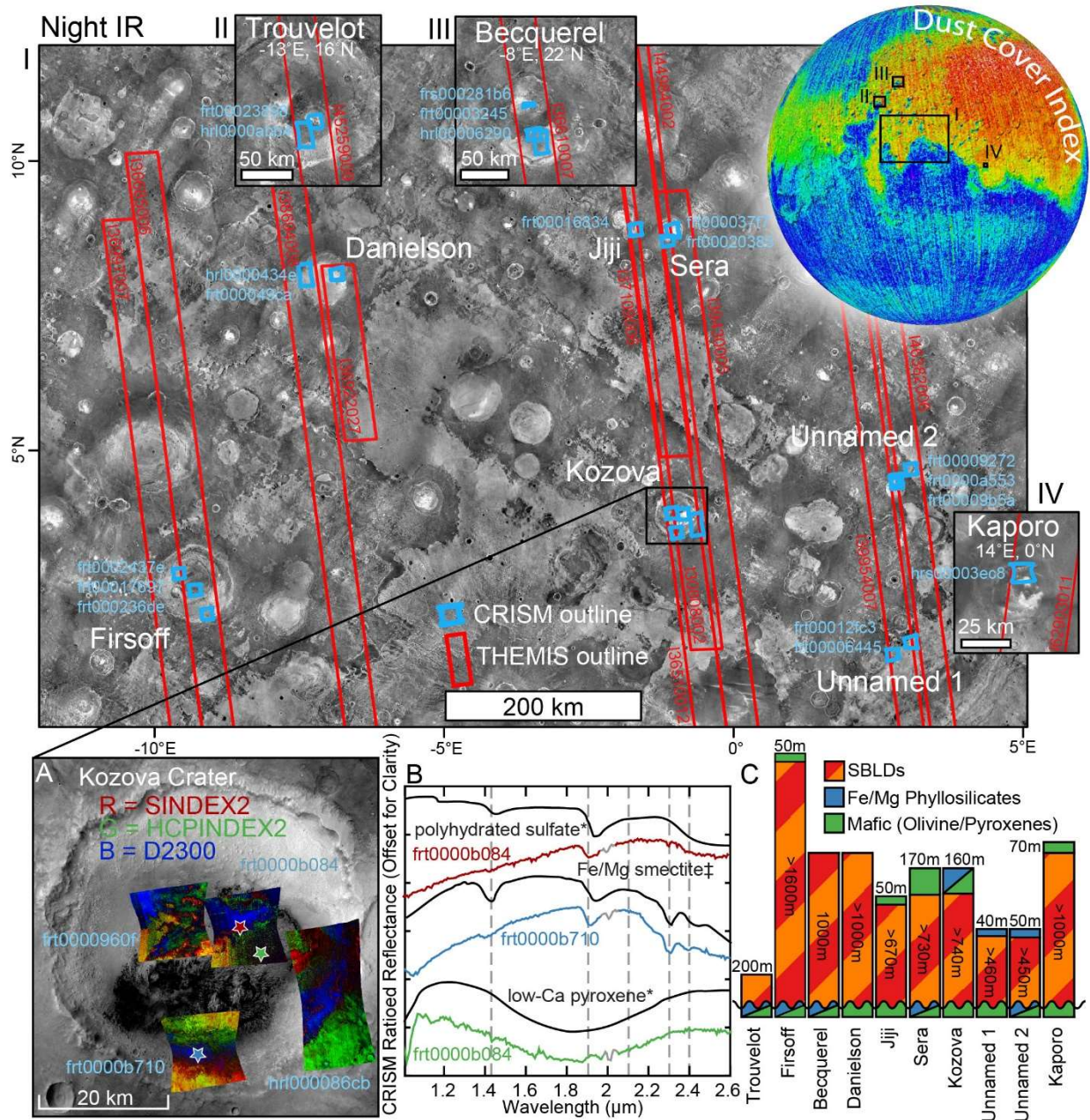
2.2. INTRODUCTION

Decameter-scale rhythmically-bedded layers are exposed within craters throughout Arabia Terra, mapping out a rich chronology of depositional surface environments that date back to the Noachian (Lewis and Aharonson, 2014; Hynek and Di Achille, 2017). Because deposition appears to have occurred in recurring episodes over millions of years (Lewis and Aharonson, 2014), these units likely record key tracers of a Martian climate in flux. Orbital observations consistently show hydrated minerals, including polyhydrated sulfates (Wiseman et al., 2010), hinting at past interactions with water. Nonetheless, without *in situ* measurements of these sulfate-bearing layered deposits (SBLDs), their physical properties and origins have remained obscure.

Elevated apparent thermal inertia (TI) in the SBLDs relative to surrounding units was previously thought to reflect enhanced induration (e.g., Ferguson and Christensen, 2008; Andrews-Hanna et al., 2010) since TI increases with cementation (Piqueux and Christensen, 2009). However, these sediments enigmatically tend to lack embedded craters and show widespread erosional landforms suggestive of relatively high erosion rates (Lewis and Aharonson, 2014). Since dust cover often masks the TI of underlying rock (Edwards et al., 2011), one explanation is that dust is heterogeneously accumulating in the region (Rogers et al., 2018). If materials surrounding the SBLDs are mantled by thicker dust deposits than the SBLDs, the relative difference in apparent TIs may not actually reflect greater SBLD induration.

Here, we expand on previous efforts to determine the style and extent of depositional processes in Arabia Terra by examining controls on the contrasting remote sensing observations. We first quantify the relationship between dust cover and TI for different surface types within large craters using orbital datasets. We then investigate the physical conditions leading to apparent TI

heterogeneity in dusty regions by considering predicted wind patterns, small crater densities, failing slope geometries, and ultimately by drawing analogies to materials measured *in situ* on Mars' surface.



al., 2014) and B) characteristic ratioed CRISM spectra from the identified units, shown with laboratory reference spectra *Viviano-Beck et al. (2014) ‡Wiseman et al. (2010). Spectra were acquired from the locations of like-colored stars in A. C) Columns showing identified units labelled with local thicknesses.

2.3. DEPOSITIONAL SETTING

While hydration-related spectral absorptions accompany the SBLDs (Wiseman et al., 2010), the extent to which water contributed to their deposition is debated. Hydrated minerals, elevated TIs, and basin-filling morphologies have led some studies to propose origins in playa, lakebed, or groundwater spring settings under persistent water-stable conditions (Wiseman et al., 2010; Zabrucky et al., 2012; Pondrelli et al., 2019). Indeed, models indicate a deep groundwater supply could have lasted in the region through the end of the Noachian (Andrews-Hanna et al., 2010). Nonetheless, mineral hydration and basin filling are not unique to aqueous deposition (Michalski and Niles, 2012), and groundwater activity does not necessitate persistent nor high water-to-rock ratios (Kite, 2019). Several observations seem instead to challenge a fully aqueous deposition model. Consistent layer thicknesses and exposures of layered deposits outside topographic lows suggest these deposits stem from depositional processes with regional extent (Lewis and Aharonson, 2014; Hynek and Di Achille, 2017; Annex and Lewis, 2020), contrary to expectations for individual paleolake basins. Shallow, topography-conforming layer inclinations (Annex and Lewis, 2020) and central-mound landforms comprising many SBLDs are also inconsistent with the horizontal layers or spring-like heaps expected in a water-fed system (Kite et al., 2013; Pondrelli et al., 2019).

As an alternative, several airfall sources have been proposed, including impact processes (Knauth et al., 2005), pyroclastic ejecta (Hynek and Di Achille, 2017), and aeolian deposition (Day and Catling, 2019). Without an aqueous depositional setting, hydration and weak cementa-

tion might occur from vapor diffusion (Bridges and Muhs, 2012), diagenesis (Fraeman et al., 2016), and/or ice sublimation (Michalski and Niles, 2012), similar to sulfate-bearing layers at Mars' poles. Generally, processes involving submergence in pooled water induce higher degrees of cementation than those involving sublimated ice or vapor (Bridges and Muhs, 2012), while diagenetic cementation varies with water-to-rock ratio (Kite, 2019). Since pore-filling cements have a strong influence on TI (Piqueux and Christensen, 2009), improving interpretations of TI in these deposits adds an integral constraint on their formation and alteration.

2.4. THE EFFECT OF DUST ON THERMAL INERTIA

Spectrally-derived dust maps of Arabia Terra (e.g., Ruff and Christensen, 2002) show widespread dust cover except in isolated patches (Figure 2-1). At >2 km/pixel, however, such maps lack the spatial resolution required to differentiate units within the region's crater basins. We identified 10 craters at the southwestern margins of the dustier central region of Arabia Terra where SBLDs appear in 18-36 m/pixel Compact Reconnaissance Imaging Spectrometer for Mars (CRISM) data (Figure 2-1). At each location, we paired 100 m/pixel Thermal Emission Imaging System (THEMIS) TI (Edwards et al., 2011) with CRISM band parameter maps (Viviano-Beck et al., 2014) as inputs to a clustering model (see Appendix 2A) to classify surface units (Figure 2-2) and quantify how TI differs between regions of different spectral character. The classified units reflect a similar set of units identified previously in the region (Edgett, 2002; Wiseman et al., 2010; Zabusky et al., 2012), including SBLDs, clay-bearing crater floors and rims, and mafic capping materials (Figures 2-1 & 2-2).

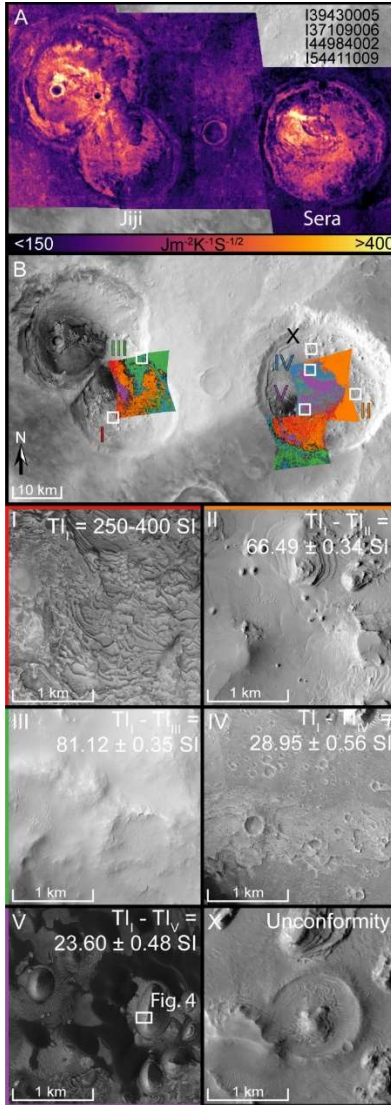


Figure 2-2. Images of Sera and Jiji craters with A) THEMIS TI and B) classification maps over CRISM stamp areas with colors linked to inset outlines. Insets show HiRISE imagery examples of classified surface units labelled with the difference in mean TI between that unit and the least dusty SBLDs. Units are I) least dusty SBLDs, II) dust-mantled SBLDs, III) smooth crater wall, which blends into the capping unit, IV) cratered floor unit, and V) mafic dune forms and sand sheets. The white rectangle indicates the location of slope failure analysis in Figure 2-4. X) A superposed crater showing the unconformable contact between units I and IV.

While SBLDs are characterized by sharp $1.9 \mu\text{m}$ and modest $2.4 \mu\text{m}$ absorption features, the majority of surrounding units, regolith, and apparently dusty layers display a broad pyroxene spectral absorption spanning $1.4-2.4 \mu\text{m}$ (Figure 2-1). SBLDs showing distinct sulfate absorp-

tions averaged TIs of $\sim 250\text{-}400 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ (hereafter SI). We note that because image-to-image uncertainty (up to 50 SI) is much larger than pixel-to-pixel uncertainty ($\sim 10\text{-}20$ SI) (Ferguson et al., 2006; Edwards et al., 2011), the differences in TI between neighboring units can be more useful for exposing regional trends than reporting absolute values alone (Figure 2A-1). At each sample site, SBLDs with distinct sulfate absorptions averaged 66.49 ± 0.34 SI higher than SBLDs missing those features and 28-89 SI higher than crater floor and wall units. Lower TI regions also showed fine-scale smooth surface textures that conform to topography (Figure 2-2), which we infer to reflect a dust mantle.

To place the potential effect of dust on TI in context, models show dust layers 40-200 μm thick can reduce bedrock surface TIs by as much as 200 SI (Edwards et al., 2011). At our easternmost site, Kapor crater, TIs reach as low as ~ 50 SI, consistent with a dust layer of at least a few cm thick (Piqueux and Christensen, 2009). When comparing dust-covered SBLDs to nearby low-albedo sand dunes, TIs averaged 33.63 ± 0.51 SI higher for the sand, reinforcing that even thin cover from dust-sized sediment lowers TI to values beneath that of sand-sized sediment (Golombek et al., 2008; Piqueux and Christensen, 2009).

2.5. DIFFERENTIAL WEATHERING

Two questions remain: why do some SBLDs retain less dust than surrounding units? And what dictates where dust is being removed? One possibility is that mechanical differences between each unit are leading to differential erosion, and erosion in some SBLDs is outpacing the rate of dust accumulation.

Modern erosion of Mars' layered sedimentary rocks is enhanced by wind stress and saltating particles (Bridges et al., 2012). Using prevailing wind directions from atmospheric models

(Toigo et al., 2012) and observational indicators of aeolian direction (e.g., Edgett, 2002), we estimated the spatial distribution of erosional stress within each crater (Figures 2-3 & 2A-2). Fiercer erosion is anticipated for wind-facing slopes (Day et al., 2016), areas impacted by slope winds (Kite et al., 2013), and downwind of saltating sand deposits (Edgett, 2002; Bridges et al., 2012). Although this approach to identifying higher-stress surfaces is qualitative, layered terrain in those zones was consistently 50-200 SI greater than other intracrater areas. In Sera crater, a wind-facing slope of a mounded portion of the crater floor unit (Figure 2-3) shows notably high TIs (>500 SI) and few craters, indicating this may be one of the few areas where the erosional force is strong enough to resurface that material.

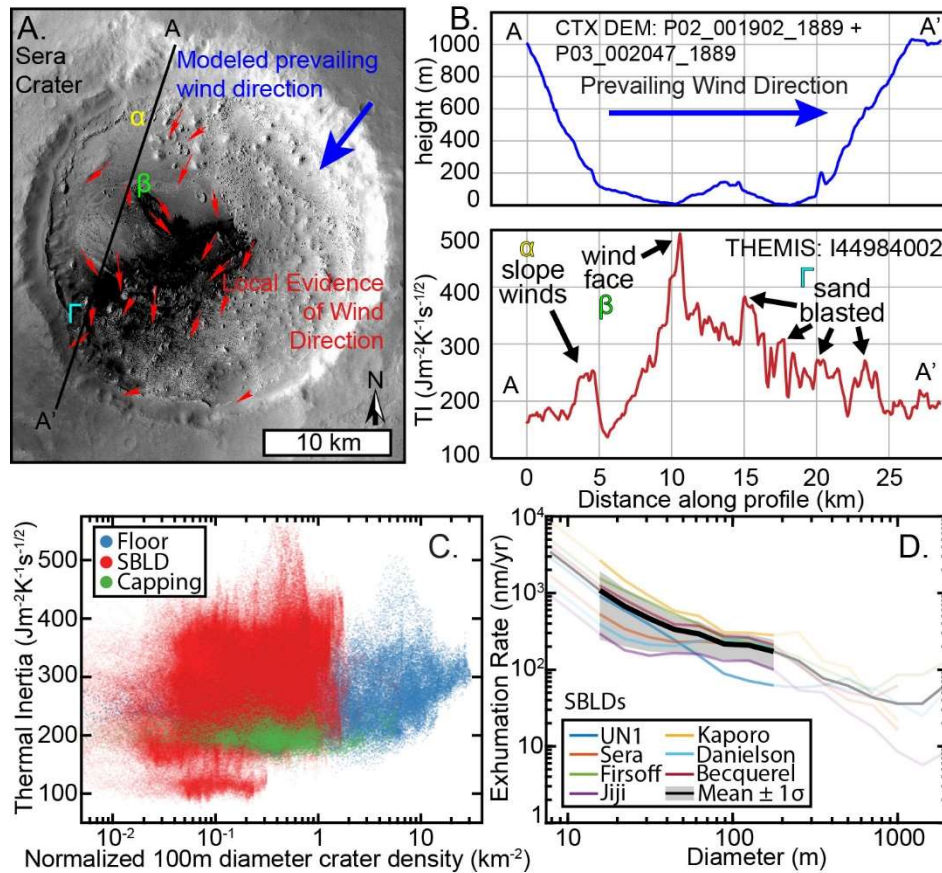


Figure 2-3. Surface features used to study local controls on apparent TI. A) CTX map of Sera crater with blue arrow showing modeled wind direction (Toigo et al., 2012) and local wind directions in red inferred from yardang orientations, wind streaks, ripple orientations, and dune orientations (see Appendix 2A). Greek letters indicate locations of enhanced aeolian stress labelled in

panel B. B) Topography (top) and TI (bottom) along profile, showing TI spikes in areas of elevated anticipated erosion. C) Crater density and TI data from the 7 craters listed in D, colored by surface unit. Each point represents one THEMIS pixel area. Details on crater density sampling are given in Appendix 2A. D) SBLD exhumation rates derived from the divergence of observed crater densities from the expected crater production function, following Kite and Mayer (2017). Grey area is the 1σ range on the mean. It is constrained between 22 m diameter by the limit of crater identifiability and 177 m by crater size frequency distribution inflection points.

Another useful indicator of erosion history is the divergence of observed crater distributions from expected crater production functions (Kite and Mayer, 2017). While crater densities can differ based on age and non-erosional processes, the similarity in expected unit ages (Hynek and Di Achille, 2017) and stark differences in crater densities (Figure 2-3) point to exhumation as a likely control.

Assuming steady exhumation, we use a model (Kite and Mayer, 2017, see Appendix 2A) for deriving SBLD erosion rates from crater densities in seven crater basins (Figure 2-3). Determining a precise erosion rate for the crater floors is difficult since crater superposition suggests prolonged burial (Figure 2-2). However, average >20 m diameter crater density is similar to what is observed for bedrock in nearby Meridiani Planum (Golombek et al., 2014), implying that the long-term erosion rates of 1-10 nm/yr derived there may be similar. The resulting mean estimate for SBLDs was 131-1088 nm/yr, in line with prior upper estimates of ~ 1000 nm/yr for other layered deposits in Arabia Terra (Smith et al., 2008) and weakly indurated materials in Meridiani Planum (Golombek et al., 2014). Given Mars' low atmospheric pressure, such high rates in the SBLDs must reflect a combination of locally heightened erosional forces and/or notable friability (Bridges et al., 2012).

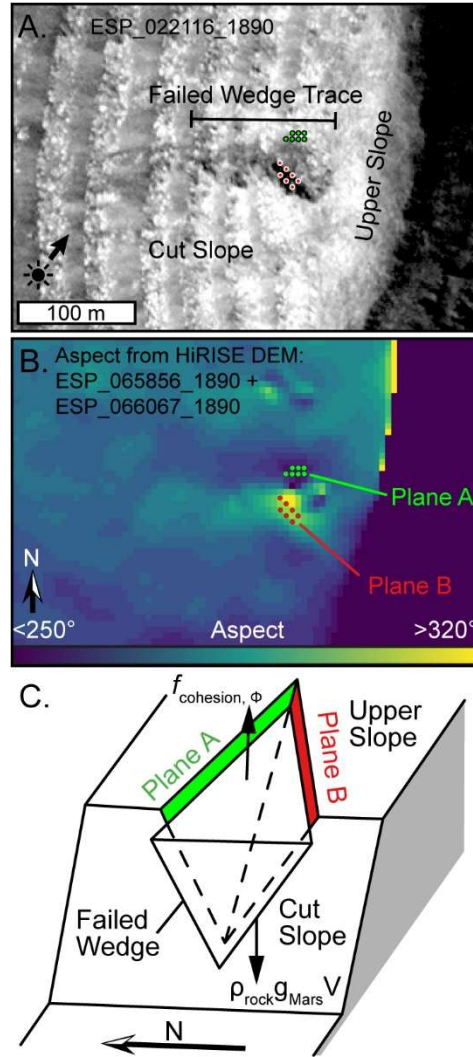


Figure 2-4. A failed slope wedge with points used to calculate failure plane geometries for cohesion derivation in A) HiRISE imagery and B) slope aspect map. C) Cartoon depiction of a wedge and the balancing gravitational and cohesive forces.

To understand if enhanced erosion of the SBLDs relates to rock strength, we applied material failure criteria, as outlined in Wyllie and Mah (2004), to derive rock mass cohesion. We measured the geometries of failed slopes at HiRISE image scales (Figure 2-4 and Appendix 2A), limiting the approach to outcrops showing evidence of failure at ≥ 50 m scales. For circular-style failures, we derived an estimate of $\sim 35 \pm 10$ kPa for the upper limits of SBLD cohesion. Using more precisely measurable wedge failure surfaces, we derived cohesions ranging from 0.13-17.9

kPa. These values are consistent with various forms of surface-crustal regolith measured *in situ* at Meridiani Planum and other mission landing sites (Golombek et al., 2008). For comparison, analog tensile strength measurements of sedimentary rocks in Gale crater (Kronyak et al., 2020), which complement prior *in situ* unconfined compressive strength measurements (Peters et al., 2018), yielded estimates of 30-100 kPa for Murray mudstone drill sites and 5,000-20,000 kPa for Stimson sandstone drill sites, both considered very soft compared to most sedimentary rock on Earth. Bulk cohesion is generally $\sim 2\times$ the tensile strength in sedimentary rock (Sivakugan et al., 2014), meaning that the SBLDs are at most as strong as the weakest Murray mudstones, but likely much weaker. TI of bedrock in Murray and Stimson outcrops was modeled from MSL temperature observations to be ~ 650 SI and ~ 700 SI respectively (Vasavada et al., 2017), >200 SI above the values we derive for SBLDs. The crusted materials in Meridiani Planum appear to be a better analog, and TI estimates of 300-400 SI for those surfaces, derived from ground-based measurements (Golombek et al., 2008), are also consistent with our observations of the highest TIs in the SBLDs.

Our estimates of low cohesion and low TI, combined with context from prior bedding measurements (Annex and Lewis, 2020), indicate that episodic weak induration similar to crusting observed in Meridiani Planum (Golombek et al., 2008) would have been enough to sustain the observed SBLD structures. Even small amounts of intergranular cement dramatically increase TI (Piqueux and Christensen, 2009), and if the sulfates within SBLDs comprise a major cementing secondary mineral, akin to gypsum-bound rocks on Earth, we should expect much higher cohesion and TI (Wyllie and Mah, 2004; Piqueux and Christensen, 2009; Peters et al., 2018). Instead, these deposits could have formed without any direct water infiltration (e.g., Bridges and Muhs, 2012; Michalski and Niles, 2012) or with only brief interactions with water

(Kite, 2019). While it is possible the SBLDs were once more cohesive and have since been degraded, post-cementation decomposition (such as from decompression, thermal heaving, mineral substitution, and impact deformation) of this magnitude covering such a large region seems unlikely given the dependency of such processes on localized conditions (Melosh, 2011). Although an exact mineral-forming process remains uncertain, we conclude that Arabia Terra’s SBLDs most likely formed via aeolian deposition and only mild subsequent induration.

2.6. CONCLUSION

Our investigation of how dust controls thermal inertia and derivation of the physical properties of layered deposits within Arabia Terra craters provides new information about their depositional history. SBLDs in Arabia Terra are among the fastest-eroding and least cohesive rocks observed on Mars, implying both local aeolian stresses above previous regionally-resolved estimates and relatively weak induration. When paired with observations of low bedding inclinations, regionally extensive sequences, and exposures of SBLDs outside of topographic lows, low cohesion in SBLDs is interpreted to result from airfall processes and intermittent wetting. If the SBLDs record conditions on Mars prior to atmospheric loss, then investigations of similar deposits by rovers in Gale crater and near Jezero crater should provide significant clues to habitability at the end of the Noachian, as well as to the form and cadence of Mars’ dehydration.

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2.8. APPENDIX 2A

Crater	THEMIS	CRISM	HiRISE	HRSC	CTX DTM
Becquerel	I36610007	frs000281b6 hrl00006290 frt00003245	PSP_005845_2015 PSP_004368_2015 ESP_024503_2015 ESP_038916_2015 PSP_001546_2015 ESP_017211_2015 ESP_016077_2015	h3231_0001	
Danielson	I36922027 I38694008	hrl0000434e frt000049ca	PSP_004434_1885 PSP_002733_1880 PSP_008930_1880 ESP_019835_1880 ESP_044507_1880 ESP_060331_1880 ESP_027615_1880 ESP_055069_1880 PSP_002522_1880 ESP_054858_1885		G21_02634 9_1880_G2 2_026626_ 1880
Firsoff	I36997007 I36685006	frt00017697 frt000236de frt0002437e	ESP_020534_1825 ESP_049531_1820 ESP_030292_1820 ESP_054568_1820 ESP_020679_1820 ESP_026270_1820 ESP_047184_1820 ESP_065276_1825 ESP_034907_1825 ESP_064643_1825 ESP_036674_1825 ESP_017132_1825 ESP_036041_1830 ESP_048753_1830 ESP_046617_1830 ESP_025769_1830 ESP_040393_1830 ESP_054146_1830 ESP_057918_1830 ESP_059553_1830 ESP_028024_1830 ESP_012385_1825 ESP_036819_1825 PSP_008772_1830 PSP_004355_1830	h1965_0000	G19_02570 3_1827_G1 9_025769_ 1827
Jiji	I37109006 I54411009	frt00016834	ESP_016657_1890 ESP_058788_1890		B18_01665 7_1881_B1 9_017013_ 1881
Kaporo	I62903011 I36210011 I02615005	hrs00003ec8	ESP_037794_1795ES P_036238_1795 PSP_002429_1800 PSP_002508_1800 PSP_002930_1800		F04_03737 2_1798_PO 4_002429_ 1799

Kozova	I36510012 I30808002	frt0000b084 frt0000960f frt0000b710 hrl00008c6b	PSP_009154_1835 PSP_006860_1840 ESP_026573_1835 ESP_017580_1840 ESP_044309_1840 PSP_008798_1840 PSP_002390_1840 ESP_017224_1835	h5242_0000	
Sera	I39430005 I44984002	frt000037f7 frt00020385	ESP_022116_1890 PSP_002047_1890 ESP_055227_1890 ESP_037834_1890 ESP_017936_1890 ESP_047421_1890		P02_00190 2_1889_P0 3_002047_ 1889
Trouvelot	I45259009	frt00023898 hrl0000abb4		h3286_0000 h3275_0000	
Unnamed 1 (3° E, 2° N)	I39954007	frt00012fc3 frt00006445		h1976_0000 h1965_0000	
Unnamed 2 (2.9° E, 4.4° N)	I46382006	frt00009272 frt00009b5a frt0000a553		h1965_0000	

Table 2A-1. Identifiers of THEMIS, CRISM, HiRISE, and HRSC data used in this study. CTX data from the Murray Lab was used as a base map (NASA/JPL/MSSS/The Murray Lab). All underlying data is publicly available in the Geosciences Node of NASA’s Planetary Data System (PDS). Derived THEMIS TIs, classification stamps, and crater count shape files are available at <https://openknowledge.nau.edu/id/eprint/5610/>. Derived CTX Digital Elevation Models (DEMs) and corresponding map projected CTX images are available at <https://doi.org/10.5281/zenodo.4663102>.

2.8.1. Mineral Mapping

We identified mineral trends and classified surfaces using CRISM targeted full and half resolution imagery (frt, frs, hrl, and hrs) in the long wavelength range (1.03-3.92 μm) as well as with CRISM MTRDR data, where available (Murchie et al., 2007). We employed multiple tools to reduce spiking and striping noise and subtract atmospheric contributions to CRISM TRDR data. This included standard ENVI CRISM Analysis Tools (CAT) methods as well as fitting methods outlined in Itoh and Parente, (2021). The Itoh and Parente (2021) method was employed on CRISM images: hrs00003ec8_07_if174l (Kaporo crater), frt00020385_07_if165l (Sera crater), frt000236de_07_if165l (Firsoff crater), and frt00016834_07_if165l (Jiji crater). The remaining CRISM images were processed using ENVI CAT version 7.4 and empirically optimized

atmospheric correction by McGuire et al. (2009) volcano scan scaling. Regions of interest were identified after full image ratioing and image color stretching (see Pan et al., 2017). Characteristic absorption features (Figure 2-1B) were then identified by ratioing spectra in regions of interest to spectrally bland locations in the same image columns. We compared the resultant spectral shapes to spectra measured in the laboratory and previously identified in CRISM data in the region (e.g., Niles and Michalski, 2009; Wiseman et al., 2010; Michalski and Niles, 2012; Pondrelli et al., 2015; Zolotov and Mironenko, 2016; Bishop et al., 2018; Quinn and Ehlmann, 2019). We ultimately produced maps from the spectral band parameters outlined in Viviano-Beck et al. (2014) as inputs to our classification pipeline.

2.8.2. Thermophysical Properties

Thermal inertia (TI) is a material property defined by the square root of the product of thermal conductivity, density, and heat capacity ($\sqrt{k\rho c}$). TI controls a material's cadence in gaining or losing heat through time, thus defining the shape of daily and seasonal surface temperature curves. On Mars, where the atmosphere is thin and the heat capacity of geological materials varies relatively little, TI depends most strongly on thermal conductivity (Piqueux and Christensen, 2009). Because solids are much more efficient heat conductors than gases, slight changes in the amount of inter-grain cements can lead to large changes in thermal conductivity and TI (Presley et al., 2009).

We derive TI by pairing nighttime THEMIS images (~ 100 m/px) (Christensen et al., 2004) with a numerical thermal model, KRC (Ferguson et al., 2006a; Kieffer, 2013; Edwards et al., 2018), that considers slope angle, aspect, elevation, albedo, emissivity, estimated component specific heat, estimated component thermal conductivities, and other observation time parameters (e.g., season, local time, solar azimuth, dust opacity, and modeled air temperatures) (Putzig

et al., 2005; Kieffer, 2013). In KRC's 'one-point' mode, models are run independently for each THEMIS pixel. We use an updated application of KRC (Edwards et al., 2018) that is distinct from other implementations (e.g., Fergason et al., 2006; Kieffer, 2013) in its use of higher resolution model inputs, and here the model is allowed to run over a longer time span (two Mars years) to achieve a seasonally-stable output.

Surface TIs in the study regions range in value from ~ 50 to $\sim 700 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ and sulfate-bearing layered deposits (SBLDs) tend to have elevated TIs relative to surrounding units. However, due to instrumental, atmospheric and seasonal differences between different THEMIS images that are difficult to correct, there can be small (e.g., $\sim 50 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$, corresponding to a ~ 3 K temperature error) systematic differences in TI values derived (Fergason et al., 2006b; Edwards et al., 2011). Pixel-to-pixel uncertainty within a single image, however, is only ~ 0.5 K, equating to $<15 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$. Therefore, the relative difference in TI between two regions in the same image were considered more strongly than absolute TI for the purpose of delineating units.

The reported TI values for each crater site in this work (Figure 2A-1) were taken either from a single image per crater or from images with overlapping areas demonstrating those images contain similar pixel values. The differences in TI values between surface units at each crater site were calculated from the ANOVA difference in means between those units, with 95% confidence interval as the plus minus error. The reported overall differences in TI values between surface units (see section 2.4) and associated uncertainties are the means of the differences in TI at each individual crater site and associated uncertainties weighted by number of pixels used to calculate each mean.

2.8.3. *Correlation Analysis*

For each study region, datasets were spatially aligned with tie pointing and resampled to 18 or 36 m/px (full or half CRISM resolution). Pixel values for CRISM band parameters and TI were then plotted by kernel density in order to roughly identify the number of clusters present. Normalized data was then assessed using principal components analysis. Effective classification was achieved by weighting normalized TI and band parameter data according to their relative component importance. Specifically, starting from the first principal component, the set of principal components that cumulatively explained more than 50% of the normalized sample variance were identified. Then, the key variables ($|\text{coefficient}| > 0.30$) within each of these principal components were identified, and only those variables were used in clustering.

We found that both this unsupervised method and human observers independently identified similar band parameters as having high variance (SINDEX2, LCPINDEX2, HCPINDEX2, OLINDEX3, BD1900_2, BD2100_2, and D2300). However, principal components that explained substantial amounts of variance in the data sometimes were a result of topographic effects in areas with high relief at multiple aspects. We prevented data subject to this effect from being incorporated in clustering by excluding band parameters with high positive or high negative (>0.4) correlations to the R1330 albedo proxy in regions of topography-dependent illumination.

Using the refined set of variables, we ultimately fit a gaussian mixture model to the data to determine a cluster probability for each data point. Data points with less than a 90% probability of being in a single cluster were assigned to cluster mixtures and not counted in cluster statistics. Our clustering method identified a total of six major surface types, each with distinct patterns in TI and CRISM band parameters. Although classification was achieved for regions cover-

ing each CRISM stamp independently, we grouped units among the different sites on the basis of consistent similarities in spectral trends, TI trends and morphology. These units are not necessarily stratigraphically-linked geologic units, but rather regions with highly correlated surface properties. The units are: I) moderate to relatively high TI SBLDs which show distinct light-toned layers and fractured textures at HiRISE image scales, II) relatively low TI SBLDs with moderate-toned and sometimes subdued layering structures and smooth textures at HiRISE image scales, III) relatively low TI pyroxene-rich cratered surfaces, sometimes hosting phyllosilicates with smooth textures at HiRISE image scales, IV) relatively high TI pyroxene-rich cratered surfaces sometimes hosting phyllosilicates and smooth to lightly fractured textures at HiRISE image scales, V) moderate TI, dark-toned, olivine-rich dunes, and VI) relatively low TI moderate-toned pyroxene-rich dunes, ripples and colluvium. In Figures 2-2 and 2A-1, unit I is red, unit II is orange, unit III is green, unit IV is blue, unit V is purple, and unit VI is not shown but reflects similar attributes as unit III. As explained in the main text, we interpret that unit II can be defined as more dust-covered exposures of unit I.

We note that it was decided after scrutinization that none of the targeted CRISM imagery within Trouvelot crater captures SBLDs even though layered deposits appear to be present within the crater nearby.

2.8.4. Regional Trends

A couple of outcomes of classification that were not included in the main text are worth mentioning here. After classifying units, we found the highest unit median TI was 394.51 (Interquartile Range [IQR]: 359.36-428.44) $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ for the SBLDs in Firsoff crater, at the western edge of our study area. The lowest median TI for a classified unit was 69.42 (IQR: 62.78-76.05) $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ for apparently dusty terrain with dominantly mafic spectral characteristics in and

around Kaporó crater, at the eastern edge of our study area. If related to aeolian activity, these numbers would reflect the broad-scale variability in the magnitude of aeolian erosion that is predicted by global climate models (e.g., Toigo et al., 2012) (Figure 2-3) and indicated by dust cover index maps (Ruff and Christensen, 2002) (Figure 2-1).

Another spatial trend is the abundance of phyllosilicate spectral signatures adjacent to or within SBLDs in the southernmost and highest elevation portion of the study area (Figure 2-1). There are also anomalously high TIs ($>500 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$) in and around these regions. If this pattern reflects the distribution of aqueous activity, it would be consistent with the higher density of inferred fluvial channels (Hynek and Di Achille, 2017; Davis et al., 2019) present in the southern portion of the study region but inconsistent with predictions for groundwater depth from hydrological models (Andrews-Hanna et al., 2010).

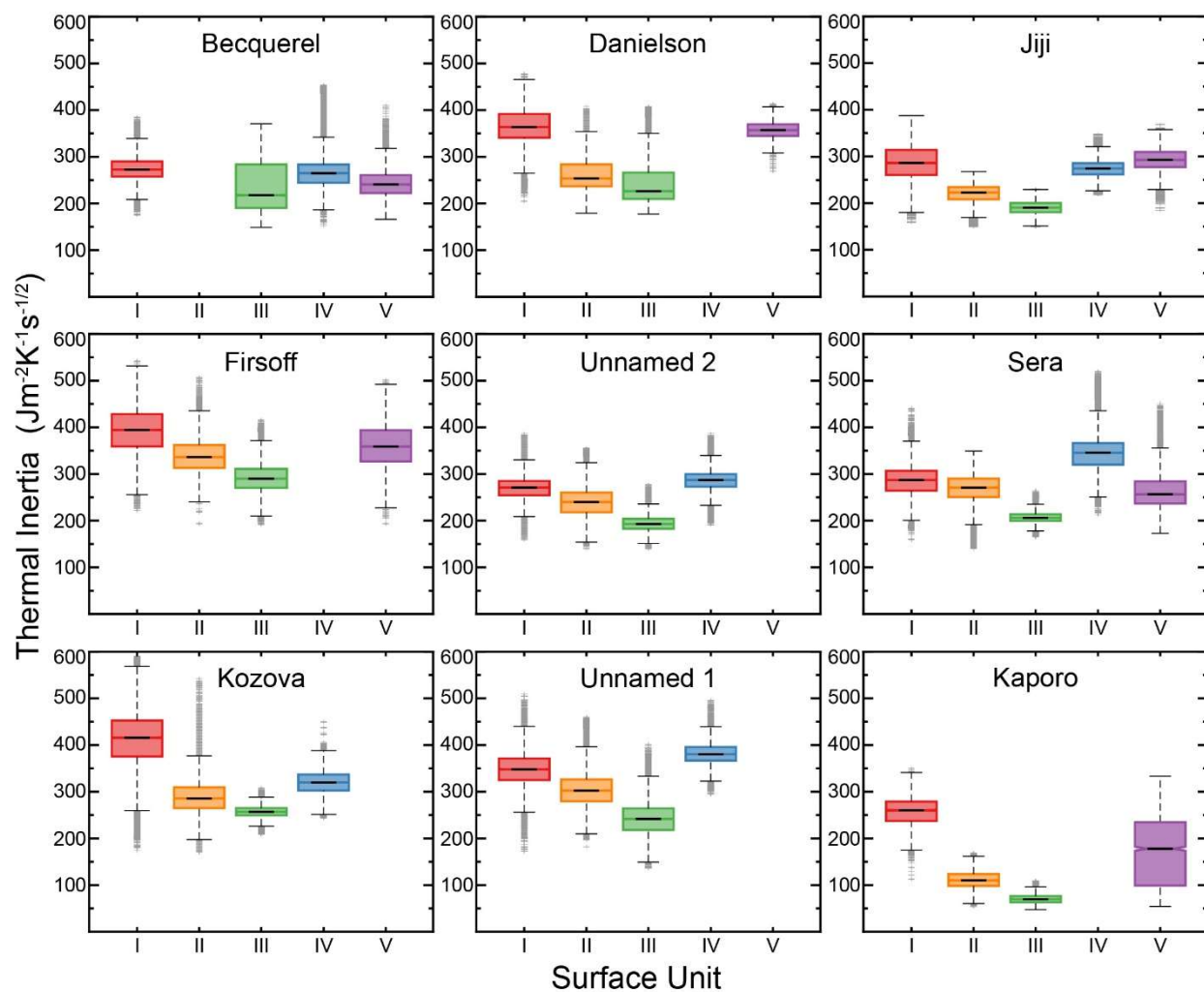


Figure 2A-1. Box plots of TI values derived for surface units at each sample location. Surface units are as follows: I) least dusty SBLDs, II) dusty SBLDs, III) dusty cratered terrain, IV) crater floor units, V) dark-toned dune forms. Colored boxes are the interquartile range for each cluster with internal black lines as medians, notched with the standard error. Dashed lines extend to edge of the data range excluding grey outliers.

2.8.5. Aeolian Activity Analysis

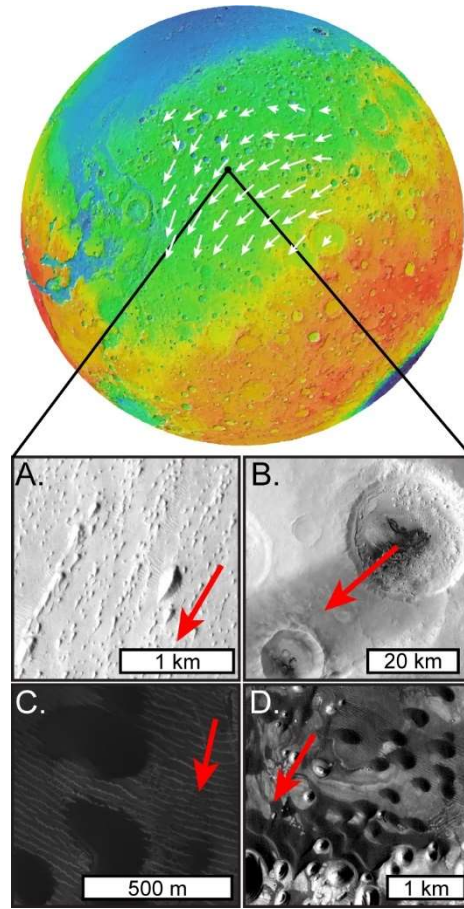


Figure 2A-2. MOLA Colorized elevation globe of Mars (NASA/JPL) centered at 0° , 0° . White arrows show grid of mesoscale model-derived wind direction (Toigo et al., 2012). Panels from near black point depict inferred local wind directions (red arrows) determined from A) yardang orientations, B) wind streaks, C) ripple orientations (paired with additional context), and D) dune orientations.

In order to assess the potential control that aeolian erosion has on apparent TI, we estimated where in the study areas aeolian erosional stress is likely to be strongest. First, we estimated prevailing regional and localized wind directions using a combination of gridded mesoscale model wind vectors (Toigo et al., 2012) and new observations of wind direction indicators (Figure 2A-2). We then considered the crater geometries and compared them to surfaces studied in 2-D slope wind erosion models (e.g., Kite et al., 2013; Steele et al., 2018) and wind tunnel ex-

periments (e.g., Day et al., 2016). Complex geometries that did not match those in the modeling studies prevented us from conducting detailed analysis with confidence in the majority of craters. However, we were able to make comparisons between TI and anticipated aeolian stress along profiles through Sera crater (Figure 2-4).

2.8.6. Crater Density Estimates

In order to gauge the relationship between crater retention and TI, as well as to assess exhumation rates, we conducted crater counts in Becquerel, Danielson, Firsoff, Jiji, Kapor, Sera and Kozova craters using the JMARS crater counting tool. We identified craters larger than ~20 m using CTX 6 m/px imagery (Malin et al., 2007) from the Murray Lab global CTX mosaic and HiRISE 30-60 cm/px targeted observations (McEwen et al., 2007), where available (images listed in Table 2A-1). To mitigate observation bias, HiRISE images were only used to confirm whether certain types of features observed at CTX scales were craters (as opposed to circular dune forms or other erosional features). These decisions were then also applied to areas without HiRISE coverage.

As a means to quantitatively compare crater retention and TI, we chose to rasterize crater counts at THEMIS pixel resolution. Crater counts were loaded into ArcGIS Pro, where a kernel density estimation tool was used to assign values representative of the nearby number of craters to each pixel. Search area was defined using the bandwidth approach, which depends on the spatial spread in points, but ultimately maintains consistently-scaled density estimates from region to region. This method is explained in Silverman (1986).

In order to ensure craters from one surface unit were not counted in adjacent ones, we set boundaries by extrapolating the contacts of the units identified through clustering and calculated crater densities for each surface unit separately. Also, instead of counting each crater as 1 point,

craters were weighted by size using the formula: $\text{weight} = \log_{10}(\text{diameter}/10)$, which makes results more comparable to standard cumulative crater density studies and normalized to 100 m diameter craters. In essence, the x-values in Figure 2-2C can be considered an approximation of the number of 100 m craters per square km.

To estimate possible erosion rates in the SBLDs, we followed a method outlined in Kite and Mayer (2017) that measures the divergence of size-dependent cumulative crater densities from the anticipated isochron slopes of crater production functions (Figures 2-3D and 2A-3). Given our focus on areas where dust cover appears to be limited as well as the absence of sediment-filled craters in these areas, we assume steady exhumation, or erosion, dominates over diffusive processes, such as sediment infilling. Under this assumption, an algebraic equation yields a rough estimate of erosion rate at each crater size bin,

$$E_D \approx 0.2D\phi / \left(\frac{N_D}{f_D a}\right)$$

where E_D is the erosion rate at a given crater size bin, D , N_D is the number of craters counted of that size range, a is the area of the region counted, and f_D is the predicted crater flux for the bin from Hartmann and Daubar, 2017) with the chronology function of (Hartmann, 2005) modified by (Michael, 2013). ϕ is the fraction of crater depth that must be obliterated before the crater is no longer recognizable, and, as in Kite and Mayer (2017), is taken to be 0.5. The 0.2 multiplier is an approximation of the depth-to-diameter ratio for craters in the size range of interest.

Kite and Mayer (2017) calculated uncertainties on the mean of erosion rates derived from multiple images. We did not specify uncertainty since only one estimate was made for each crater, rather than estimates from each image, producing an already imprecise range. However, the exhumation rate range was limited at the upper end by the identifiability limit of craters <20 m (~22 m in $2^{1/2}$ bin space). The lower limit on the range was selected based on inflection points

at 177 m present in the cumulative distributions for each region, suggesting a different cratering or preservation regime for craters of that size. Also, the cumulative number of identified craters with diameters larger than 177 m drops off dramatically, generating large uncertainties on the density of those craters. For these reasons, we exclude the exhumation rates derived from those larger crater size bins from our estimate.

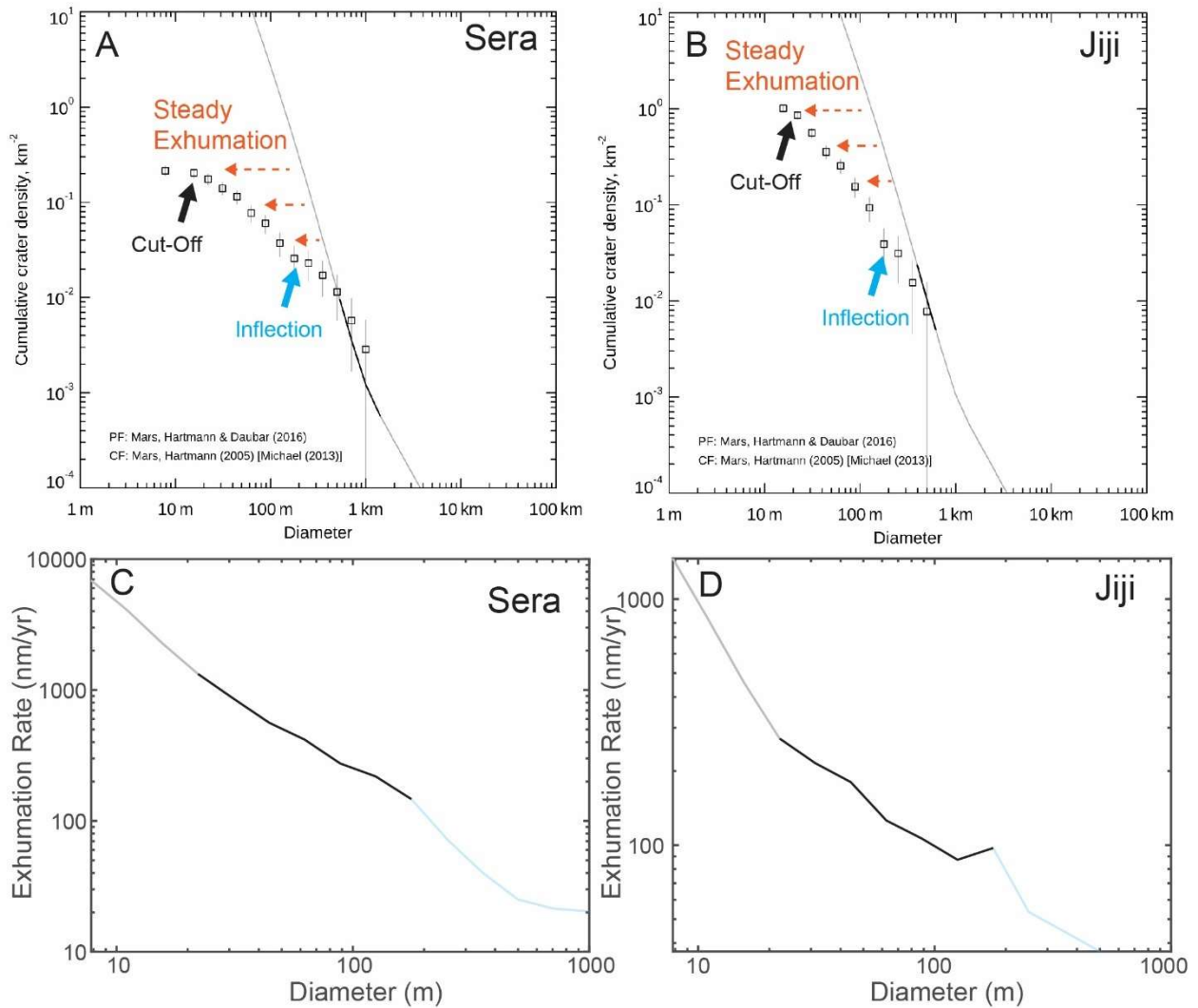


Figure 2A-3. Cumulative crater densities of sulfate-bearing layered deposits in A) Sera and B) Jiji craters plotted in $2^{1/2}$ bin spacing using Craterstats 2.0 (Michael, 2013 and sources therein) with modeled crater production function isochron (solid line, (Hartmann, 2005; Michael, 2013; Hartmann and Daubar, 2017) shown for reference. Divergence of crater counts from modeled isochron may result from exhumation or infilling. Survey incompleteness cut-offs at 22 m diameter for both regions are shown with black arrows. Cyan arrows show inflection points, suggesting

regime change with larger crater preservation. The estimates of exhumation rates at each bin for C) Sera and D) Jiji craters for the range stated in the study are shown in black; incompleteness cut-offs in gray; and the excluded larger crater regimes are in cyan.

2.8.7. *Slope Stability Analysis*

Estimates of cohesion were achieved using slope stability analysis. We located eight sites where recent wedge failure is observed and 15 sites where recent circular slope failure is visible at HiRISE image resolutions (~100 m in size) within areas covered by overlapping HiRISE stereo pairs (Tables 2A-2 & 2A-3, Figures 2-4, 2A-4, & 2A-5). These features were identified by their characteristic failure trace morphologies (see Wyllie and Mah, 2004) as well as by large debris piles located directly down slope of the failure sites. We followed the methods outlined in Wyllie and Mah (2004), which is based on theoretical work from Hoek et al. (1973), for backward derivation of cohesion. For these calculations, we made a few simplifying assumptions: that pore pressure and liquid content of the materials are negligible, that no external forces are present, that the cohesive strength and internal friction angle of all slip faces are approximately the same, and that cohesion at the failure site is representative of overall deposit cohesion.

At sites of wedge failure, we measured the geometry of the wedge trace surfaces in HiRISE image-derived digital terrain models using the qgSurf tool (Alberti, 2019) in QGIS, which fits planes to a group of DTM point inputs. By setting the factor of safety to 1, the point at which a slope is unstable, we were able to equate the downward force of the weight of the wedge to the resistant cohesive force at the failure surfaces and derive an upper estimate for cohesion at the failure site. In this scenario cohesion can be calculated as:

$$C = \frac{1 - (A+B)\tan\phi}{(X+Y)} \cdot \frac{\rho_{rock}g_{Mars}H}{3}$$

Where ϕ is the rock's angle of internal friction, ρ_{rock} is the density of the rock, g_{Mars} is Mars' gravity (3.711 m/s^2), H is the measured height of the wedge, X , Y , A , and B are dimensionless factors that depend on the wedge failure plane geometries (see Wyllie and Mah, 2004, Ch. 7). In our calculations we used a range of internal angles of friction ($10\text{-}60^\circ$) and density ($1200\text{-}2000 \text{ kg/m}^3$), which are representative of sediments and sedimentary rocks observed on Mars (Golombek et al., 2008).

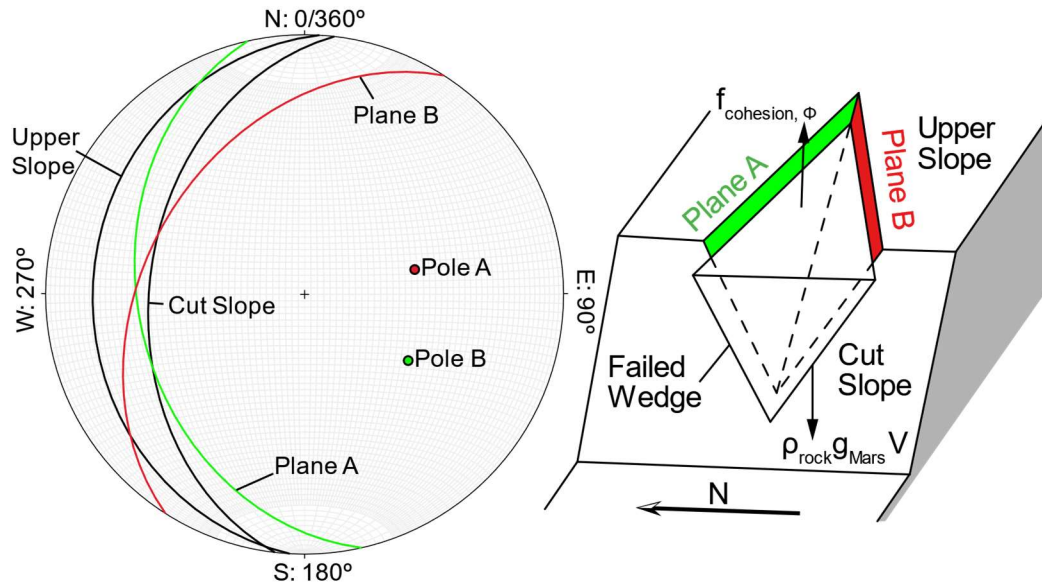


Figure 2A-4. Geometries of the failed wedge trace in Figure 2-4 plotted on a stereonet with a cartoon depicting a simple model of the wedge and the balancing gravitational and cohesive forces during failure.

Crater + Failure Site ID	Latitude (°N)	Longitude (°E)	HiRISE DTMs	Plane A Strike and Dip (°)	Plane B Strike and Dip (°)	H (m)	Derived Cohesion Range (kPa)
Sera W1	8.764	-1.112	ESP_065856_1890_E SP 066067 1890*	167.3, 35.9 W	212.5, 39.2 W	39.5	2.30-11.25
Firsoff W1	2.171	-9.041	ESP_026270_1820_E SP 027747 1820	333.7, 46.3 E	274.1, 48.9 E	117.9	1.65-5.65
Firsoff W2	2.164	-9.040	ESP_026270_1820_E SP 027747 1820	119.3, 37.0 W	97.3, 37.2 W	55.3	0.65-4.56
Firsoff W3	2.156	-9.057	ESP_026270_1820_E SP 027747 1820	82.8, 39.1 E	145.9, 45.2 W	63.0	2.79-17.90
Firsoff W4	2.146	-9.063	ESP_026270_1820_E SP 027747 1820	347.1, 36.1 W	283.6, 43.4 W	26.2	1.39-12.79
Firsoff W5	2.153	-9.169	ESP_039404_1820_E SP 047184 1820	208.3, 45.6 W	303.4, 61.4 E	53.6	1.41-9.50

Firsoff W6	2.113	-9.127	ESP_039404_1820_E SP_047184_1820	286.4, 40.9 E	358.3, 53.5 E	68.9	2.18-8.10
Firsoff W7	2.186	-9.143	ESP_039404_1820_E SP_047184_1820	261.7, 41.5 W	352.0, 53.2 E	26.4	0.13-15.90

Table 2A-2. Wedge failure sites analyzed for cohesion derivation. *All DTMs are available from the Geosciences Node of NASA's Planetary Data System (PDS) except for ESP_065856_1890_ESP_066067_1890, which is available from <https://doi.org/10.5281/zenodo.4681216>.

At sites of circular failure, we measured the height and slope angle. To estimate heights and slope angles, we also used digital elevation models derived from HiRISE images and extracted two-dimensional slope profiles. Then, using Figure 8.6 from Wyllie and Mah (2004), with a factor of safety set to 1 and the same tested range of internal angles of friction, we estimated a range of possible values for $C/\rho_{\text{rock}}g_{\text{Mars}}H$, where H is now the height of the failed portion of the slope. We then estimated a maximum cohesion at each site from the same range of internal angle of friction and density combinations. A similar method to this has been applied on smaller scales to study materials at multiple Mars lander sites (e.g., Moore et al., 1987; Golombek et al., 2020). Resultant cohesion estimates were slightly higher for the circular failure style estimates. In both cases, lower internal angles of friction and higher densities correspond to higher cohesion.

Table S3

Crater + Failure Site ID	Latitude (°N)	Longitude (°E)	HiRISE DTMs	H (m)	Slope angle (°)	Upper Limit on Cohesion (kPa)
Sera C1	8.767	-1.092	PSP_002047_1890_PS P_001902_1890	36.8	37.85	27
Sera C2	8.730	-1.068	PSP_002047_1890_PS P_001902_1890	29.9	37.77	22
Jiji C1	8.842	-1.720	ESP_016657_1890_ES P_017013_1890*	25.6	45.25	25
Jiji C2	8.906	-1.659	ESP_016657_1890_ES P_017013_1890*	81.0	36.27	60
Danielson C1	8.202	-6.864	PSP_002878_1880_PS P_002733_1880	58.1	35.77	43
Danielson C2	8.044	-6.790	PSP_002878_1880_PS P_002733_1880	28.2	27.98	17
Firsoff C1	2.166	-9.043	ESP_026270_1820_ES	47.1	34.43	35

			P_027747_1820			
Firsoff C2	2.264	-9.056	ESP_026270_1820_ES P_027747_1820	37.3	40.74	33
Firsoff C3	2.166	-9.062	ESP_026270_1820_ES P_027747_1820	34.3	45.31	33
Firsoff C4	2.140	-9.063	ESP_026270_1820_ES P_027747_1820	46.0	35.19	34
Firsoff C5	2.166	-9.043	ESP_026270_1820_ES P_027747_1820	61.9	38.52	51
Firsoff C6	2.187	-9.009	ESP_026270_1820_ES P_027747_1820	57.6	32.72	41
Firsoff C7	2.150	-9.108	ESP_039404_1820_ES P_047184_1820	36.4	46.11	35
Firsoff C8	2.148	-9.109	ESP_039404_1820_ES P_047184_1820	72.1	36.99	54
Firsoff C9	2.137	-9.397	ESP_029514_1820_ES P_030292_1820	57.2	34.78	42

Table 2A-3. Circular failure sites analyzed for cohesion derivation. Plane A is always the shallower dipping plane. *All DTMs are available from the Geosciences Node of NASA's Planetary Data System (PDS) except for ESP_016657_1890_ESP_017013_1890, which is available from <https://zenodo.org/record/3378969>.

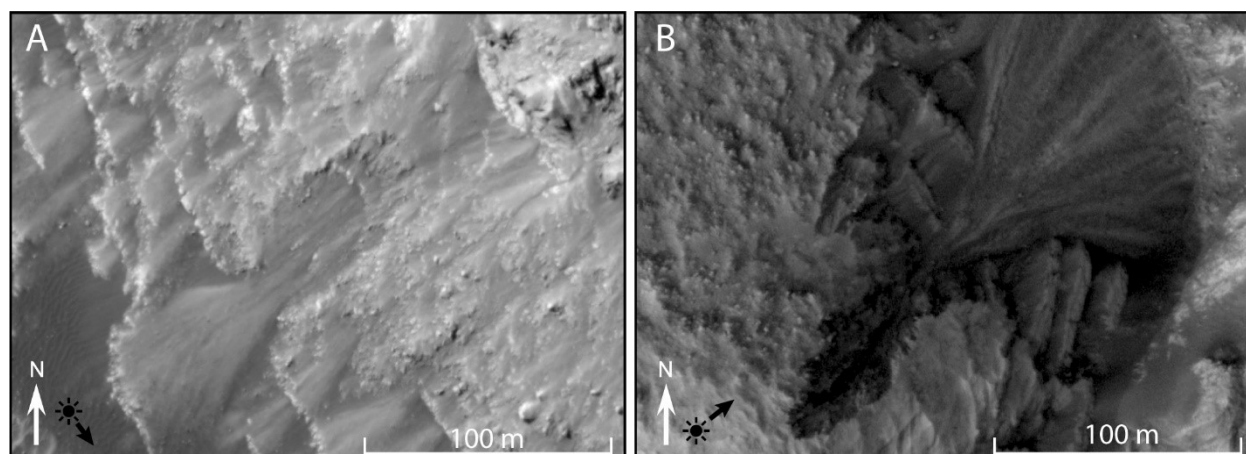


Figure 2A-5. Example of A) circular slope failure (Firsoff C6, -9.009°E 2.187°N , ESP_26270_1820) and B) wedge slope failure (Firsoff W6, -9.127°E 2.113°N , ESP_039404_1820) from Firsoff crater.

2.8.8. Data Proccession Tools

Data Processing was completed using JMARS, ENVI/IDL, ArcGIS Pro, QGIS, Matlab, Python, and the Ames Stereo Pipeline (Beyer et al., 2018). All data products used in this work are derived from data available at the Geosciences Node of NASA's Planetary Data System

(PDS) (<https://pds-geosciences.wustl.edu/>). Derived products not directly available from that archive are available from <https://openknowledge.nau.edu/id/eprint/5610/>. Modeling was conducted using the KRC (<http://krc.mars.asu.edu>) thermal model in Davinci (<http://davinci.asu.edu>; <https://github.com/NASA-Planetary-Science/krc>) and the Monsoon computing cluster at NAU. A statistical summary of TI data derived for this study is available at <https://pubs.geoscienceworld.org/gsa/geology/article/50/2/152/608434/A-fragile-record-of-fleeting-water-on-Mars>.

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CHAPTER 3

MANUSCRIPT II: A NOVEL METHOD FOR DERIVING THERMAL INERTIA ON EARTH, WITH APPLICATION TO MARS

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3.1. ABSTRACT

Surface thermal inertia derived from satellite imagery offers a uniquely valuable tool for remotely mapping the physical structure and volatile abundance of planetary soils, sediment, and regolith. Efforts to quantify thermal inertia using surface temperatures on Earth, however, have consistently yielded large uncertainties and suffered from lack of reproducibility. Unlike dry airless bodies, Earth's abundant water and dense atmosphere lead to dynamic thermal conditions that are a greater challenge to model than on a world like Mars. In this work, we developed an approach using field experiments to inform and fine-tune a thermophysical model of terrestrial sediment and calculate thermal inertia on Earth with higher precision than has previously been achieved remotely. Ultimately, we aim to use data from analog sites to develop better interpretations of sediments on Mars, and an accurate thermal model for Earth is the key step to enable translation between the two worlds.

3.2. INTRODUCTION

Satellite-derived surface temperatures offer an invaluable tool for remote geologic studies on Earth, Mars, and numerous other solar system bodies where surface access is limited, or broad

coverage is beneficial. On Earth, such datasets have been used to track the effects of ecological and climate change (Prata et al., 1995; Li et al., 2013), monitor volcanoes (Wright et al., 2008; Ramsey et al., 2016), and classify land surface type (Kahle, 1976; Scheidt et al., 2010; Nowicki et al., 2019). On Mars, thermophysical modeling of the surface has guided safe spacecraft landings (Nowicki and Christensen, 2007), identified subsurface ice (Piqueux et al., 2019), and contributed foundationally to our understanding of the materials there (Golombek et al., 2008; Mellon et al., 2009).

Ground heat flux is controlled by soil thermal inertia (TI), which can be defined as the willingness of a material to change temperature in response to a given thermal input. It is a function of thermal conductivity (k), density (ρ), and specific heat capacity (c_p) as follows $TI = \sqrt{k\rho c_p}$, typically in units of $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$. Because TI is controlled by the physical structure of a rock, sediment, or soil, estimating its value using temperature data can be a valuable tool for interpreting geology and surface features remotely.

A major outstanding hurdle for conducting TI studies on Earth, however, is that no remote approach has been able to accurately quantify soil-atmosphere heat exchange (Price, 1985; Li et al., 2021) without a soil-specific calibration (e.g., Murray and Verhoef, 2007; Minacapilli et al., 2012; Morrison et al., 2017). Heat transfer models have historically failed to make adequately high-precision predictions for the effects that the multitude of heterogeneities in natural surfaces on Earth have on orbitally derived TI (Sabol et al., 2006; Mellon et al., 2009). Many studies have opted instead to use more qualitative metrics such as apparent TI (Price, 1985; Scheidt et al., 2010; Qin et al., 2013; Zhang and Zhou, 2016). Yet, if we are to use TI to probe the physical properties of sediments independent of environmental conditions and without significant

knowledge of the surface, such as in studies of remote settings or analog studies for Mars, we need an updated model that controls for the effects of soil moisture and atmospheric dynamics.

We developed a novel non-disruptive approach to calculate bulk TI in sediment on Earth. We deployed an instrument suite that is capable of tracking environmental inputs with enough precision to calibrate thermal imagery and constrain surface heat flux through multiple diurnal cycles. The system is comparable to the tools deployed to Mars' surface in recent years (Spiga et al., 2018; Martínez et al., 2021; Rodriguez-Manfredi et al., 2021; Zou et al., 2021) that have enabled detailed *in situ* investigations (Grott et al., 2021; Martínez et al., 2021; Piqueux et al., 2021; Savijarvi et al., 2022; Jiang et al., 2023).

An energy balance model compiled for this work incorporates those measurements and predicts surface temperatures, as they would be observed using nadir infrared observations. Using Markov Chain Monte Carlo simulations, modeled surface temperatures were aligned to observed temperatures by fitting tunable parameters and deriving TI. Ultimately, we gauged the sensitivity of our model through rigorous testing, validated our results using hand-held heat pulse probes, and we demonstrated that our results are reproduceable by returning to one of our field sites in a different season. In sum, we developed, calibrated, and tested a soil-agnostic thermophysical model for application to Earth and Mars. In demonstrating the model's efficacy, we also uncovered a previously unknown thermal banding pattern at our test site, a basaltic dune in Northern Arizona. We intend for this tool to facilitate an advance in how thermophysical studies are conducted on both Earth and Mars.

3.4. WOODHOUSE MESA FIELD SITE

For this study, data was collected over two field seasons at a site 40 km NE of Flagstaff, AZ atop Woodhouse Mesa (Figure 3-1, 35.48176 N, -111.38738 E, 1630 m elev.). The site was selected for its mineralogical similarities to sediment on Mars, its mechanistic relevance to a major depositional process on Mars, wind, its accessibility to Flagstaff, and its relative homogeneity, which minimized complexity during model testing and development. We chose to visit the site twice, in May 2021 and September 2022 to assess model repeatability.

The site is situated on a $\sim 10^4$ m² falling dune that extends with a maximum slope angle of 7° down to the north from a scarp formed by the edge of a lava flow and is overlying the Moenkopi Formation. The unconsolidated sediment is primarily wind-reworked vesicular basaltic tephra from the ~ 1085 CE eruption of Sunset Crater in the San Francisco Volcanic Field (Hooper et al., 2012). The tephra is moderately sorted and median grain size in the top 10 cm of soil is 1.3 mm with a coarse lag of 5-10 mm diameter grains dominating the top few cm. Clasts are mostly subrounded with moderate sphericity. Bushes and Juniper trees sparsely populate the region surrounding the dune, but vegetation is nearly absent from the sloping dune face itself. The climate is semi-arid with winter air temperature lows near -5° C and summer highs near 30° C. In addition to consistent westerly winds, small aeolian vortices that redistribute surface grains are a common feature here.

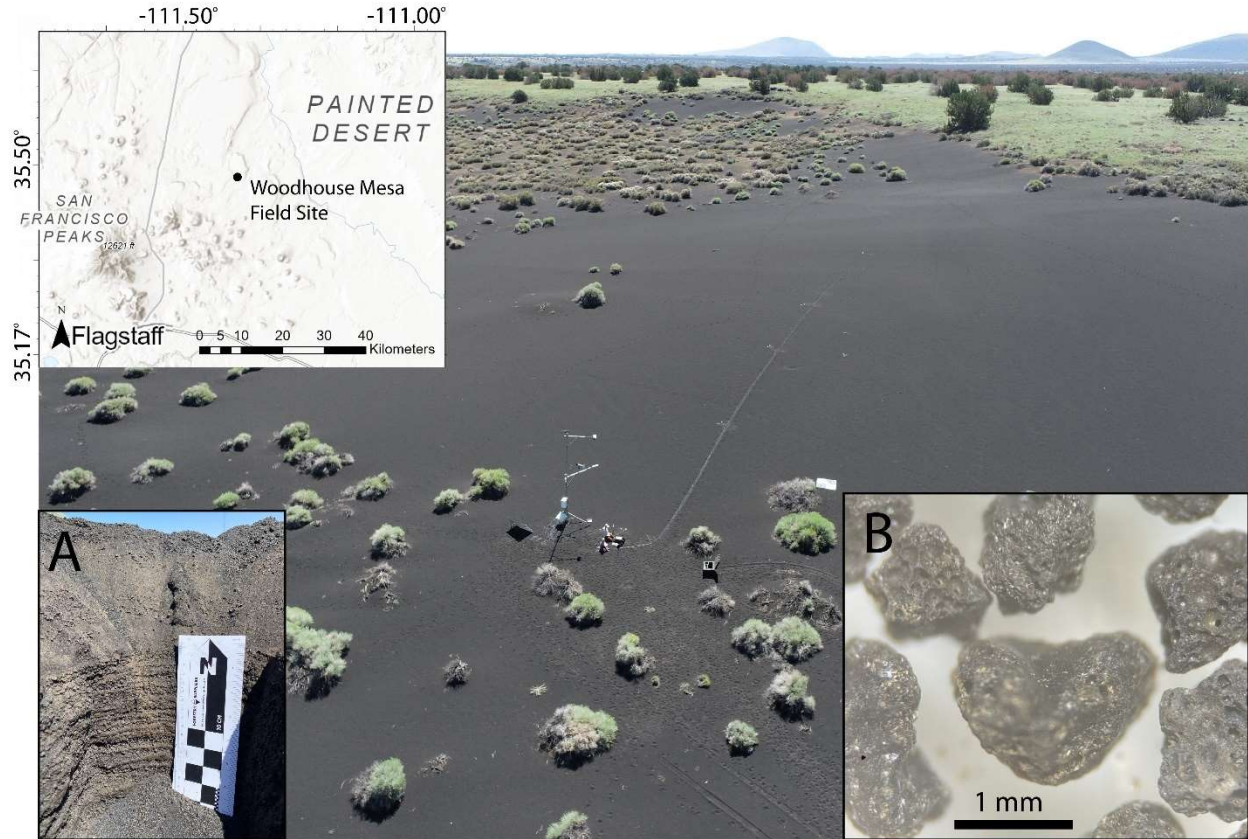


Figure 3-1. Context image of the Woodhouse Mesa field site captured from UAV with 7 m tall instrument tower in center of image located at the NW corner of a 50 m by 50 m square region that was the focus of thermal mapping. The site is located 40 km NE of Flagstaff, AZ, and is dominantly composed of wind-distributed sub-rounded basaltic tephra falling to the North from a buried scarp. A) Inset image of a 30 cm deep trench showing some subtle subsurface structure is present. B) Inset microscope image of median grain size fraction (~ 2 mm).

Data was collected at one-minute intervals over 3 days for the May 2021 campaign and over 4 days for the September 2022 campaign. A 7 m tower with two cross arms was used to mount the instruments. The infrared camera was placed on the upper arm at 7 m, while all other instruments discussed in this work were placed on a lower 3 m-high arm. We focused our observations at the flattest portion of the site, near the bottom of the slope.

3.4. METHODS

3.4.1 Forward Model and Optimization Overview

To effectively model thermophysical behavior, it is necessary to trace the energy flux for the system (Figure 3-2). By doing so, the temperature response of a material can be quantitatively linked to the physical properties of that material and not any outside influences. In laboratory studies, the energy inputs can be finely controlled (Minacapilli et al., 2012). However, because experiments were conducted in the field, it was necessary to incorporate the effects of natural fluxes acting on the soil surface. Those effects were constrained by collecting data *in situ* (Figure 3-3) with a state-of-the-art instrument suite in combination with models of the physical processes that control radiative, convective, conductive, and latent heat exchange (Figure 3-4).

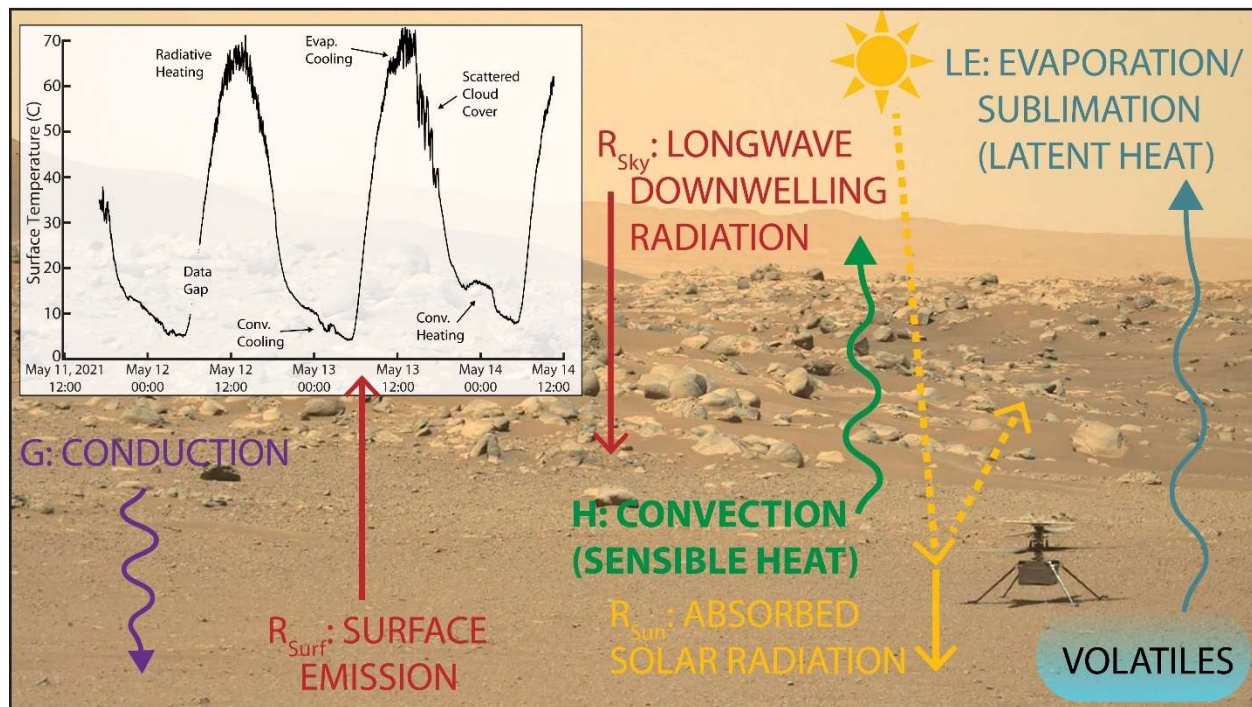


Figure 3-2. Conceptual depiction of surface energy balance model and its influence on surface temperatures, showing measured temperatures from Woodhouse Mesa in May 2021 (inset). The shape of the diurnal temperature curve is primarily driven by solar radiation and the response of heat conduction into and out of the subsurface. More subtle temperature features appear as a result of atmospheric convection, evaporation of soil moisture, and heat radiated by the atmosphere. Background image from Perseverance Rover Sol 114 (NASA/JPL-Caltech/ASU/MSSS).

The objective in developing the model was to accurately derive thermophysical properties of a surface from detailed temperature measurements. The observed weather station data, along with samples collected from the field, provide a basis for estimating the energy flux and predicting the surface response. In circumstances where in situ weather data is not available, predictions, such as from circulation models, might be used in place of measured environmental data at the expense of a broadened uncertainty range.

The model in this work uses six free parameters, selected to be as agnostic as possible about a given soil's properties without leading to non-physical overfitting. The primary parameter of interest is bulk dry thermal conductivity (k_{dry}), for which a single layer approach is implemented. The model also considers a free coefficient for sensible heat (C_H), which controls the magnitude of heat exchanged between surface and atmosphere, and another for latent heat (C_E), which controls the magnitude of heat exchanged due to evaporation or condensation. Additionally, two parameters are used to determine how the sediment pore structure controls the distribution of soil moisture. The first is water capacity in percent by volume (θ_k), and the second is a pore fluid network connectivity parameter (m). Finally, another parameter (θ_E) determines the volumetric water content at which the soil transitions from pore-dominated conductivity regime to a grain interface-dominated regime as water accumulates along the grain contacts.

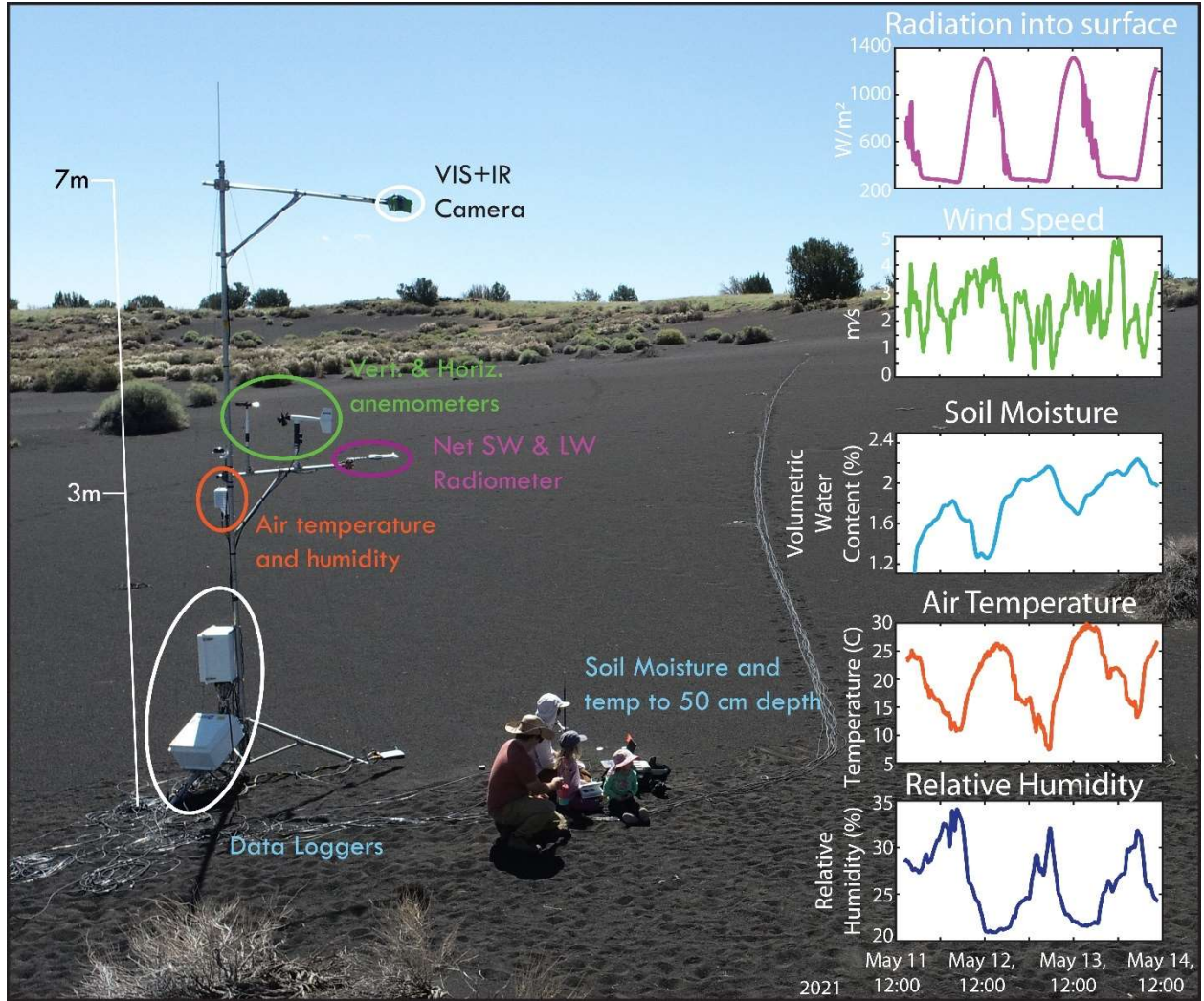


Figure 3-3. Experimental setup at Woodhouse Mesa, showing weather instruments and 72 hours of data from May 2021. Instruments include a FLIR Duo Pro R, which captures downfacing infrared and visible imagery, anemometers, a net radiometer, air temperature and humidity sensor, pressure sensor, and soil moisture and temperature probes.

Since the model contains multiple unknowns that require fitting, a Markov Chain Monte Carlo (MCMC) simulation approach based on Bayesian inference is well-suited to fit calibrated surface temperatures and identify the most probable k_{dry} . We employed a cascaded affine invariant ensemble MCMC sampler (Goodman and Weare, 2010). Relative to other optimization tools, this MCMC implementation achieves good convergence for diversely scaled parameter-sets with efficient use of computational resources. The program was employed to iterate through a one-

dimensional surface energy balance on the upper boundary of a soil column and calculate subsurface heat transfer with temperature-dependent parameters.

To calculate soil thermal conductivity, observed surface temperatures were fit by calculating surface heat flux at each timestep (Figure 3-4). Once the energy flux to the system is known, the surface temperature is simply a function of its TI. The goodness-of-fit was assessed with the reduced chi-squared (χ_v^2) metric, which is the sum of the squared differences in observed vs modeled temperature at each time step divided by the measurement error and number of degrees of freedom. MCMC simulations were designed to minimize the χ_v^2 by optimizing the free parameters.

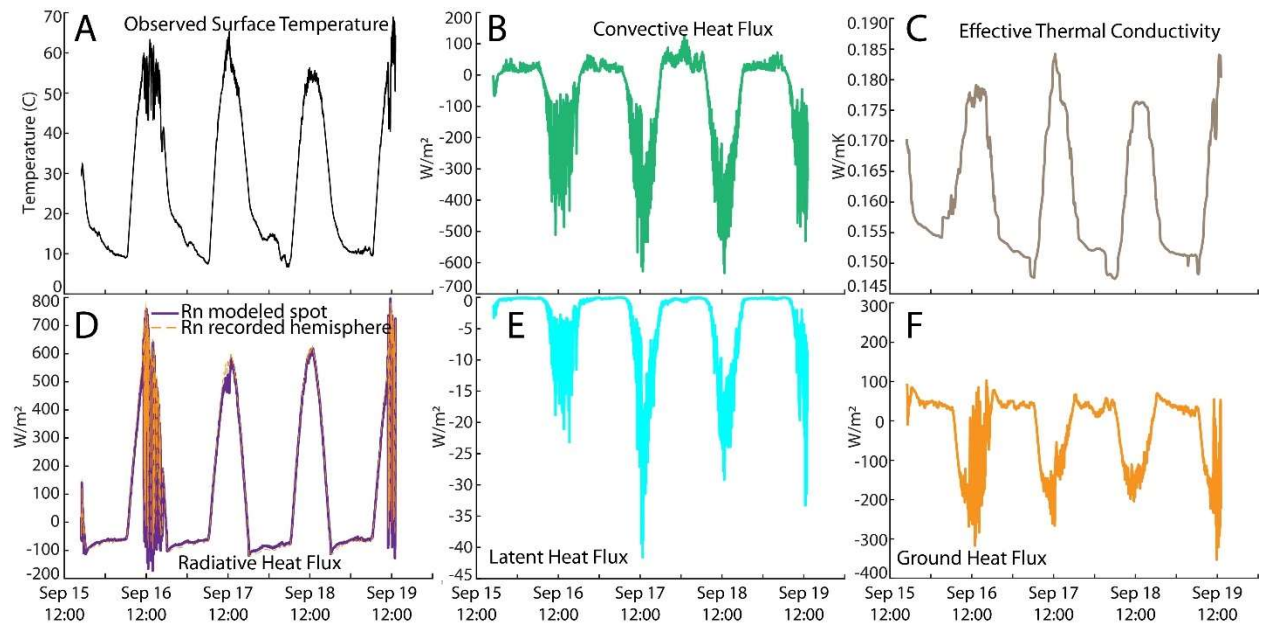


Figure 3-4. Key modeled surface layer features from the September 2022 field campaign showing the variability that occurs with the diurnal cycle. A) Observed surface temperature, B) convective heat flux, C) effective thermal conductivity, D) radiative heat flux, E) latent heat flux, F) ground heat flux.

3.4.2. Capturing Surface Temperature

Surface temperatures were captured from a FLIR Duo Pro R infrared camera set up facing straight down, a geometry meant to replicate the viewing angles of satellite imagers. The imager simultaneously captures a 640 x 512 pixel broadband 7.5-13.5 μm (TIR) image using an uncooled VOx microbolometer and a 4000 x 3000 pixel visible RGB image. By mounting the camera on the end of a raised 2 m long crossarm at 7 m height, an undisturbed surface adjacent to the tower was captured. The TIR field of view at 7 m height was 5.9 x 4.7 m with 9 mm/px resolution. The camera was set to capture images of a fixed surface region once per minute. The TIR data was first radiometrically calibrated using an internal software procedure that considers known air temperature and humidity to account for atmospheric and instrument effects. Additionally, integrated flat-field-corrections were applied at capture time to reduce instrument noise due to sensor and lens temperature changes. Potential sources of noise were further reduced by protecting the camera from direct sun exposure and moisture using a white insulated cover. Remaining vignetting effects were corrected by calculating and subtracting a dynamic flat field. The flat field was derived from the mean of all images after box filtering and was multiplied by the center-to-corner temperature ratio for each image.

Finally, to further improve instrument precision, the observed temperature was additively adjusted to match that of two calibration targets. The calibration targets are 30 cm square v-tiles sprayed with light-diffusing paint (one black, one white). They are fitted with two back-of-surface platinum resistance thermometers (PRTs). The factory camera uncertainty is ± 5 K or 5% of readings in the -25°C to $+135^{\circ}\text{C}$ range, while individual PRT uncertainties are only $\pm (0.15$ K + 0.2%). For model-fitting, the overall uncertainty considered was the PRT uncertainty plus the ± 0.05 K pixel to pixel uncertainty of the FLIR microbolometer.

3.4.3. Thermal Conductivity Mixing

Effective bulk thermal conductivity (k_{eff}) has the strongest influence on the thermal response of planetary surfaces, and it is distinguished from our implementation of k_{dry} in that it is dynamic and includes the effects of water and temperature. The k_{eff} of a column of soil or regolith can be defined as the negative heat flux divided by the thermal gradient. Since k_{eff} varies by several more orders of magnitude than either ρ or c_p in sediments (Piqueux and Christensen, 2009a, 2009b), it is the primary control on TI. Thermal radiation and convective heat transfer are relatively minor components of internal heat transfer in a soil or regolith, although temperature changes do affect k_{eff} (Piqueux and Christensen, 2011). At a given temperature, k_{eff} depends on the conductivities and relative proportions of the solid components (mineral grains, cements, and the nature of their contacts) and pore-filling liquid and gas components (Presley and Christensen, 1997; Bristow, 2002; Minacapilli et al., 2012).

The primary challenge to mixing models in the terrestrial setting has been the accurate prediction of how k_{eff} changes with volumetric water content (θ) for multiple different soil types (Dong et al., 2015; Zhang and Wang, 2017). The manner in which the conductivities of different phases mix together is nonlinear and strongly depends on the grain-scale structure of a sediment (Dong et al., 2015; Lu and Dong, 2015). Because we were ultimately interested in applying the model results to Mars, where liquid phases are likely absent at the surface, it was necessary to isolate the dry thermal conductivity (k_{dry}) of soils using an appropriately broad mixing model. If the effects of water are accounted for, k_{dry} can be directly translated from Earth to Mars by substituting the gas conductivity, ρ , and c_p measured on Earth to the expected values for Mars (Presley and Craddock, 2006; Piqueux and Christensen, 2009).

We sought a model that considers the complexity of a three-phase system with water infiltration occurring in dynamic geometries. Analyses of porous media (Shetty and Cerro, 1993; Zhang and Voss, 2006) have demonstrated the efficacy of a thin film approach, wherein liquids laminate the solid grains until reaching high enough water content that the films join together in an interconnected fluid matrix. This conceptual model has been validated for thermal conductivity with laboratory measurements (Presley et al., 2009; Smits et al., 2010). Multiple analytical approaches have been developed following this model, and as part of model development in this work, three models were tested (Côté and Konrad, 2005; Lu et al., 2007; Lu and Dong, 2015). Each model is applicable to porous soils and includes a parameter representing the soil's pore structure (Figure 3-5), which we denote as m , the pore connectivity parameter. Since the three-phase mixing scenario is only present when θ is between dry and full saturation, we also include the soil saturation value (θ_k) for fitting. At saturation, a simple geometric mean mixing model does a good job of predicting k_{eff} , where $k_{eff} = k_{sat}$, since the system simplifies to only two phases (Johansen, 1975; Zhang and Wang, 2017).

$$k_{sat} = k_{H_2O}^{\theta_k} \cdot k_{solid}^{1-\theta_k} \left(\frac{W}{mK} \right) \quad (\text{Eq. 3-1})$$

Since variations in k_{H_2O} are relatively small compared to that of gas, a constant value for that term was used: $k_{H_2O} = 0.6096 \text{ W/mK}$ (Haigh, 2012). For k_{solid} , an experimentally derived relationship for basaltic material is used (Clauser and Huenges, 1995; Piqueux and Christensen, 2011): $k_{basalt} = 1.18 + 474/(350 + T_{soil} - 273.15)$.

The shape of the k_{eff} - θ relationship below saturation is dependent on both the overall equation design, and the m and θ_k terms. θ_k defines an inflection point between dry and nearly saturated regimes, while m defines the slope at that inflection point, where the rate by percent volume at which the pores are filled with increasing θ depends on pore connectivity. If the slope

is steep and pores well-connected, small additions of water to a dry soil can have a major impact on k_{eff} by connecting otherwise disjointed grains with thin films of water. However, in a soil with poorly connected pores, more water would be required to achieve a similar effect. In the soils studied for this work, natural θ ranged from 0 to 0.08 m³/m³. However, artificially wetting of the soil to saturation while measuring θ allowed the model to consider a wider range of wetting conditions when fitting free parameters.

The first mixing model tested was from Côté and Konrad, 2005, which considers granular soils with no hydration regime:

$$k_{eff} = k_{dry} + \frac{m\left(\frac{\theta}{\theta_k}\right)}{1+(m-1)\left(\frac{\theta}{\theta_k}\right)} (k_{sat} - k_{dry}) \quad (\text{Eq. 3-2})$$

The m values used by Côté and Konrad, 2005 were 4.60, 3.55, 1.90, and 0.60 for gravel and coarse sand, medium and fine sand, silty and clayey soils, and organic fibrous soils, respectively. One challenge to this model is that its asymptotal lower limit (Figure 3-5) is not physically realistic.

Lu et al., 2007 also developed a model for granular soils, but with a more realistic lower limit that can reflect hydration (Figure 3-5):

$$k_{eff} = k_{dry} + e^{m\left(1-\left(\frac{\theta}{\theta_k}\right)^{m-1.33}\right)} (k_{sat} - k_{dry}) \quad (\text{Eq. 3-3})$$

Finally, Lu and Dong, 2015 developed an approach focused on clay-bearing soils that do host a mineral hydration regime:

$$k_{eff} = k_{dry} + 1 - \left(1 + \left(\frac{\theta}{\theta_{sat}}\right)^m\right)^{\frac{1}{m}-1} (k_{sat} - k_{dry}) \quad (\text{Eq. 3-4})$$

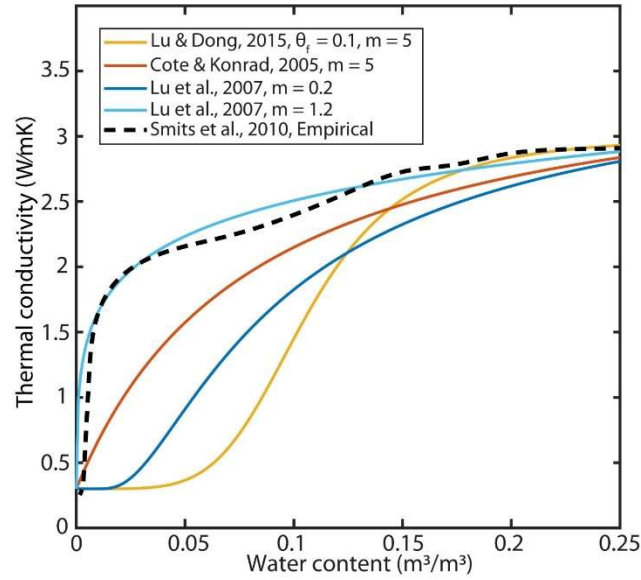


Figure 3-5. Thermal Conductivity with water content for the analytical models considered in this work (Côté and Konrad, 2005; Lu et al., 2007; Lu and Dong, 2015) along with experimental results for sandy soil from Smits et al., 2010. Following Smits et al., 2010, models were fit for $k_{dry} = 0.3 \text{ W/mK}$, $k_{wet} = 3.0 \text{ W/mK}$ and $\theta_k = 33\%$.

We found that the Lu et al., 2007 model consistently produced more precise m and θ_k fits in the soil that we studied. That result is consistent with experimental results that show this model performs well for the types of sandy soils that dominate our field areas with $0.6 < m < 1.33$ (Lu and Dong, 2015). With the right pore-network parameter (m), the Côté and Konrad, 2005 model also tends to provide a good fit for sandy soils but does not seem to consider other soil types as well, such as salt- or clay-bearing soils. The Lu and Dong, 2015 model is well-suited for salt- or clay-bearing soils with a hydration regime but does not provide good fits to sandy soils. The Lu et al., 2007 model is tunable to fit both scenarios and the shape of this curve (Figure 3-5) was also well-suited to optimization with a known lower and upper limit on k_{eff} .

In addition to moisture dynamics, temperature fluctuations can also have an effect on k_{eff} . Watson, 1964 suggested based on experimental work that k_{eff} depends on the third power of changes in temperature. This relationship tended to produce excellent fits to observed tempera-

tures with very high variation in thermal conductivity—sometimes > 1.5 W/mK over 24 hrs. However, more recent modeling suggests that k_{eff} should only vary by a few hundredths of W/mK on Earth (Piqueux and Christensen, 2011), indicating that too strong a temperature- k_{eff} relationship could lead to nonphysical overfitting. While such relationships may approximate the temperature dependence in thin atmospheres, porous soils in Earth's dense and moisture-rich air necessitate more complexity that mitigates the temperature control.

The magnitude of the difference in actual k_{eff} from the average k_{dry} value that the model fits for was ultimately estimated from soil temperature and θ . At low humidities, gas thermal conductivity (k_{gas}) increases nearly linearly with temperature (Piqueux and Christensen, 2009). However, as humidity increases, gas conductivity begins to decrease due to the addition of the larger H₂O molecules to the gas (Tsilingiris, 2008). Despite liquid water's high thermal conductivity, in vapor form it contributes to a decrease in thermal conductivity that is expounded by temperature increases. By fitting a computationally simple equation to Figure 3 in Tsilingiris, 2008, an estimate of air thermal conductivity, k_{gas} , was made from soil temperature, T_{soil} , and humidity, RH_{soil} . Soil humidity was derived from the same set of equations used to calculate latent heat flux (discussed in Section 3.4.6.), and depends on θ .

$$k_{gas} = 0.024 + 7.78 * 10^{-5} * (T_{soil} - 273.15) - 3 * 10^{-5} * e^{0.0591(T_{soil}-273.15)} * RH_{soil} \left(\frac{W}{mK} \right) \quad (\text{Eq. 3-5})$$

Similarly, a simple equation relating k_{eff} to k_{gas} in dry soils of porosity ϕ was produced from Figure 8 of Piqueux and Christensen, 2009a. At the range of temperatures relevant to this study, it is a nearly linear relationship.

$$k_{eff,dry} = 3.66 * k_{gas} + 0.05 + 0.72 * (0.476 - \phi) \quad (\text{Eq. 3-6})$$

Although, this equation produces an empirical estimate of k_{dry} , it only applies to idealized spherical soils. Rather than use it to directly estimate thermal conductivity, we instead use it to adjust our modeled k_{dry} with temperature and humidity. A reference temperature was set to be the average of the maximum and minimum observed temperatures, and a reference soil humidity of 0 was used. At each timestep, and for each soil layer, a ratio of k_{dry} at current and reference temperatures and soil humidities was calculated and multiplied with the model-fit k_{dry} . That result and θ was then input into Eq. 3-3 to calculate k_{eff} .

3.4.4. Ground Heat Flux

The transfer of heat into and out of the subsurface was modeled as an iterative solution to the heat conduction equation using a grid of subsurface layers, following Kieffer, 2013. Layer-to-layer heat transfer is a function of the thickness, k_{eff} , ρ , and c_p of each layer, as well as the data timestep. Density measurements are described in Section 3.4.8 and c_p (in J/kgK) was determined using an empirically-derived function, applicable to natural soils: $c_p = \frac{2 \cdot 10^3}{\rho_{dry}^2 \cdot 2.65} + \frac{4.2 \cdot 10^6 \cdot \theta}{\rho}$ (Hillel, 1982), where ρ is the soil density including measured water content and ρ_{dry} is the density without water. Heat flux was then calculated as follows, with ∂z as the layer size, ∂t as the time step, and T as layer temperature.

$$\frac{\partial T(z,t)}{\partial t} = \frac{k}{\rho c_p} \frac{\partial^2 T(z,t)}{\partial z^2} \quad (\text{Eq. 3-7})$$

The layer grid was constructed by first defining a maximum grid depth. A depth of 50 cm was used, informed by observations that diurnal temperature variation below this depth tended to be very small (<1 K) (Figure 3-6). The size of subsurface layers was then defined. Larger layer sizes reduce computation time but decrease model accuracy since heterogeneities in vertical temperature are less well-resolved. Smaller values increase resolution at the expense of computa-

tion time, but a grid that is too fine for a given thermal conductivity can lead to instability in the modeled temperature response as the thermal wave outpaces the sampling cadence.

Ideally, a grid is defined to be as high resolution as possible without causing the model to be unstable. Thus, to minimize grid step size, a test case of the forward model was run while iterating through a list of increasing top layer sizes, until the test model converged. A geometric layer thickness multiplier, FLAY, defines how grid layer size grows with depth. We found that an FLAY of 1.3 provided a good balance between computational efficiency and grid resolution. For our model runs using tower observations, a 1-minute time step, matching sampling cadence, was used, and the subsurface grid converged to produce 12 layers with a top layer of 7.5 mm, which is conveniently the approximate size of grains that dominate the field site surface.

Prior to model fitting, starting temperatures for each subsurface layer as well as boundary conditions were defined. Starting temperatures were determined through an equilibration scheme that uses the observed surface temperatures from the first day of observations and a lower boundary temperature equal to the mean of the maximum and minimum observed surface temperatures. It was confirmed that the first day of observations was roughly consistent with recent weather conditions for the prior week. After first assigning a simple linear trend to the subsurface temperatures, a conductivity model looped through the single day observations 20 times, at which point the subsurface temperatures show a natural curve between the surface and lower boundary temperatures (Figure 3-6), defined by the diurnal thermal forcing. The initialization procedure was ultimately validated using sets of seven subsurface temperature probes buried in a column down to 50 cm depth. Subsurface grid temperatures resampled to align with probe burial depths had an R^2 of 0.99 when compared to the modeled temperatures at the end of the first day of observations.

As it relates to the model, the flux of heat through the subsurface has the effect of either heating (typically at night) or cooling (typically during day) the topmost soil layer for which the overall model is being fit. Because subsurface temperatures lag behind that of the surface, the soil properties determine how strongly buffered the surface temperature is against other elements of energy flux.

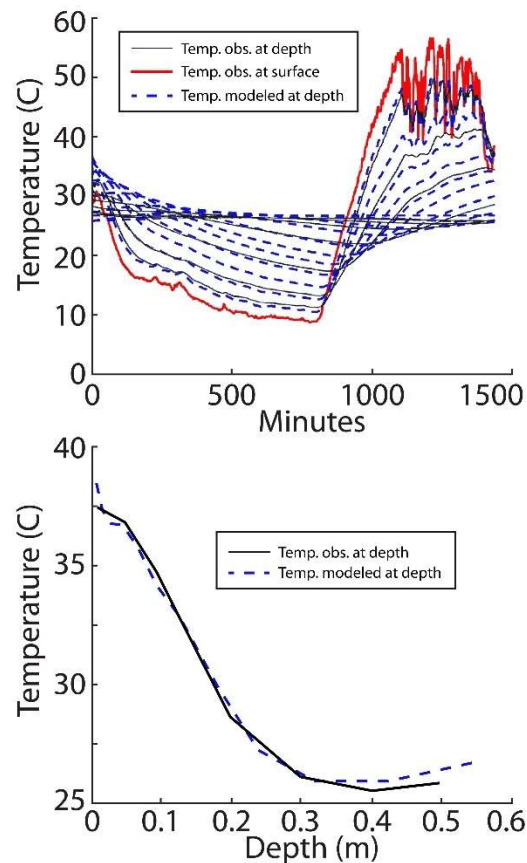


Figure 3-6. Subsurface layer temperature initialization results during the September 2022 campaign at Woodhouse Mesa. The top plot shows one day of temperature observations at the surface and at 6 points down to 50 cm depth, with modeled grid layer temperatures showing similar overall form. The bottom plot shows both modeled and observed temperatures down to ~50 cm depth at 6:00 PM on September 15th, 2022.

3.4.5. Sensible Heat Flux

Sensible heat is the energy imparted into or drawn from the surface due to convection into the atmosphere. Several approaches exist to track the energy flux due to sensible heat, with the most direct approach being the covariance method (Albertson et al., 1996; Evett, 2002), which tracks paired deviations in wind speed and direction and air temperature. The challenge with this approach lies in collecting measurements at fast enough sampling rates (usually 20-1000 Hz) and with at high enough collocated precision to capture truly representative deviations from the mean. The requirements become even more challenging for measurements closer to the surface where the air is more chaotic. Due to the short-term nature of our experiments and the necessity for mobile deployment, we used relatively short weather towers (3-7 m), making the covariance approach a challenge. Additionally, it would currently be insurmountably challenging to apply a model using this approach using only remote sensing data.

Another approach to measuring sensible heat is to use a forced convection scheme, where the rate at which air is carried away from the surface is a function of horizontal wind speed. The standard aerodynamic resistance method achieves this following Monin–Obukhov similarity theory while accounting for surface roughness and near-surface air stability (Van De Griend et al., 1985; Daamen and Simmonds, 1996). For sensible heat, H :

$$H = \frac{-\rho_a c_{p,a} (T_s - T_a)}{R_a} \quad (\text{Eq. 3-7})$$

Where ρ_a and $c_{p,a}$ are the density and specific heat of air, and T_s and T_a are the surface and air temperatures, respectively. R_a is the aerodynamic resistance, defining how readily convective heating/cooling affects the surface temperature, and it is a function of the horizontal wind speed, U , surface roughness, and displacement height of the layer that is most affected by convective heating from the surface (Daamen and Simmonds, 1996).

We adopt an agnostic version of the aerodynamic model (Van De Griend et al., 1985; Daamen and Simmonds, 1996) that requires only horizontal wind speed and air temperature, taken from approximately the same height, as inputs (Hartmann, 1994; Cellier et al., 1996). We combine other site-specific parameters into a searchable free parameter, C_H , representing an adjustment to the resistance to convection. The equation ultimately takes the form:

$$H = \frac{-\rho_a c_{p,a} U}{C_H} (T_s - T_a) \quad (\text{Eq. 3-8})$$

To measure horizontal wind speed, an R.M. Young 05103 propeller-style anemometer was used and is accurate to ± 0.3 m/s with a threshold wind speed of 1 m/s (if wind < 1 m/s, it was set to 1 m/s). To measure air temperature, a Campbell Scientific EE181 Platinum Resistance Thermometer housed in a RAD10E shelter was used. The probe is accurate to $\pm 0.2^\circ\text{C}$ at encountered temperatures.

3.4.6. Latent Heat Flux

Latent heat flux is the energy consumed or released through phase changes at or near the surface, such as through evaporation or condensation of water. In our field settings, the latent heat flux is the product of L , the latent heat of evaporation, and E , the rate of evaporation by mass. The model is flexible, however, in the sources of latent heat flux that can be considered, and in contexts where sublimation is more dominant than evaporation (e.g., frozen landscapes in dry atmospheric conditions), the latent heat of sublimation and sublimation rate could instead be used. We use an empirically derived temperature-dependent (in degrees Kelvin) latent heat constant: $L = (2.501 - 2.37 \cdot 10^{-3} \cdot T_s) \cdot 10^6$ J/kg (Bolton, 1980; Evett, 2002).

Evaporation rate tends to receive a similar treatment to sensible heat since it is largely driven by near-surface atmospheric conditions. Instead of the surface-atmosphere temperature difference dictating heat flux, the difference in water vapor concentrations was used to calculate

evaporative flux. Also, an additional set of terms was included to account for the effects of soil moisture on both the soil resistance to evaporation and the availability of near-surface water vapor in terms of specific humidity.

The specific humidity is the amount of water vapor by weight present for a given mass of air. The specific humidity at wind and temperature sensor height, q_a , was calculated at each time step using measured relative humidity (RH), air pressure (P in Pa), and T_a :

$$q_a = \frac{M_v}{M_d} * \frac{P_v}{P - \left(1 - \frac{M_v}{M_d}\right) * P_v} \quad (\text{Eq. 3-9})$$

Where M_v and M_d are the molar masses of water vapor and dry air (0.0289652 and 0.018016 kg/mol respectively). P_v is the partial pressure of water vapor in the air (in Pa), derived from the product of RH and the saturation vapor pressure at air temperature. An empirically derived formula (Sonntag, 1994) for air over liquid water was used to derive P_v :

$$P_v = RH \cdot 100e^{-\frac{6096.9385}{T_a} + 16.635794 - 2.711193e-2 * T_a + 1.673952e-5 * T_a^2 + 2.433502 * \ln(T_a)} \quad (\text{Eq. 3-10})$$

The specific humidity of air near the surface depends on both atmospheric and soil conditions. Remote sensing studies of soil moisture have led to the development of multiple models for the effect of soil moisture on near-surface humidity (Mahfouf and Noilhan, 1991; Lee and Pielke, 1992; Tran et al., 2016). A moisture availability factor and various evaporation resistance terms have been used to incorporate simultaneous effects of wind and soil moisture on the rate at which near-surface moisture is exchanged. We found that our highest confidence fits resulted from using a single aerodynamic resistance constant and a moisture availability term multiplied by wind speed (Lee and Pielke, 1992). This approach lends itself well to our use-case because of its very generalized form that allows the model to be applied to a wide variety of soil types without significant prior knowledge of their properties.

The equation for latent heat flux that we ultimately chose takes the form:

$$LE = \frac{-L\rho_a U \beta}{C_E} (q_s^* - q_a) \quad (\text{Eq. 3-10})$$

Where q_s^* is the saturated specific humidity at the surface temperature (Eq. 3-9 with RH = 1 and $T_a = T_s$). C_E is the free parameter adjusting aerodynamic resistance to evaporation, and β is a moisture availability function that defines both the relative humidity of air near the surface and the resistance of the soil to evaporation as a function of θ . The shape of the β function is defined by a transition between dry and wet boundary conditions. In the case of standing water, soil resistance to evaporation should be zero and moisture availability should be at a maximum. As a soil dries beyond a threshold level, however, surface tension, and other limits to diffusion make evaporation less efficient (Lee and Pielke, 1992; Tran et al., 2016).

$$\beta = \begin{cases} \frac{1}{4} * \left(1 - \cos\left(\frac{\theta}{\theta_E} \cdot \pi\right)\right)^2, & \theta < \theta_E \\ 1, & \theta \geq \theta_E \end{cases} \quad (\text{Eq. 3-11})$$

Another free parameter, θ_E , is used here and represents a threshold moisture content, similar to field capacity, over which the specific humidity near the surface reaches its maximum (Mahfouf and Noilhan, 1991). θ_E roughly represents the transition from water discontinuously coating grains to an established network of liquid water connecting each pore between grains, allowing for easier diffusion.

A key consideration for the application of this latent heat model in a context where θ_E and C_E are being fit, is that accurate fitting requires observations that include a broad range of possible moisture conditions at the surface. Since our observations were taken during dry weather, natural soil wetting had to be simulated. The design and execution of the soil wetting experiments, as well as additional insights that resulted from them, are the subject of a partner paper (Eifert et al., in prep). Here we focus only on the soil wetting as it applies to the surface energy balance and developing a well-parametrized model fit of surface temperature.

Volumetric water content was measured using 12 cm Campbell Scientific CS655 two-prong reflectometer probes ($\pm 3\%$ accuracy) and 50 cm Campbell Scientific SoilVue10 rods hosting time-domain reflectometers ($\pm 1.5\%$ accuracy) at 5, 10, 15, 20, 30, 40, and 50 cm depth. The effects of evaporative cooling do not occur throughout the soil column, but are focused at the depth of the evaporative front, above which the soil is too dry, and below which water wicks upward rather than evaporating. Our analysis of subsurface soil moisture and temperature data indicate that the evaporative front at our study site remained near 7.5 cm depth. Thus, when moisture was present, a latent heat flux was applied only to grid layers shallower than 7.5 cm.

The EE181 instrument used for air temperature also carries a capacitive relative humidity sensor with an uncertainty of $\pm 1.5\%$ in conditions encountered. Air pressure was collected using a Setra model 278 capacitive barometer, with an accuracy of ± 1.0 mbar under operating conditions.

3.4.7. Solar Flux

The primary energetic forcing at our field sites was from solar radiation. Solar flux was measured using a Kipp and Zonen CNR4 net radiometer. The device hosts four light sensors, sets of up- and down-facing thermopile pyranometers (0.3-2.8 μm) and pyrgeometers (4.5-42 μm) with nearly 180° fields of view to capture total radiant energy into and out of the surface. An internal thermistor is used to radiometrically calibrate the data. The shortwave sensors have a $\pm 5\%$ daily flux uncertainty. The long wave sensors have $\pm 10\%$ daily flux uncertainty.

Radiant flux measurements Were fed into an equation for net radiation at the surface.

$$R_n = (1 - a) \cdot R_S \downarrow + \omega \epsilon R_L \downarrow - \omega \epsilon \sigma T_s^4$$

Where $R_S \downarrow$ is the downwelling shortwave flux, $R_L \downarrow$ is the downwelling longwave flux, and T_s is the fitted surface temperature. ω is the percent view of sky from the surface of interest

and σ is the Stefan-Boltzmann constant. ε is the surface emissivity, which we derived from laboratory measurements described in Section 3.4.8., and which ranged from 0.91-0.99. a is the albedo, which is a function of the ratio of the measured upwelling shortwave flux to the downwelling shortwave flux. The instrument-observed albedo was modified slightly by smoothing out values near sunrise and sunset to remove measurement inaccuracies when solar elevation was very low.

3.4.8. Sample Analysis

To constrain soil density and emissivity, samples were analyzed in the laboratory. Known volumes of sediment were collected using a metal cylinder and spatula. An 8 cm diameter and 4 cm long cylinder was chosen to be at least ten times the diameter of the mean grain size at the surface, such that representative samples could be captured. Four samples were collected in this manner and weighed in the laboratory. Following initial weighing, samples were dried and reweighed to assess moisture content. Estimated density uncertainty from scale uncertainty and cylinder volume uncertainty was $\pm 5\%$.

Following weighing, samples were sieved by hand in 0.5ϕ (logarithmic grain size scale) intervals down to 4.5ϕ ($\sim 50 \mu\text{m}$). Characteristic thermal emission spectra of 0 and 0.5ϕ subsamples and individual cobbles were captured using a Thermo Scientific Nicolet iS50R FTIR over 200 to $2,000 \text{ cm}^{-1}$ ($5\text{-}50.0 \mu\text{m}$) at a 90° viewing angle to the sample surface. The instrument was configured with gold coated optics, a CsI beamsplitter, DLaTGS detector, and a CsI-coated window. Samples were first heated in a 90°C oven for at least 12 hours and then placed on a 90°C heating element within a purged chamber cooled to 10°C . For each sample, 180 scans over the course of 6 minutes were captured and averaged. To obtain a standardized emissivity spectrum, averaged spectra were compared to measurements of a conical black body depression held at

60°C and 100 °C, taken before and after respectively. Single emissivity values were then calculated by averaging the emission spectra from 7.5-13.5 μm , the range of the infrared cameras used in the field.

3.4.9. UAV Imagery

In tandem with data collection from the tower station, uncrewed aerial vehicles (UAVs) were also used to capture thermal imagery extending over a larger field area (Figure 3-7). By expanding the observable field area, greater soil heterogeneity can be captured and a spatial area that is more applicable to satellite observation scales can be considered. Once temperature mosaics of the field area were produced, they were then used to model pixel-by pixel TI. This was achieved by assuming that on the ten-minute scale similar environmental conditions existed at the tower and across the field area, which extended no more than 75 m from the tower. In this way, the model was first run for the soil underneath the tower to acquire the environmental parameters fit by the model (C_H , C_E , θ_E , θ_k , and m). The model was then run for each pixel, fitting only k_{dry} and using data downsampled to 10-minute intervals to reduce computational load. Due to thermophysical heterogeneity across the field site, the thickness of subsurface grid layers required to achieve model stability had to accommodate k_{dry} values that were both higher and lower than k_{dry} at the tower site. The assigned top-layer thickness was thus 1 cm for UAV TI mapping. For the purposes of UAV mapping, the effects of soil moisture on thermal conductivity were ignored, such that derived thermal conductivity is k_{eff} rather than k_{dry} . Using Eq. 3-3, k_{dry} can be calculated from k_{eff} once soil moisture for a given spot is known or estimated.

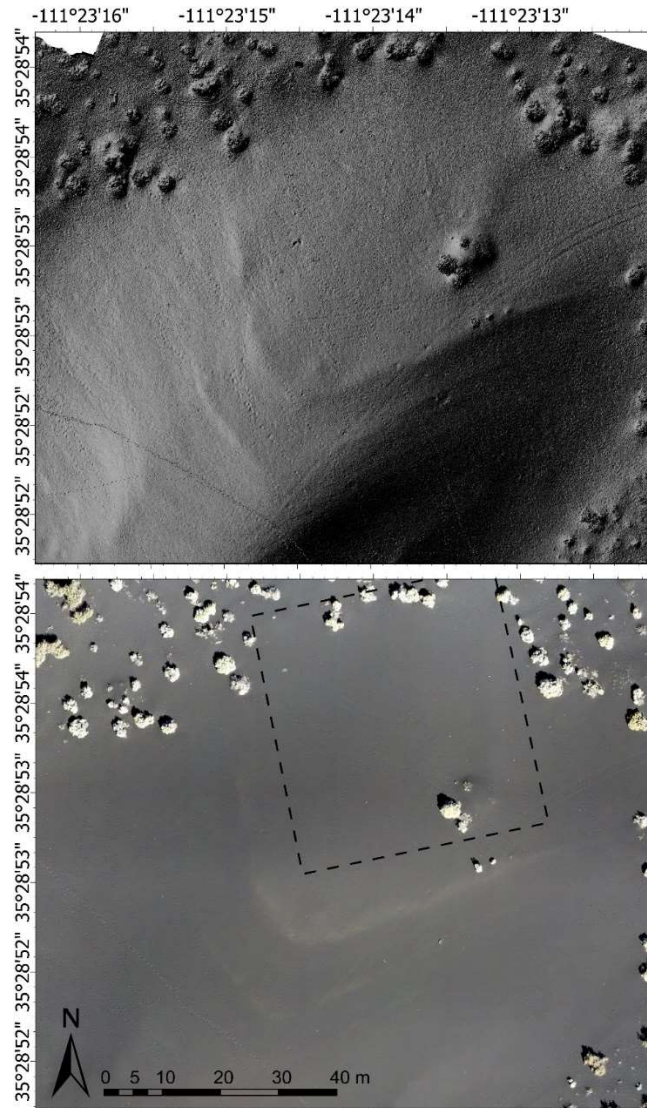


Figure 3-7. UAS-derived maps of Woodhouse Mesa prior to disturbance. 5x exaggerated hillshade (top) showing topographic banding and visible mosaic (bottom) with region of thermal analysis outlined with dashed line.

Two UAVs were used: a DJI Matrice 600 carrying a FLIR Duo Pro R, identical to the one mounted on the tower, on a stabilized gimbal, and a DJI Phantom 4 Pro mounted with a FLIR Vue Pro R, an imager that is equivalent to the thermal imaging component of the FLIR Duo. Flights were conducted in an automated grid pattern that optimized single flight battery ca-

pability while balancing spatial resolution and image overlap with flight speed to avoid blurring. In May 2021, surface temperature was mapped at <4 cm/pixel for 10 flights over three days.

Prior to model fitting, UAV thermal images were first radiometrically calibrated using parameters captured by the weather instruments (air temperature and humidity) and by the UAV (flight height). From each flight, a temperature mosaic was produced using Agisoft Metashape software. Mosaics were finely coaligned using tie pointing and resampling techniques in ArcGIS Pro. The mosaics were then further calibrated to the surface temperature beneath the tower observed by the calibrated tower FLIR camera. In two cases, the surface temperature deviated significantly across the image due to a significant gust of wind or a passing cloud during the ~ 12 minute flight duration. Those flights were omitted.

Agisoft Metashape was also used to develop mosaics from DJI visible camera imagery (Figure 3-7) and 10-band Micasense RedEdge-MX Dual Camera imagery. The visible mosaicking yielded a high-resolution digital terrain model (DTM), developed using Agisoft's structure from motion software. Albedo was calculated by taking the mean of 10-band Micasense RedEdge-MX Dual Camera imagery (444, 475, 531, 560, 650, 668, 705, 717, 740, and 842 nm). Those values were then calibrated to the median daytime CNR4-derived albedo at the tower site — multiplicatively adjusting all values so that the values of the region under tower matched. We also used the 10-band imagery to mask out vegetation using the Normalized Difference Vegetation Index (NDVI).

Because the field area was not flat lying, the difference in solar incidence angle and effects of shadowing needed to be considered. This was achieved using the DTM to map the slope and azimuth of the site and calculate solar incidence angle at each time step using the known solar positions for the sampling timespan. Shadows were mapped across the field site at 5 cm

roughness resolution at ten-minute intervals throughout the day using the DTM. With a clear sky, as determined by deviation from the running mean in the radiometer shortwave data, shadowed regions were allocated 12% of the incident light that would otherwise reach those surfaces. Under cloudy conditions shadows were ignored. With incidence angle and shadowing known, the radiative flux was adjusted from the radiometer data for each surface point.

Given the data-intensive nature of processing pixel-by-pixel TI over 1390×1692 pixels, and given that only one parameter needed fitting, Matlab's `fminbnd` tool was used for fitting the χ_v^2 metric instead of the MCMC approach, a change that achieved greater computational efficiency. Fitting 10 data points over the course of 3 days yields higher uncertainties than fitting minutely data, however by capturing surface temperatures at key times of day (Figure 3-8, just after sunset, just before sunrise, and during the heat of the day) any potential for dramatic misfitting was mitigated.

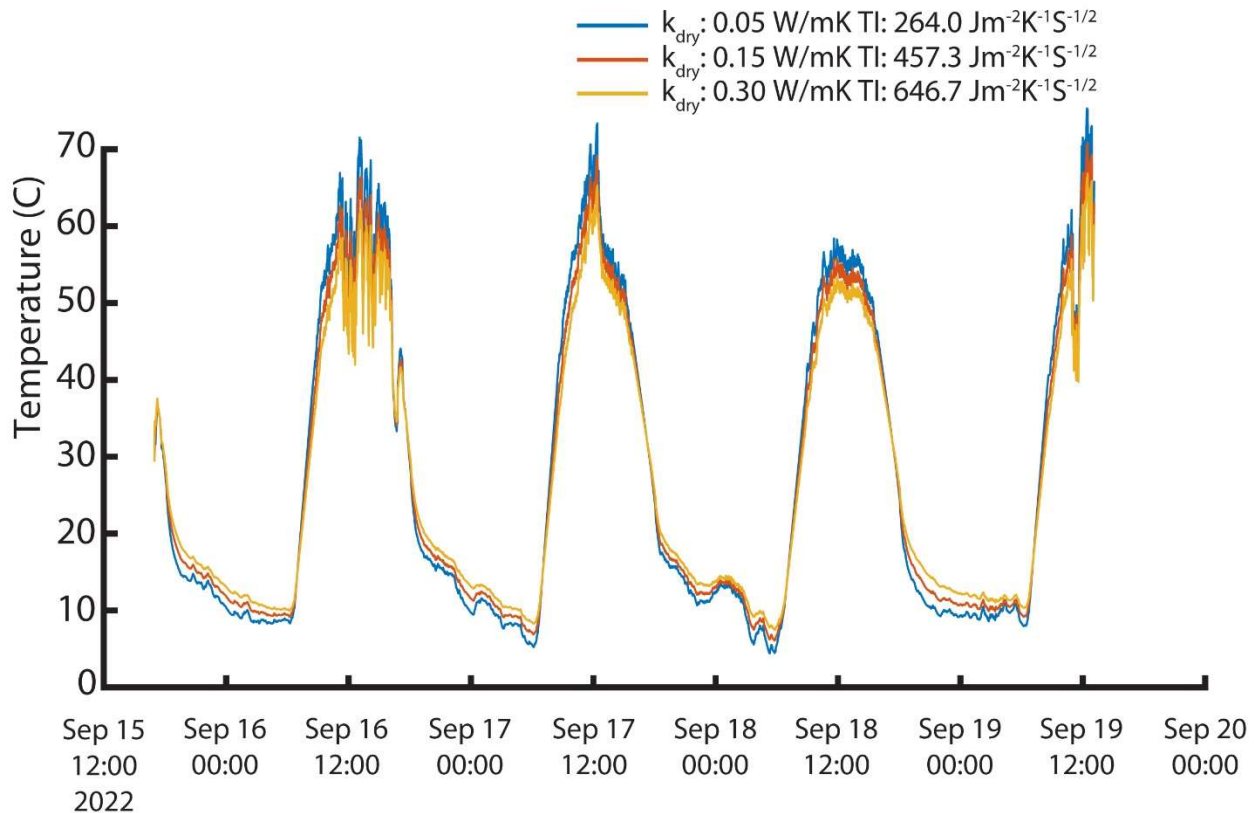


Figure 3-8. Forward model surface temperature results using September 2022 data from Woodhouse Mesa, run for the range of plausible thermal conductivities of the surface material. Curves can be difficult to differentiate in the early morning and late afternoon but show trends that differ by up to 5° C at night and midday.

3.4.10. In Situ Thermophysical Measurements

To test the validity of the model, we used thermophysical measurements taken in the field by hand (Figure 3-9). A transient plane source thermal inertia probe, a Thermtest TPS-EFF, was used to get an independent estimate of the thermophysical nature of the sediment. The tool works by applying a fixed current to a circular heating film in contact with the sample and measuring its temperature response using adjacent thermocouples. It is noted, however, that readings from the TPS-EFF change dramatically based on how it is situated on the surface of interest. Homogeneous surface contact and fine grain sizes ($\sim 150\ \mu\text{m}$) yield higher TI readings than when there is low contact that might be typical of rough surfaces, very porous soils, or coarse-grained sediment. During our measurements we captured two sets of readings, first with the device placed lightly on the surface, and then with the device placed onto compacted and smoothed fine-grained subsurface material.

A transient line source thermal conductivity probe was also deployed to provide an additional thermophysical estimate. The TLS works by applying a fixed current to one end of a needle probe in contact with the sample and measuring its temperature response with a thermocouple embedded at the other end of the needle. The TLS encounters a separate obstacle to accurate readings. Although it is well-suited to coarse soils, in moist, fine-grained soils, clumping and vapor diffusion can cause anomalously high k readings. We attempt to correct for the effects of water vapor by using the same moisture calibration equations (Eq. 3-3) employed in the thermal model.



Figure 3-9. Thermtest TPS-EFF (left) and TLS-100 (right) capturing thermophysical data at Woodhouse Mesa for model validation.

3.5. RESULTS AND DISCUSSION

3.5.1. Tower Site

Modeling efforts using data from both the May 2021 and September 2022 campaigns yielded well-constrained parameter posterior distributions and good overall χ_v^2 fits (Figure 3-10, Table 3-1). Goodness of fit was simultaneously assessed for natural and artificially-wetted soils, in order to achieve realistic parameter fits that considered a dynamic enough range in θ . Using a measured near-surface density of 1487 kg/m^3 ($\pm 5\%$), the resulting k values were 0.148 ± 0.002 and $0.149 \pm 0.002 \text{ W/mK}$ for the 2021 and 2022 data respectively. This near perfect match provides a key demonstration from this study – that the methods are reproducible, fitting the same bulk k_{dry} to a soil under different environmental conditions.

At the derived k_{dry} value, k_{eff} ranged from ~ 0.15 to 0.185 W/mK for the September 2022 campaign (Figure 3-4). This diurnal k_{eff} variation of 0.035 W/mK with a 60 K temperature varia-

tion is consistent with predictions from modeling of glass beads in Earth atmospheric conditions, where k_{eff} varied by 0.02 W/mK over 30 K (Piqueux and Christensen, 2009).

Another promising result from this effort came when comparing the model to *in situ* measurements. From modeled k_{dry} , a c_p of 1083 J/kgK, and the range of measured densities at the field site (1199-1487 kg/m³), the modeled TI range was 436.2- 492.7 Jm⁻²K⁻¹s^{-1/2}. c_p uncertainty, while not directly quantified, is expected to be small, expanding that range perhaps by only a few Jm⁻²K⁻¹s^{-1/2} (Farouki, 1981). The average TI result from three measurements using the Thermtest TPS-EFF plane probe when placed on a smoothed surface was 479.27 ± 23.96 Jm⁻²K⁻¹s^{-1/2}, in very good agreement with the model results. Similarly, the average moisture-corrected result from three TLS-100 needle probe measurements, again using a c_p of 1083 J/kgK and the measured soil density at the spot of probing of 1199 kg/m³, was 473.36 ± 23.67 Jm⁻²K⁻¹s^{-1/2}.

To add another validation tool, thermal conductivity was separately derived using the sinusoid method (Evelt, 2002) wherein measured temperatures from multiple depths are related to the daily thermal wave period. The average conductivity of six interlayer estimates from a Soil-Vue10 probe measuring temperature down to 50 cm was 0.368 W/mK. This value corresponds well to the TLS-100 k_{eff} value before moisture calibration of 0.374 ± 0.019 W/mK. Together, using three independent *in situ* tools, we have established confidence in our model accuracy.

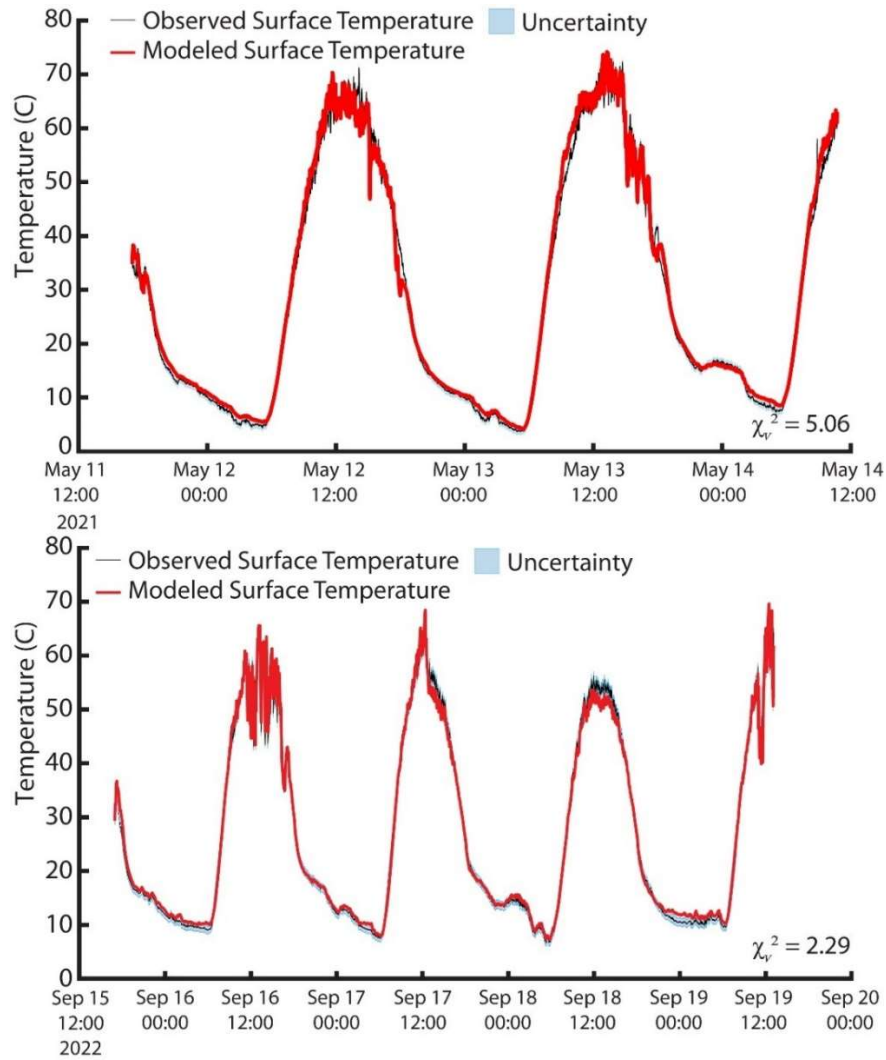


Figure 3-10. Surface temperature observations and modeling results for Woodlouse Mesa data taken May 2021 (top) and September 2022 (bottom). Posterior distributions of fitting parameters can be found in Figure 3-11.

It is worth noting that TPS-EFF measurements taken by placing the probe lightly on the surface yielded TIs significantly lower in value ($225 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ or $\sim 0.03 \text{ W/mK}$ when converted to k). We interpret this result to reflect the thermophysical nature of a very thin ($\sim 7.5 \text{ mm}$) porous lag deposit that sits at the surface (Figure 3-1). Since the heat pulse of the TPS-EFF instrument lasts only on the order of tens of seconds, the skin depth it is sampling is very thin. The diurnal surface temperature curve fit by the model, on the other hand, probes to a much deeper skin

depth (>5 cm). Hence, when the TPS-EFF is placed on a smoothed surface that is more representative of the bulk of the subsurface, the TPS-EFF and model results align more closely.

Model Parameter	Description	May 2021 Output	September 2022 Output
k_{dry}	Bulk dry thermal conductivity (W/mK)	$0.148^{+0.002}_{-0.002}$	$0.149^{+0.002}_{-0.002}$
m	Pore fluid network connectivity parameter	$0.79^{+0.01}_{-0.01}$	$0.93^{+0.013}_{-0.016}$
C_H	Sensible heat coefficient (aerodynamic resistance)	$680.5^{+4.4}_{-4.3}$	$404.2^{+1.4}_{-1.3}$
C_E	Latent heat coefficient (aerodynamic and soil resistance)	6698^{+39}_{-39}	2902^{+28}_{-39}
θ_k	Soil water capacity (m^3/m^3)	$0.29^{+0.005}_{-0.005}$	$0.57^{+0.021}_{-0.024}$
θ_E	Soil water evaporation transition threshold (m^3/m^3)	$0.044^{+0.0003}_{-0.0003}$	$0.065^{+0.0005}_{-0.0005}$

Table 3-1. Output parameters from model fitting in May 2021 and September 2022 campaigns with descriptions.

Unlike k_{dry} , the other parameters that the model fits for do not necessarily closely align. This outcome is not entirely unexpected. Under ideal experimental conditions, we would expect the values to match. However, slight changes in the positioning of instruments could have a profound impact on the fitting parameters. For example, setting up the anemometer a few cm higher or lower would have the effect of sampling aerodynamic conditions at a different level and would alter how its response relates to near-surface convection, thus changing the magnitude of C_H . Similarly, minute differences in the placement and burial depth of the soil moisture probes would alter m , C_E , θ_k , and θ_E . Reassuringly, however, the m values of 0.79 in 2021 and 0.93 in 2022 are both consistent with the range of experimental results for coarse soils of the type that dominates the field site (Lu et al., 2007). Similarly, derived C_H coefficients were 680.5 in 2021 and 404.2 in 2022, translating (via $1/C_H$) to 0.0015 and 0.0025 aerodynamic drag coefficients, assuming neutral static stability (Stull, 2006). These values are both consistent with roughness lengths under 5 mm, which is expected for sparsely vegetated smooth landscapes.

3.5.2. Sensitivity Testing

In order for the model in this work to be applicable on remote sensing scales, the environmental conditions that were tracked would ultimately have to be replaced by less well-constrained values from orbital data, general circulation models (e.g., Toigo et al., 2012), or other sources. While observed surface temperature uncertainty might only increase incrementally, assumptions made for the atmospheric and subsurface variables could introduce large sources of uncertainty elsewhere. To understand the potential sources of error when translating this work into the remote sensing context, we conducted extensive sensitivity testing (Table 3A-1).

Overall, the baseline model posterior distributions appeared very well constrained (Figure 3-11), an indicator of good model design and normal distributions on measurement uncertainties. After establishing a baseline model design, plausible uncertainties were introduced one-at-a-time to measured inputs (Table 3A-1). In each case, changes in the resulting parameter fits and their respective uncertainties were assessed.

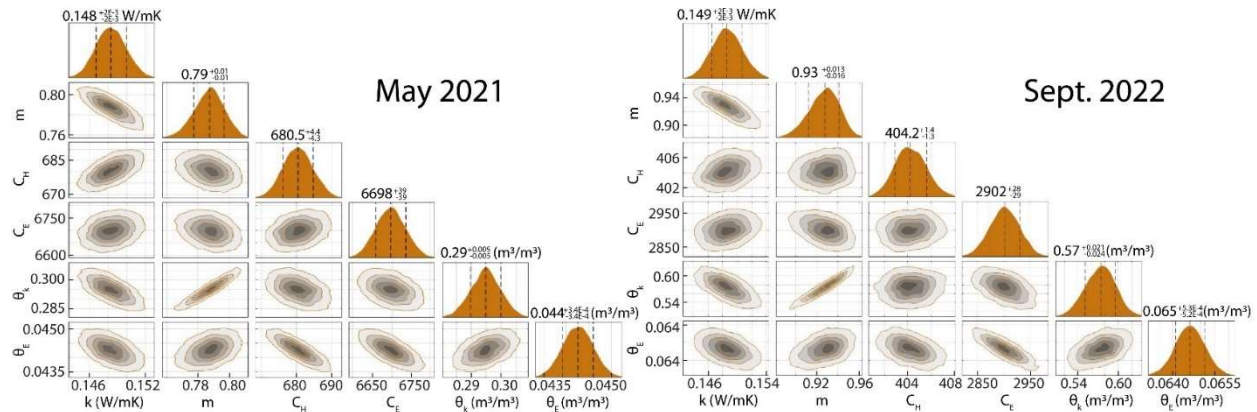


Figure 3-11. Markov Chain Monte Carlo posterior distributions for model fitting in Figure 3-10. The gaussian distributions indicate that the parameters are well-constrained and that the uncertainties associated with the measurement tools are normally distributed. Paired posterior distributions show consistent positive correlations between m and θ_k and negative correlations between k_{dry} and m , k_{dry} and θ_k , and C_E and θ_E .

3.5.2.1. Temperature

Surface temperature observations are the primary input to deriving TI. In order to fully appreciate the influences of potential sources of measurement error on derived TI, we tested how a variety of different forms of error would influence the model results. As discussed previously, the initial uncertainty for surface temperature measurements was taken to be $\pm (0.2 \text{ K} + 0.2\%)$. We also considered larger additive uncertainty (± 5 and $\pm 10 \text{ K}$) as well as multiplicative uncertainty ($\pm 10\%$). Since incident radiation can affect instrument performance, we also investigated uncertainties as a function of $R_{S\downarrow}$ ($0.5+ R_{S\downarrow}/200$ and $5.5- R_{S\downarrow}/200$).

Increasing the measurement uncertainty tended to slightly increase median k_{dry} , as the model was more likely to accept lower daytime temperatures. Increasing the measurement uncertainty also increased the spread in MCMC posterior distribution, indicating a poorer constraint on the result. By changing the observed temperature values by the assigned amounts, both adding and subtracting, tended to also increase median k_{dry} , since increasing nighttime lows requires larger k_{dry} , as does decreasing daytime highs. This effect seems to supersede the effects of decreasing nighttime lows or increasing daytime highs for model fitting. Nevertheless, model fits proved poor in these scenarios. The cases where model fits improved were the ones where temperature was set as a function of $R_{S\downarrow}$. Though these scenarios do not represent realistic conditions, they do demonstrate how the model is able to fit a very simple temperature curve based only on incident light, as might be expected for an airless body.

3.5.2.2. Soil Density

Model runs were initially implemented using soil density values derived from field and lab sample measurements. However, there are two main reasons why this approach could hinder

model performance: first, due to error in density measured, or second, because the density of the sampled layer is not representative of all the material in the modeled soil column.

To assess the sensitivity of the model to changes in density, we used two fixed values in addition to our measured value for the surface directly beneath the tower, a) 1300 kg/m^3 , a value derived from lander measurements that is often used for Martian regolith (Piqueux et al., 2021), and b) 2900 kg/m^3 a typical value for non-porous basalt and approximate crustal density from gravity measurements of Mars (Wieczorek et al., 2022). Changing the input density tended to produce somewhat worse fits ($\chi_v^2 = 2.54$ for $\rho = 1300 \text{ kg/m}^3$ and $\chi_v^2 = 2.58$ for $\rho = 2900 \text{ kg/m}^3$), but TI remained fairly constant by compensating with changes in k_{dry} .

In addition to static changes in density, we also experimented with allowing density to be a free parameter constrained by a normal distribution based on estimated measurement uncertainty (± 5). The model tended to produce higher density values and lower k_{dry} values, but the TI remained within the previously derived range. These results indicated that the model is robust to errors in density input when it comes to ultimately deriving TI.

3.5.2.3. *Atmospheric conditions (Radiative Flux, Air Pressure, Temperature, Wind Speed, and Humidity)*

To understand of the sensitivity of the model to error in meteorological inputs, and to specifically assess model applicability to *in situ* Mars science, we assessed the sensitivity of the model to the uncertainty ranges associated with the MEDA instrument suite aboard the Mars 2020 Perseverance rover (Martínez et al., 2023). The recent availability of high quality near-surface climate data (e.g., Martínez et al., 2023) also provided a sense of the expected uncertainty for circulation models when modeling surface energy flux in the context of Mars (Holmes et al., 2020; Newman et al., 2021; Sánchez-Lavega et al., 2023). For individual meteorological pa-

rameters, we assessed how systematic error might influence the model. The model was rerun for the maximum and minimum of the error range for each input.

Reported uncertainty for MEDA relevant to this work includes $R_L\downarrow$ ($\pm 6.9 \text{ W/m}^2$), R_S ($\pm 9.6 \text{ W/m}^2$), Pressure ($\pm 3.5 \text{ Pa}$), Wind ($\pm 1 \text{ m/s}$ at below 10 m/s and 10% above 10 m/s , 1.25 m/s at 293 K), Humidity ($\pm 6\%$), and Air Temp ($\pm 2.83 \text{ K}$) (Martínez et al., 2023). Satellite derived atmospheric parameters have uncertainties that are similar in magnitude to the MEDA suite (Holmes et al., 2020; Sánchez-Lavega et al., 2023), albeit at much coarser spatial resolutions (the finest orbital data derived circulation models have a 1.4 km grid spacing [Newman et al., 2021]), and predictions from atmospheric models for Jezero crater are a good match to observations made by the MEDA instrument (Newman et al., 2021; Sánchez-Lavega et al., 2023). Thus, the results of sensitivity analysis here are applicable to surface analyses at both rover scales and a patch of the surface covering an area similar in size to the circulation model grid.

Altering pressure and humidity within the uncertainty ranges have minimal effect on the overall fit. Both increasing and decreasing air temperature led to slightly poorer fits with higher k_{dry} values. Similarly, both increasing and decreasing $R_L\downarrow$ and $R_S\downarrow$ increased k_{dry} . These trends seem to emerge as the model is compensating for irregularities in energy flux by buffering the soil against temperature change. It follows that observational errors in these input datasets will tend to have the effect of generating TIs that are higher than they should be. The test that did not follow this trend was applying changes to wind speed. Decreasing wind speed did increase k_{dry} and increasing wind speed decreased k_{dry} , as enhancing convective heat exchange also offered a route to buffering temperature.

3.5.2.4. Emissivity and Albedo

Remote thermal inertia studies of Mars generally assume spectral properties of the surface as derived from orbital infrared imaging or ground-based spot observations. However, the instruments that capture that data host associated uncertainties. The TES instrument has an uncertainty of ± 0.0013 - 0.0035 , depending on wavelength, in its derived surface emissivities (Christensen et al., 2001). The Insight lander reports a ± 1 /-2% error on emissivity (Morgan et al., 2018). We use an error of 2% to gauge how changes within this range might affect our modeling. We set emissivity to be a free parameter bound by a normal probability distribution with $\sigma = 0.02$, and $\mu = 0.966$ as the mean measured value.

We found that by allowing emissivity to be free, the model pushed its value toward unity, tending toward a perfect exchange of radiant energy. This both improved model fit and increased k_{dry} since it forced the soil to be more buffered against radiative heat loss. From this result, we note that diligence in applying constraints on surface emissivity provides an important safeguard on model performance.

3.5.2.5. Soil Water Content

The aim in considering soil water content in this work was primarily to consider the effects on thermal conductivity and evaporative cooling. The instruments we deployed hosted general uncertainties of $\pm 1.5\%$ for SoilVue 10 and $\pm 3\%$ for CS655. To assess how changes in moisture affect the model, we systematically increased and decreased the measured values by 3%. Because soil moisture readings also depend on temperature, we also assessed a synthetic temperature-dependent soil moisture ($\theta = T_{surf}/30 - 273.15/30$). We also tried fixing θ at 0 and 10%.

According to Eq. 3-3, a larger observed θ should increase k_{eff} . It follows that artificial increases in θ will force k_{dry} compensate by decreasing and vice versa. We see this trend emerge in

the $\pm 3\%$ tests. Dramatic changes in soil moisture (setting θ to 0 or 10% and as a pure function of temperature) had the additional effect of generating very poor model fits. This result reinforces the importance of diligently considering the soil moisture in studies of TI on Earth. In the context of Mars, soil moisture is expected to play a less important role on thermophysics since water vapor cannot be sustained in the same abundance as it can in Earth's denser atmosphere.

3.5.3. *TI Mapping*

When applying the model over the larger field area using the UAV data, the majority of surfaces showed excellent temperature fits, with pixel χ_v^2 values ranging from ~ 1 to 15 (Figure 3-12). Some areas, such as frequently shadowed regions and vegetation showed poorer fits. Vegetation hosts additional complexities in heat transfer that the model did not consider, and shadowed regions experience a diffuse sky radiation input that was also not fully captured by the model as it changes non-linearly with solar position, atmospheric haze, and cloud cover.

TI ranged across the field area from ~ 350 to $550 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$, with a TI near the tower site of $446 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ that was consistent with the TI retrieval from the tower data. TI increased upslope towards the south of the image, and curved bands of alternating elevated and subdued TI ($\pm 50 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$) appeared across the scene – bands that do not appear in visible imagery but do align with visible features and topography farther up slope (Figure 3-7). We believe the elevated bands of TI are associated with the thickening and thinning of a lag layer of coarser clasts at the surface, a subtle surface bedding effect not readily apparent in other remote sensing datasets. It was a challenge, however, to test this theory with surface sampling since the banding occurs on scales that are finer than handheld GPS uncertainty ($\pm 3\text{m}$).

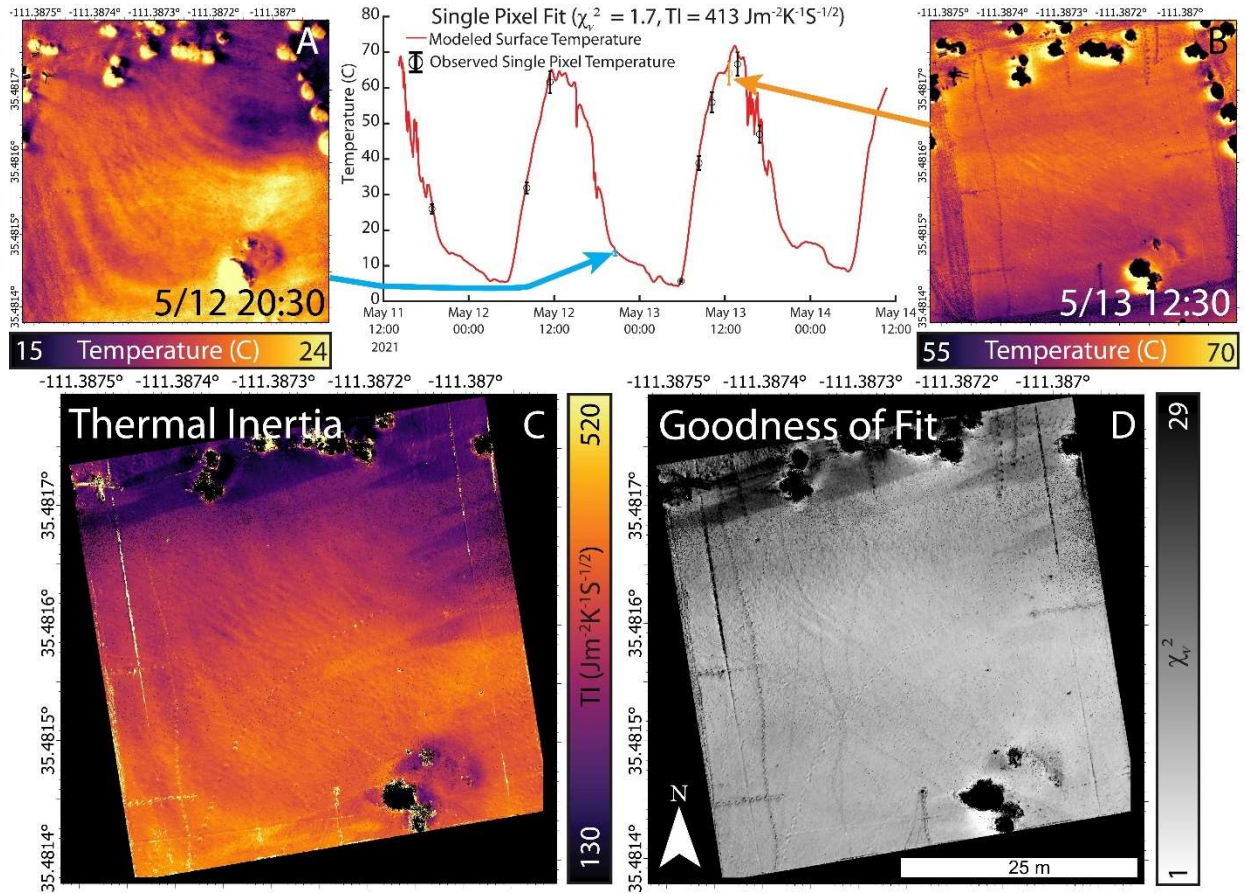


Figure 3-12. Thermal inertia modeling results for uncrewed aerial system mapping area from May 2021. A (8:30 PM) and B (12:30 PM) show 2 of 10 temperature mosaics collected over 3 days with arrows indicating the points on the single pixel temperature plot (top center) that were captured from those mosaics. The bottom row shows the resulting thermal inertia map (C) and associated χ^2 goodness of fit (D). Fitting was fairly strong across the field site, although frequently shadowed regions show the worst fits.

3.6. CONCLUSION

We have developed a closed-form model for deriving thermal inertia in unvegetated natural sediment using observed weather data while accounting for soil moisture's effect on conductivity and evaporative cooling. We tested the approach's sensitivity to the parameters whose accuracy is most likely to be limited in remote sensing contexts. Sensitivity testing revealed that the greatest sources of uncertainty stem from emissivity, soil moisture, and wind speed, although none posed a major hurdle to confidently modeling within standard uncertainty ranges. Since,

however, emissivity can vary significantly between adjacent surfaces in natural settings, it is important to ensure that emissivity inputs adhere to the same spatial resolutions, or finer, as the derived TI. We also note that model subsurface layering scales and meteorological sampling rates must be balanced with the temporal scale assigned to the model steps to achieve model stability at a reasonable level of computational efficiency.

Our results demonstrate that we have developed a physically realistic and novel approach for calculating TI on Earth that minimizes necessary knowledge or assumptions about a specific surface. We have shown that the model results are reproducible, using two different sets of observations of the same sedimentary setting, and that the model results are consistent with *in situ* thermophysical measurements. Our methodology for deriving thermal conductivity without surface contact appears to be a robust tool assessing properties relevant to remote sensing data. By mitigating Earth-specific uncertainty and isolating the controls that are most relevant to Martian sediments, this work provides a new avenue to conducting thermophysical experiments that will ultimately improve interpretations of thermal data for the Martian surface.

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3.8. APPENDIX 3A

Table 3A-1. Results of model sensitivity testing.

Test	χ^2	k_{dry} (W/mK)	k_{dry} -(%)	k_{dry} +(%)	m	C_H	C_E	θ_k	θ_E	TI (Jm ⁻² K ⁻¹ s ^{-1/2})
Woodhouse 2021 Dry Surface	4.31	0.088	1.5	1.6	1.29	559.0	9922	0.89	0.040	352.38
Woodhouse 2021 Experimentally Wet Surface	12.95	0.156	0.8	0.8	0.12	601.9	5916	0.36	0.059	477.74
Woodhouse 2021 Simultaneous Wet and Dry Surfaces	5.06	0.148	1.4	1.4	0.79	680.5	6698	0.29	0.044	488.20
Woodhouse 2022 Dry Surface	1.66	0.186	4.4	5.1	1.04	580.4	203	0.73	0.186	546.53
Woodhouse 2022 Experimentally Wet Surface	1.72	0.095	2.0	2.1	1.08	353.5	2841	0.77	0.076	391.59
Woodhouse 2022 Simultaneous Wet and Dry Surfaces	2.29	0.149	1.3	1.3	0.93	404.2	2902	0.57	0.066	489.90
Woodhouse 2022 with gaussian uncertainty on density ($\rho = 1470 \pm 70$ kg/m ³)	2.22	0.112	1.8	1.9	0.97	394.1	2899	0.64	0.065	452.27
Woodhouse 2022 with fixed density of ($\rho = 1300$ kg/m ³)	2.54	0.185	1.3	1.0	0.65	407.2	3009	0.35	0.062	521.53
Woodhouse 2022 with fixed density of ($\rho = 2900$ kg/m ³)	2.58	0.051	1.4	1.2	1.00	368.6	2748	0.83	0.065	368.98
Woodhouse 2022 with gaussian uncertainty on emissivity ($\epsilon = 0.96 \pm 0.02$)	2.11	0.144	1.4	1.3	0.95	412.8	2958	0.57	0.068	481.95
Woodhouse 2022 with temperature = 0.5 K+R short upper/200	1.22	0.104	13.1	1.0	0.08	371.7	3218	0.53	0.086	408.54
Woodhouse 2022 with temperature = 5.5 K-R short upper/200	1.96	0.266	0.9	0.0.8	0.19	436.8	2094	0.73	0.082	654.64
Woodhouse 2022 with temperature = observed - 5 K	11.68	0.167	0.7	0.8	0.09	825.0	1341	0.75	0.028	518.34
Woodhouse 2022 with temperature = observed + 5 K	9.30	0.282	0.9	6.8	0.91	733.2	4993	0.20	0.115	674.22
Woodhouse 2022 with temperature = observed*1.1	2.83	0.148	0.9	0.9	0.92	566.7	4706	0.41	0.083	488.19
Woodhouse 2022 with temperature = observed*0.9	4.32	0.179	0.8	0.8	0.06	355.4	1842	0.75	0.040	537.31
Woodhouse 2022 with temperature = temperature error = ± 5 K	0.07	0.150	8.6	8.3	0.92	403.3	2877	0.58	0.064	491.93
Woodhouse 2022 with temperature error = ± 10 K	0.02	0.158	11.9	10.4	0.73	402.0	2978	0.47	0.063	505.09
Woodhouse 2022 with temperature error = observed*0.1	0	0.161	26.3	28.0	0.53	400.6	2904	0.47	0.065	509.39
Woodhouse 2022 with air temperature = observed + 2.3	3.06	0.170	0.7	0.7	0.05	444.7	2630	0.75	0.045	522.50

Woodhouse 2022 with air temperature = observed - 2.3	2.58	0.147	1.0	1.2	0.92	435.9	3373	0.37	0.078	486.79
Woodhouse 2022 with pressure = observed + 3.5 Pa	2.42	0.137	1.4	1.4	0.97	399.3	2839	0.64	0.066	468.82
Woodhouse 2022 with pressure = observed - 3.5 Pa	2.42	0.137	1.5	1.4	0.97	399.4	2840	0.64	0.066	468.83
Woodhouse 2022 with humidity = observed + 6%	2.36	0.140	1.4	1.5	0.98	403.1	2620	0.71	0.066	474.07
Woodhouse 2022 with humidity = observed - 6%	2.47	0.133	1.4	1.5	0.96	395.8	3057	0.60	0.066	463.55
Woodhouse 2022 with soil moisture = observed + 3%	3.31	0.140	1.4	1.4	0.85	392.4	2909	0.48	0.068	474.15
Woodhouse 2022 with soil moisture = observed - 3%	3.76	0.164	1.5	9.5	1.01	332.6	1789	0.65	0.066	513.54
Woodhouse 2022 with soil moisture = 0	12.93	0.096	0.6	0.6	0.64	266.7	2470	0.75	0.249	393.23
Woodhouse 2022 with soil moisture = 10%	12.43	0.049	0.2	0.2	0.42	401.6	1821	0.75	0.453	280.31
Woodhouse 2022 with soil moisture = (observed temperature) /300+273.15/300	9.88	0.066	1.1	1.1	0.43	438.3	4787	0.75	0.485	326.05
Woodhouse 2022 with downwelling longwave radiation = observed + 6.9 W/mK	2.81	0.144	0.8	0.8	0.04	393.9	2956	0.75	0.057	482.19
Woodhouse 2022 with downwelling longwave radiation = observed - 6.9 W/mK	2.13	0.143	1.3	1.3	0.96	406.8	2995	0.54	0.071	479.54
Woodhouse 2022 with upwelling shortwave radiation = observed + 9.6W/mK	2.10	0.144	1.2	1.1	0.96	409.9	3054	0.51	0.072	481.84
Woodhouse 2022 with upwelling shortwave radiation = observed - 9.6 W/mK	2.59	0.147	2.0	2.3	0.93	391.1	2772	0.60	0.064	487.22
Woodhouse 2022 with wind speed = observed + 1 m/s	1.85	0.123	0.9	1.1	0.56	473.7	4812	0.35	0.055	445.71
Woodhouse 2022 with wind speed = observed - 1 m/s	3.75	0.164	1.6	18.3	1.01	332.3	1790	0.66	0.068	514.48

CHAPTER 4

MANUSCRIPT III: LINKING SEDIMENT THERMAL INERTIA TO DEPOSITIONAL CONTEXT ON EARTH AND MARS

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4.1. ABSTRACT

Satellite-derived surface temperatures have been a valuable tool for geologic mapping since the first deployments of thermal infrared imagers to Earth orbit and Mars in the 1970s. Special attention has been given to the utility of these datasets for identifying hazards to landers and rovers and for detecting subsurface volatiles for *in situ* resource utilization. However, efforts to quantify the physical properties and environmental histories of rocks and sediments using thermal data have consistently yielded large uncertainties. Combinations of grain size, packing geometry, cementation, volatile abundance, subsurface heterogeneity, and sub-pixel horizontal mixing lead to multiple scenarios that would produce a given thermal response at the surface. We use Mars-analog settings on Earth as natural laboratories to study how the interplay of these traits control thermophysical properties. We completed field campaigns at eight unique sites located in the U.S. Southwest, Hawai'i, and Iceland, each providing a unique sedimentary endmember for constructing an inclusive model of environmental settings relevant to past Mars. At each site we collected *in situ* data and deployed a modular weather station that constrains the surface energy flux in a manner that enables remote thermophysical analysis. By pairing thermo-

physical results with spectroscopic analyses and systematic grain characterization, we were able to identify key grain features related to thermal conductivity and determine how combinations of orbitally derived properties can be used in tandem with thermal infrared imagery to differentiate the environmental settings recorded by sedimentary deposits. This work paves the way for future studies to use Earth as a thermophysical analog to study a wide array of materials on other worlds.

4.2. INTRODUCTION

Despite decades of satellite thermal infrared imaging of the Martian surface, uncertainty over what thermal trends signify about geologic materials has persisted. Combinations of grain sizes, packing geometry, cementation, volatile abundance, subsurface heterogeneity, and sub-pixel mixing can each lead to similar non-unique thermal inertias (TIs) (Ahern et al., 2021; Presley and Christensen, 1997a). TI is a material property controlling the rate of heating or cooling in response to an energy flux, and it has been an effective measure for remotely interpreting some geologic features (Mellon et al., 2009), identifying volatiles (Piqueux et al., 2019), and ensuring safe spacecraft landings (Nowicki and Christensen, 2007). For geologic materials, higher TIs are associated with cemented surfaces and bedrock, while unconsolidated sediment shows lower TIs. Because of the relationship between thermal and physical properties of sediment, thermal studies offer a valuable route to sedimentology that complements other remote sensing datasets (e.g., hyperspectral, visible, radar).

Laboratory studies (Presley and Christensen, 2010a, 2010b, 1997b; Presley and Craddock, 2006) and modeling efforts (Piqueux and Christensen, 2009b, 2009a) have begun to constrain how different physical properties of sediment, such as grain size and cementation, work in tandem to control TI. But laboratory studies are limited in their ability to quantify many

of the controls on TI inherent to natural sedimentary environments. Influential features like surface crusts, lag deposits, grain size distributions, grain orientations, and grain contact geometries are prohibitively difficult to replicate in the lab or model.

Recent thermophysical observations from rovers and landers have renewed interest in understanding the physical controls on thermal inertia relevant to Mars. Together the Mars Science Laboratory (MSL), InSight, and Mars 2020 missions have captured diurnal temperature observations of a wide range of surface materials over numerous sols (Edwards et al., 2018; Grott et al., 2021; Hamilton et al., 2014; Martínez et al., 2023; Piqueux et al., 2021; Savijarvi et al., 2022; Vasavada et al., 2017; Weintraub, in prep). Surfaces observed in Gale crater include fluvio-lacustrine deposits, active sand dunes, poorly sorted regolith, and duricrusts. InSight also observed poorly sorted and weakly consolidated regolith and Mars 2020 is analyzing the thermal properties of an additional suite of deposits in Jezero crater that includes volcanic and fluvio-deltaic materials. These observations provide hints that individual depositional settings appear to lead to the development of unique combinations of physical properties, mineralogy, and thermal inertia, which can be used together for more confident interpretation than with any single property alone (Ahern et al., 2021; Koeppel et al., 2021). However, rover observations are limited to very small regions of the planet.

In order to better understand the linkages between TI and other observable properties for natural depositional environments relevant to Mars, we conducted thermophysical analyses of a breadth of surface materials on Earth. Our goals were to 1) develop an expanded thermophysical dataset of natural materials relevant to present and past depositional environments on Mars, and 2) probe nuanced controls on thermal inertia to interrogate how additional remote data sets might further constrain sedimentary properties and processes on Mars.

To achieve these goals, we collected paired thermophysical, spectral, compositional, and morphological data at eight unique analog sites on Earth. We derived TI using both *in situ* measurements and remote infrared observations paired with an energy balance model that derives TI on Earth in a manner that is comparable to orbitally derived TI (Chapter 3). We then translated TI values to Martian atmospheric conditions, and a multivariate analysis approach allowed us to explore and test multiple hypotheses for the controls on apparent TI relevant to Mars. By providing updated constraints on how TI is correlated to other traits, we develop two new approaches for interpreting grain-scale features and sedimentary history from orbit. We test the models by applying results to two sites hosting diverse suites of sedimentary materials, one on Mars and one on Earth. Ultimately, disentangling the grain-scale correlations to TI will open the door to new revelations for granular surfaces on Mars and perhaps other bodies across the solar system.

4.3. THERMOPHYSICAL ANALOGS AND THE NATURAL LABORATORY

Mafic sedimentary environments on Earth provide a useful natural laboratory for studying how the interplay of physical traits control diurnal temperature curves. TI is a function of the square root of the product of thermal conductivity (k), density (ρ), and specific heat capacity (c_p), and Martian basalts appear to host similar k , ρ , and c_p as basalts on Earth (Opeil et al., 2012). We also know that similar environmental processes have constructed the sedimentary features on both worlds (e.g., Banham et al., 2018; Carter et al., 2015; Edgar et al., 2018; Farrand et al., 2018; Horgan et al., 2017; Kite, 2019; Navarre-Sitchler and Brantley, 2007; Rasmussen et al., 2010; Zolotov and Mironenko, 2016), and the thermal properties of the solid components of sedimentary deposits derived from basalts on the two worlds are likely to also be the same. As a result, by studying the thermal responses of sediment on Earth, we can better identify controls on

TI relevant to both worlds.

For this study, we visited eight field sites (Figure 4-1) representing a diversity of depositional settings expected for modern and ancient Mars (Table 4-1), including eolian, fluvial, lacustrine/playa, periglacial, and volcanic. Sites were selected primarily for their mineralogical and/or mechanistic similarities to environments on Mars; however, several other factors were also key in site selection. Minimal vegetation was necessary for unobstructed surface exposure and minimal influence of root systems on subsurface heat transfer. Because of the bulky nature of the instrumentation, reasonably easy access via 4wd track was also a requirement.

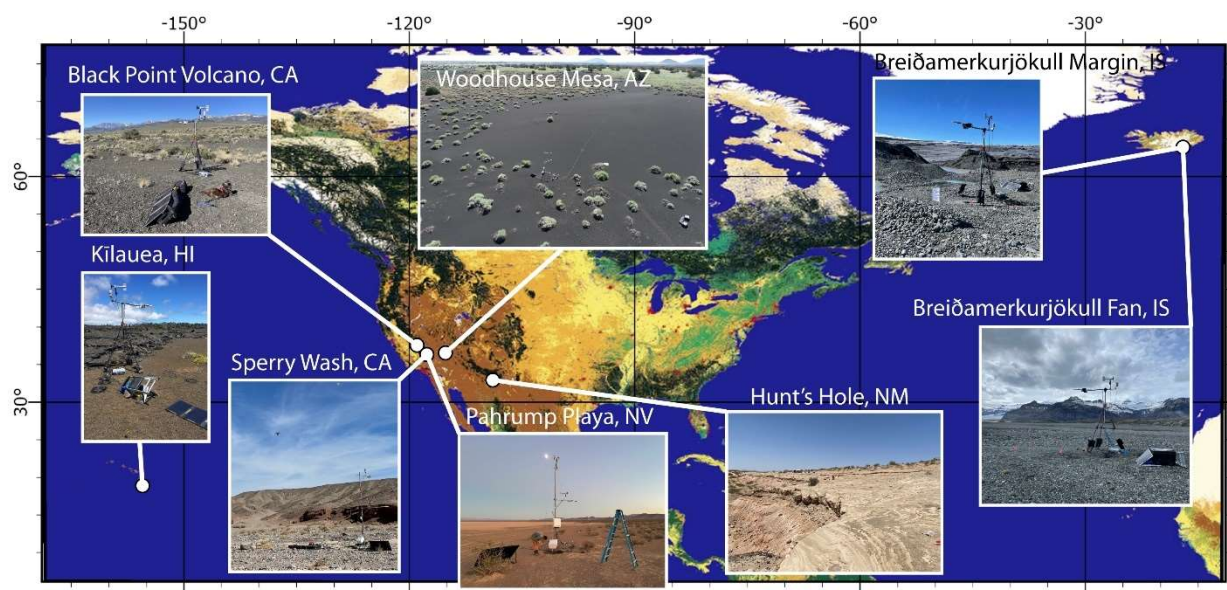


Figure 4-1. Field locations with images of the tower deployments at Black Point, a basaltic volcano that erupted subaqueously, Woodhouse Mesa, an eolian dune made of basaltic tephra, Kilauea, a site with glassy basaltic tephra and an intact lava flow, Sperry Wash, a fluvial fan, Pahrump Playa, an ephemeral lake basin, Hunt's Hole, a hydroclastic maar, and Breiðamerkurjökull, a glacial outwash plain.

At each site, thermal and environmental data was collected over a 30 to 84-hour span, at one-minute intervals. Two different instrument setups (Figure 4-1 inset panels) were used depending on travel requirements. For all sites in the continental U.S. except Black Point, a 7 m tower with two cross arms was used. The infrared camera was placed on the upper arm at 7 m,

while all other instruments were placed on a lower 3 m-high arm. At all other sites, a surveyor's tripod hoisted to 3 m and mounted with a single cross arm was used to hold all instruments. The main advantage of the taller cross arm is a wider field of view to capture more soil diversity. More details on the instrument suite can be found in Chapter 3.

The Woodhouse Mesa Site is located 40 km NE of Flagstaff, Arizona, and we chose to visit the site twice, in May 2021 and September 2022. The site is situated on a $\sim 10^4$ m² falling dune of wind-reworked sand-sized basaltic tephra from the ~ 1085 CE eruption of Sunset Crater in the San Francisco Volcanic Field (Hooper et al., 2012). The dune extends down slope to the north from a scarp formed by the edge of a lava flow and overlies sandstone of the Moenkopi Formation. Bushes and juniper trees sparsely populate the region surrounding the dune, but vegetation is nearly absent from the sloping dune face itself. The climate is semi-arid with consistent westerly winds.

In August 2021, we deployed our instrument suite at a site near the summit of Kīlauea Volcano on the Big Island of Hawai'i. The site is at the western rim of Keanakāko'i crater, and hosts four major material types at the surface: vesicular pahoehoe emplaced during a 1974 fissure eruption to the southwest, unconsolidated glassy tephra deposited by the 1959 pyroclastic eruption of Kīlauea Iki's Pu'u Pua'i, consolidated tuff from the 1700s surge eruptions of Keanakāko'i, and dense basaltic lithic clasts deposited by any number of large explosive eruptions (Decker and Christiansen, 1984; Schiffman et al., 2000; Seelos et al., 2010). Unconsolidated angular sand to gravel-sized 1959 tephra is the dominant surface material here and trenching revealed welded tuff to underlie it at ~ 40 cm depth. Low shrubs sparsely populate the region, but vegetation is nearly absent at the observation site. Although tropical, the site sits at the edge of two microclimates, temperate rainforest to the east and semi-arid to the west, controlled by vol-

canic fumes and the rain shadow of Kīlauea’s summit against the Easterly trade winds. We observed a misting rain event on August 15th, 2021.

In October 2021, we visited two sites in the Mojave Desert, west of Las Vegas, Nevada: Pahrump Playa and Sperry Wash. Pahrump Playa is an ephemeral shallow lakebed (dry when visited) at the foot of the Nopah Mountain Range. Its surface was defined by m-scale desiccation cracks, and it is dominated by indurated and clumped clay-to-silt-sized particles. Composition is predominantly phyllosilicates, carbonates, evaporites and fine feldspathic minerals. Sperry Wash, to the southeast, is a canyon carved by the ephemerally active Amargosa River. Initiation of a seeping flow took place during observation. The field site itself is situated at the mouth of the canyon, where it opens to a fan at the edge of the Dumont Dune Field. The sampling site consists of diverse and poorly sorted clasts, ranging from 10 cm-scale sub-rounded clasts of felsic and mafic igneous rock to eolian sand and indurated silt-dominated fluvial channel deposits. While sporadic desert shrubs are present nearby, vegetation is minimal at both sites. The region is arid to hyper-arid.

In April 2022, we visited Hunt’s Hole, New Mexico, a phreatomagmatic vent in the El Potrillo Volcanic Field 45 km northwest of El Paso, Texas. We chose a site on the north rim of the crater on an exposed surface of weakly lithified pyroclastic surge beds, with predominantly sand sized mafic and felsic constituent grains. Adjacent surfaces include basaltic lava, eolian bedforms, and fluvial channels and gullies, which incise both the surge beds and underlying sediment of the Camp Rice Formation. The region is arid, with frequent high winds out of the West.

In May and June of 2022, we brought the analytical equipment to two sites in southern Iceland at the toe of Breiðamerkurjökull Glacier. The first site sits on a fluvial fan formed by glacial outwash into lake Breiðarlón. The surface is comprised of well-rounded clasts of inter-

mediate to mafic igneous rocks that range in size from sand to cobble. The second site was situated at the glacier margin (with the tower 20 m from the visible ice front at the time of data collection) on a portion of a large sandur that appeared to host a thick subsurface ice/permafrost layer beginning at and extending below ~40 cm depth. The surface here was similar to the first site, but included small fluvial channels dominated by lightly indurated fine sand ~5 cm thick. This region hosts a subpolar oceanic climate with frequent precipitation. We observed a rain event on May 25th, 2022. Long daylight hours here also tested the efficacy of our system to track the influences of a less dynamic solar forcing. Vegetation as small clumps of grass was extremely sparse.

Finally, in July 2022, the equipment was deployed at Black Point Volcano in Long Valley, CA. The site is northeast of the main Black Point Edifice and was approximately 1 km from the shoreline of Mono Lake as of visitation. The site is dominated by unconsolidated cm-scale highly vesicular glassy basaltic clasts from the ~13 ka Surtseyan eruption of Black Point Volcano into Pleistocene Lake Russell (Verolino et al., 2018). Some aggregated clasts cemented by lacustrine precipitates were present, as were some rhyolitic pumice clasts from nearby volcanoes. While dense regions of shrubs and grass were present nearby, the field site was largely void of vegetation. The area is semi-arid with high winds out of the West.

Site (Coordinates, Elevation)	Geologic Setting	Avg. Annual Precip (mm)	Avg. Annual Temp. Rng (°C)	Lithology	Avg. Surf. Density (kg/m ³)
Woodhouse Mesa (35.48176 N, -111.38738 E, 1630 m)	Eolian/Pyroclastic	216*	-5-30*	Basaltic	1250
Kīlauea (19.399230 N, -155.26568 E, 1123 m)	Pyroclastic/Effusive lava	1354*	10-23*	Basaltic	1120
Black Point (38.04037 N, -119.08155 E, 1966 m)	Eolian/Lacustrine/Pyroclastic	442*	-15-33*	Basaltic	1180
Breiðamerkurjökull Margin (64.09354 N, -16.33646 E, 300 m)	Glacial	2972 [‡]	0-15 [‡]	Basaltic	2320
Breiðamerkurjökull Fan (64.06988 N, -16.34977 E, 140 m)	Fluvial	2972 [‡]	0-15 [‡]	Basaltic	2290
Pahrump Playa (36.00850 N, -115.99281 E, 770 m)	Lacustrine	126*	-3-50*	Mixed	1300
Sperry Wash (35.69849 N, -116.24744 E, 200 m)	Fluvial	90*	-3-50*	Mixed	1700

Hunt's Hole (31.93286 N, -106.97047 E, 1266 m)	Pyroclastic/Alluvial	241*	-1-36*	Mixed	1590
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Table 4-1. Descriptions of the surface environments at each site. *National Climatic Data Center
‡Icelandic Met Office

4.4. METHODS

4.4.1. Thermophysical Measurements

At each field site, we derived TI using multiple approaches. Our least disruptive tool for retrieving TI, and the approach most similar to that used by MSL, InSight, and Mars 2020, was to capture surface temperatures in time series using infrared imagery. The camera field of view at 3 m height was 2.5 x 2.0 m with ~4 mm/px resolution, and at 7 m height was 5.9 x 4.7 m with ~9 mm/px resolution. Paired with surface energy flux data from a weather station, temperatures were used to fit bulk dry thermal conductivity with a 1D energy balance model (detailed in Chapter 3). These values represent the average k of the top 50 cm, and thus can be paired with *in situ* surface measurements to reveal subsurface heterogeneity. The thermal model also fit for physical properties specific to each sediment, including a pore network connectivity parameter (m), volumetric water content at saturation (θ_k), and volumetric water content at the transition between evaporation regimes (θ_E).

Where feasible, a transient plane source probe (Thermtest TPS-EFF) was used to make direct *in situ* TI measurements (Figure 4-2). The tool works by applying a fixed current to a circular heating film in contact with the sample and measuring its temperature response using adjacent thermocouples. Since the instrument requires homogenous surface contact, rough surfaces (e.g., bedrock) or sediment with large minimum grain sizes (>1 mm) that could not be smoothed out, tended to show anomalously low TI readings.

A transient line source thermal conductivity probe (Thermtest TLS-100) proved somewhat better suited to course-grained and cohesive sediment (Figure 4-2). The TLS works by ap-

plying a fixed current to one end of a needle probe in contact with the sample and measuring its temperature response using a thermocouple embedded at the other end of the needle. Clumping and vapor diffusion may skew results in soils that are too moist, though measurement outputs affected by this phenomenon are easy to spot as they are physically unrealistic ($k_{measured} \gg k_{solid}$). Additionally, very porous soils (> 0.6 porosity) might provide poor contact with the probe and reduce measured k .



Figure 4-2. Thermtest probes collecting thermophysical data in the field. Poor contact due to surface roughness or porous soil had to be mitigated.

To mitigate the potential challenges to measurement accuracy, we collected three measurements from each probe, ignoring the lowest value and averaging the remaining two. Wherever possible, we collected measurements using both tools and selected the larger values of the two sets of readings (after converting k to TI) that were still within a physically realistic range. For collected samples, we calculated water content by weighing the samples before and after baking at 90° C for 12 hrs. At sites where the soil contained measurable water content, we corrected for k_{dry} using Eq. 2-1. If distinct subsurface layering is present, the Thermtest probes will not necessarily reflect the orbitally derived TI for that site, since we only probed the top few cm. Still, the *in situ* probes provided valuable tools for investigating thermal properties of materials at the probes' physical scales, and for validation of remote measurements from the tower.

4.4.2. Grain Properties and Density

Grain size and shape has been shown to play an important role in soil heat transfer (Piqueux and Christensen, 2009b; Presley and Christensen, 2010b, 1997b, 1997a; Presley and Craddock, 2006). Although these traits cannot be measured directly from orbit, morphological indicators such as slope angle of repose (Beakawi Al-Hashemi and Baghabra Al-Amoudi, 2018), surface texture (Bridges and Muhs, 2012), and spectral indicators such as single scattering albedo (Lapotre et al., 2017), can provide clues to potential grain parameters. More importantly, however, linking grain features together with TI allows us to make additional predictions about depositional history that might otherwise have been a challenge with TI alone.

In order to calculate the natural density of the near surface soils, known volumes of material were collected using a metal cylinder and spatula. Cylinders were chosen to be at least 10 times the diameter of the median grain size at the surface, such that representative samples could be captured. These samples were then weighed in the lab. For samples in which the clasts were too large to get a statistically inclusive sample using the cylinder method, individual clasts were collected, and their volumes calculated by measuring water displacement.

Following initial weighing, samples were dried and reweighed, then sieved by hand in 0.5 ϕ (logarithmic grain size scale) intervals between -5 ϕ (3.2 cm) and 5 ϕ (31 μ m). Each size was then weighed, and data was input into a sequential fragmentation and transportation (SFT) program (Wohletz, 2018) to parametrize the shape of the resulting smoothed grain size histogram (Figure 4-3). Metrics included graphical median ($Md\phi$), sorting as standard deviation of histogram ($\sigma\phi$), and skewness (Folk, 1966). Generally, median grain size and sorting reflect the dominant transport and depositional mechanisms, where different depositional environments will lead to different facies and different facies associations (Folk, 1966; McLaren, 1981).

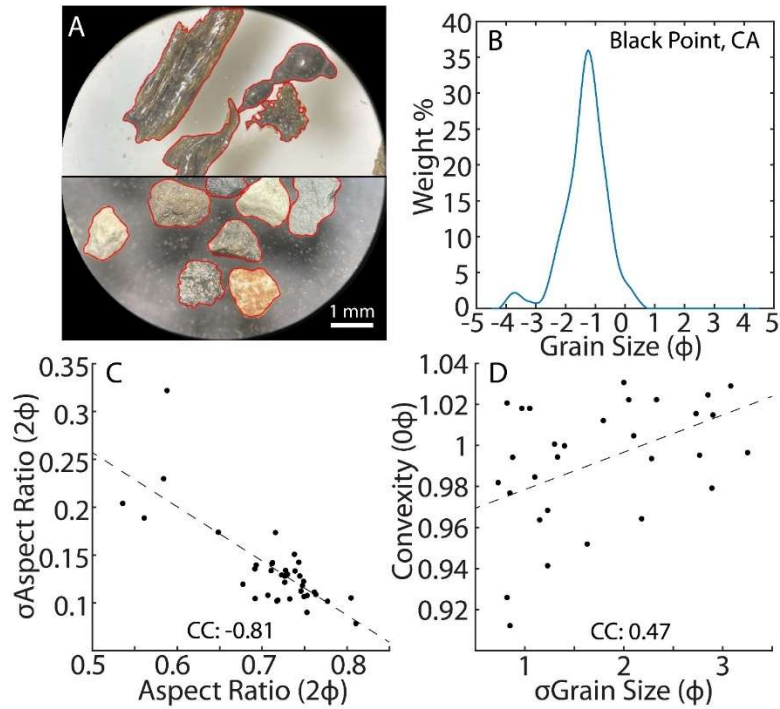


Figure 4-3. A) Example digital grain identifications of mm-sized grain from the Kīlauea-Keanakāko'i (top) and Breiðamerkurjökull Glacier Margin (bottom) sites. B) Grain size distribution from a Black Point Volcano sample. C) Relationship between aspect ratio and its standard deviation for all 2ϕ subsamples, showing a strong negative correlation coefficient. D) Relationship between convexity of 0ϕ samples and the sorting measure $\sigma\phi$, showing a moderate correlation coefficient.

In addition to sorting, grain shape tends to reflect depositional setting and transport history, where higher energy mechanical weathering environments or farther transport lead to more rounding (Folk, 1951). Very angular clasts are typical of fresh pyroclastic material. Much of the literature on thermophysical experiments has analyzed ideal spherical particles, however Presley and Christensen, 2010b showed that variations in grain shape could have a profound effect on TI by enhancing or reducing grain-to-grain contacts and the density achieved through grain packing.

For each sample, we imaged two grain sub populations, 0 and 2ϕ (1 and 0.25 mm respectively), under an 40x optical microscope using a contrasting background (Figure 4-3). These size bins were selected because they represent two distinct compositional regimes. The 2ϕ grains tend to be composed of single mineral crystals, while the 0ϕ grains tend to be aggregates or mul-

ti-crystalline rocks. Using Matlab's segmentation tool, we identified grain boundaries for at least 10 randomly selected grains for each subsample. Mean and standard deviation of aspect ratio, solidity, roundness, and convexity were calculated from the boundary shapes. Aspect ratio is the ratio of the minor to major axis lengths. Solidity was defined as the proportion of the grain filling the smallest convex shape that can surround the grain. For roundness, we use the equation $Roundness = \frac{4 \cdot Area}{\pi \cdot MajorAxisLeng^2}$. For convexity, we use the ratio of the perimeter of the smallest convex shape to the actual perimeter length.

To check the efficacy of our approach for measuring grain shape metrics, we sought out whether expected trends in sorting and rounding relationships were present (Figure 4-3). Indeed, the spread in measured aspect ratio is strongly anticorrelated to aspect ratio itself. In other words, as a sediment's grains become more rounded, in the absence of external mixing, they also become more homogenous. Another relationship we observed was the positive correlation between standard deviation in grain size and average grain convexity. Like roundness and aspect ratio, convexity decreases with processing. Since, in general, the spread in grain size also decreases with processing (i.e., becomes more well-sorted), we expect there to be some correlation here.

4.4.3. Spectral Characterization

Hyperspectral and multispectral visible and infrared images of the surface of Mars provide insight into the chemical and mineral constituents of observed surfaces, aiding in interpretation of sedimentary origins (Ehlmann and Edwards, 2014). Sensors in orbit around Mars include the 0.36-3.92 μm Compact Reconnaissance Imaging Spectrometer for Mars (CRISM) (Murchie et al., 2007), the 0.38-5.1 μm Observatoire pour la Minéralogie, l'Eau, les Glaces et l'Activité (OMEGA) (Bibring et al., 2004), the 0.3-150 μm Thermal Emission Spectrometer (TES) (Christensen et al., 2001), and the 0.42-14.88 μm Thermal Emission Imaging System (THEMIS)

(Christensen et al., 2004). These tools also inform us about albedo, emissivity, and dust cover, amongst many other properties, and provide valuable complements to TI when interpreting surface features (Johnson et al., 2009). We sought to capture data from each set of samples that would characterize the spectra in a manner relevant to those Mars instruments.

Visible and near infrared reflectance spectra (0.35-2.5 μm) of sieved subsamples (0 ϕ and 2 ϕ) and individual cobbles were captured using a Malvern Panalytical ASD FieldSpec in a controlled lighting setting using collimated light from a QTH lamp, a 30° incidence angle, and a 30° viewing angle offset by 90° from the plane of incident light. Spectra were calibrated using a Spectralon white reference.

The same sample subsets were also measured for their thermal emission spectra (200 to 2,000 cm^{-1} or 5-50 μm) using a Thermo Scientific Nicolet iS50R FTIR at a 90° viewing angle to the sample surface. The instrument is configured with gold coated optics, a CsI beamsplitter, DLaTGS detector, and a CsI-coated window. Samples were first heated in a 90°C oven for at least 12 hrs and then placed on 90°C heating elements within a purged chamber cooled to 10°C. For each sample, 180 scans over the course of 6 minutes were captured and averaged. To obtain a standardized emissivity spectrum, averaged spectra were ratioed to measurements of a conical black body depression at 60°C and 100 °C taken before and after respectively.

For both reflectance and emission, distinguishing spectral features were parametrized from band depths. We used the spectral parameters used in CRISM summary products (Pelkey et al., 2007; Viviano-Beck et al., 2014) for the reflectance spectra. From the emission data, we obtained average emissivity (ϵ) across the wavelengths of the infrared cameras (7.5-13.5 μm) and parametrized the weighted absorption center (WAC) in μm of the Reststrahlen feature from 7 to 15 μm , which is associated with silica content (Salvatore et al., 2018; Smith et al., 2013)

4.4.4. Multivariate Analysis

The goal of statistical analysis was to determine how deposit features that can be used to interpret environmental setting might correlate to TI and other model-derived parameters when paired with other remotely observable features. This approach builds a multivariate framework for interpreting weathering history using orbital spectral imagery. While similar approaches have been employed to explore remote sensing data (e.g., Karunatillake et al., 2012; Marzo et al., 2006), no work to date has included *in situ* grain-scale measurements, thermophysical data, and associated depositional setting interpretations. We built a library of paired *in situ* thermophysical, spectral, size, and morphological measurements taken for Mars-analog sediment. Each sample was also assigned to a classification representative of dominant depositional setting. Loose sediment was assigned to either an eolian, fluvial, lacustrine, glacial, or pyroclastic type. Cohesive rocks were assigned either igneous or sedimentary classes.

We first assessed pairwise correlation to determine which variables were most highly correlated to TI as well as each individual grain metric. Using the refined set of variables, we ultimately fit multivariate models to the data to determine how remote sensing observations might be used to make predictions for grain properties and for depositional setting. To test the utility of the multivariate analysis results we analyzed raster data from two sites, one on Earth and one on Mars (Koeppel et al., 2021).

For our Earth site, we used UAV data over a 12,765 m² area of Sperry Wash to make predictions about grain properties. There, we captured 14 surface temperature mosaics over three days following the methodology described in Chapter 3. At 4 cm/pixel, we modeled TI, θ_k , and m using surface temperature, tower data, UAV-derived slope geometries and shading, and soil moisture data from across the site as inputs. We then trained stepwise linear regression models to

make predictions from TI, θ_k , m , and surface albedo and applied it to each pixel at the site. We set up the model to iteratively consider intercepts and a linear term for each predictor, as well as product pairs of predictors. Using a backward implementation, the model then removes terms one at a time that do not significantly contribute to model predictive power (removal results in a <0.1 decrease in sum of squares of the prediction residuals for the training data) or are linearly dependent with other variables.

For the Mars application, we selected a site in Sera crater (1.0971 °W, 8.8291 °N) with known heterogeneity. From our experimental data, we first estimated the TI as it would appear if the material was on an average surface on Mars ($T = 210$ K, $P = 600$ Bar) using $c_{p,Earth} = 997$ J/kgK, $c_{p,Mars} = 630$ J/kgK, porosity = $\rho/2900$, $k_{gas,Earth} = 0.024$ W/mK, and $k_{gas,Mars} = 0.0028$ W/mK (Morgan et al., 2018; Piqueux and Christensen, 2009b). Using a geometric mean for k of a two phase mixture (Dong et al., 2015), we solved for k_{solid} , and recalculated TI assuming Martian k_{gas} . We then input that converted TI, the spectral parameter dataset, and assigned classes into a classification model that uses support vector machines (SVMs) applied in a multiclass system using Error-Correcting Output Coding (ECOC). This approach has been shown to be an effective tool for multiclass prediction of land surfaces (Falco et al., 2020; Pal, 2009). Ultimately, we apply the model on THEMIS-derived TI (Edwards et al., 2018; Koeppel et al., 2021), daytime THEMIS emissivity (Christensen et al., 2004), and CRISM MTR band parameter data (Pelkey et al., 2007; Viviano-Beck et al., 2014), all taken from Mars orbit.

4.5. RESULTS

4.5.1. Thermophysical Results

In total, thermophysical data of 79 distinct materials was collected over the 8 sites, and 22 surfaces had TI modeled using the remote method. The two Woodhouse Mesa campaigns resulted in derived TIs for the eolian surface of 436.2- 492.7 Jm⁻²K⁻¹s^{-1/2}. Further details from that site are outlined in Chapter 3. The rest of the sites are discussed here. Observations from two locations (Kīlauea and the Breiðamerkurjökull Fan) captured precipitation events, which were effectively accounted for by the model. The model was also able to detect major subsurface heterogeneity beyond 40 cm depth at two field sites (Kīlauea and the Breiðamerkurjökull Glacier Margin), demonstrating that thermal conductivity of layers beneath the predicted diurnal skin depth can still play an important role in controlling surface temperature fluctuation.

In comparing the results of tower data to *in situ* data, the two generally agreed. However, the tower consistently calculated higher TIs for poorly sorted surfaces over larger areas. This appears to be a result of the Thermtest instruments only sampling the interstitial finer component or surface layering and not the larger clasts or high TI subsurface materials. Conversely, we noticed that large clasts perched on the surface show lower TIs than would be expected for their material types. This effect seems to be more a function of exposure to convective heat exchange than the inherent properties of the material, as similar clasts embedded in the surface show high TIs.

4.5.1.1. Black Point

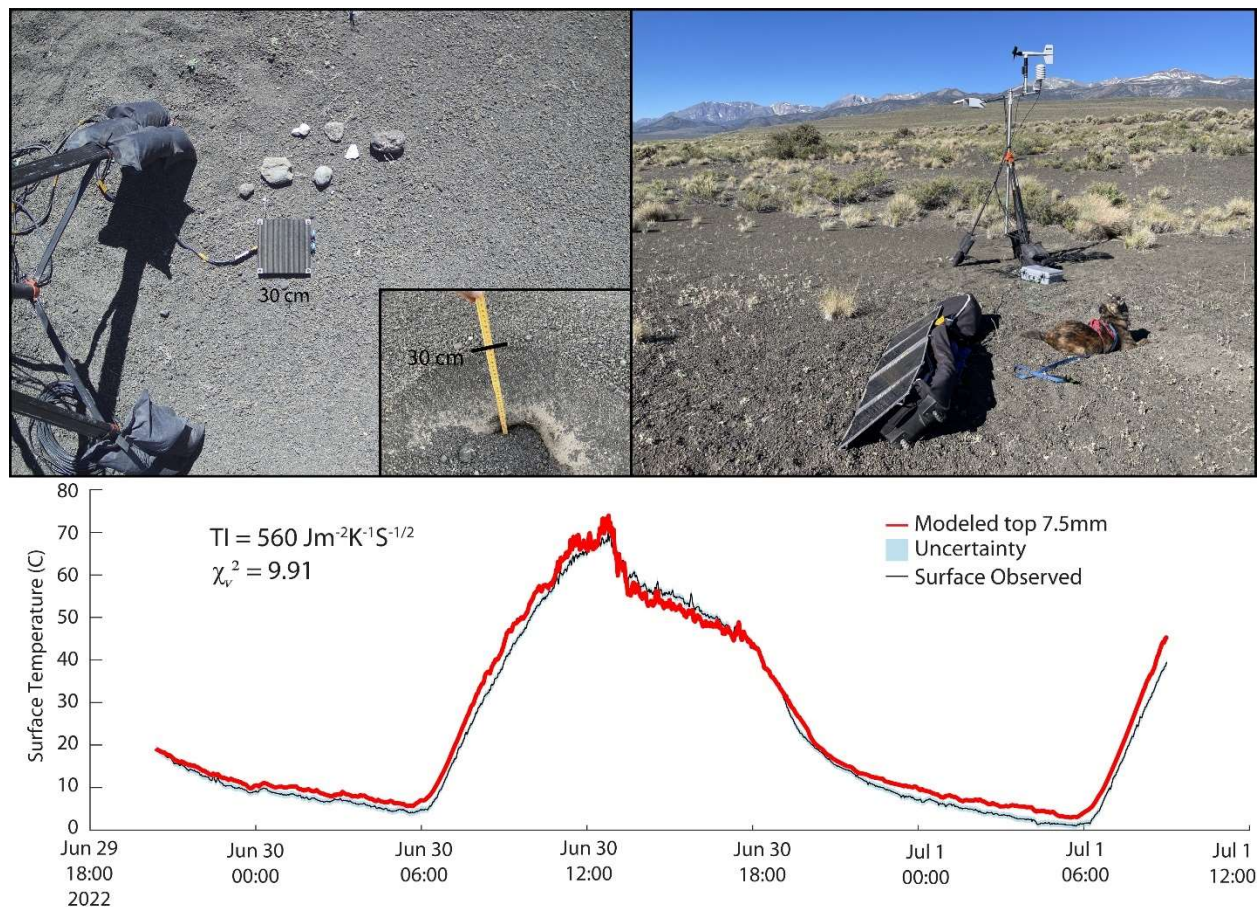


Figure 4-4. Context Images and thermal inertia fit at Black Point Volcano, CA

At Black Point, we sampled TI using only the remote technique, capturing the primary surface and several unique float rocks. During initial field reconnaissance, the surface at Black Point showed a very similar appearance to the surface at Woodhouse Mesa. Cohesionless mm-scale rounded vesicular basaltic grains were dominant, and the porous surface depressed similarly underfoot at both sites. However, a derived TI of $560 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ for the dominant surface at Black Point was elevated relative to Woodhouse Mesa (Figure 4-4). Trenching revealed an abundant fine-grained component to the soil at Black Point that was absent at Woodhouse Mesa. While the material at Woodhouse Mesa down to 50 cm depth was deposited entirely subaerially, at Black Point, the study region was once inundated by a lake. Eolian modification is a likely ex-

planation for the removal of fine grains from the top 10 cm, however, the subsurface still seems to host tracers of the aqueous history in a manner that Woodhouse Mesa's subsurface does not. It is likely that the intermixing of the fine-grained and larger-grained components at Black Point leads to a higher bulk thermal conductivity as there are more solid pathways for heat to conduct.

Another trend to emerge from observations at Black Point was the very low TIs of cobbles lying atop the primary surface. To compare their thermal responses, we placed 5 cobbles, collected from the immediate vicinity, within the scene. These clasts included very low density pumice and rhyolite, vesicular basalt, cemented tephra, and lacustrine precipitate alone. Each of these cobbles were found to display TIs lower than the soil. This result is expected for very low density clasts, but for the precipitate and cemented tephra, this result is likely not indicative of the material properties of the cobbles themselves, since they were of much higher density and cohesion than the soil. Instead, by perching the cobbles atop the highly porous surface, a very high portion of the clasts' surface areas were exposed to convective heat transfer, while a very small number of contact points were available for conducting heat with the subsurface. The result is that these cobbles are less buffered against the diurnal temperature cycle than they would be if they were embedded in or a part of a more extensive outcrop.

4.5.1.2. Hunt's Hole

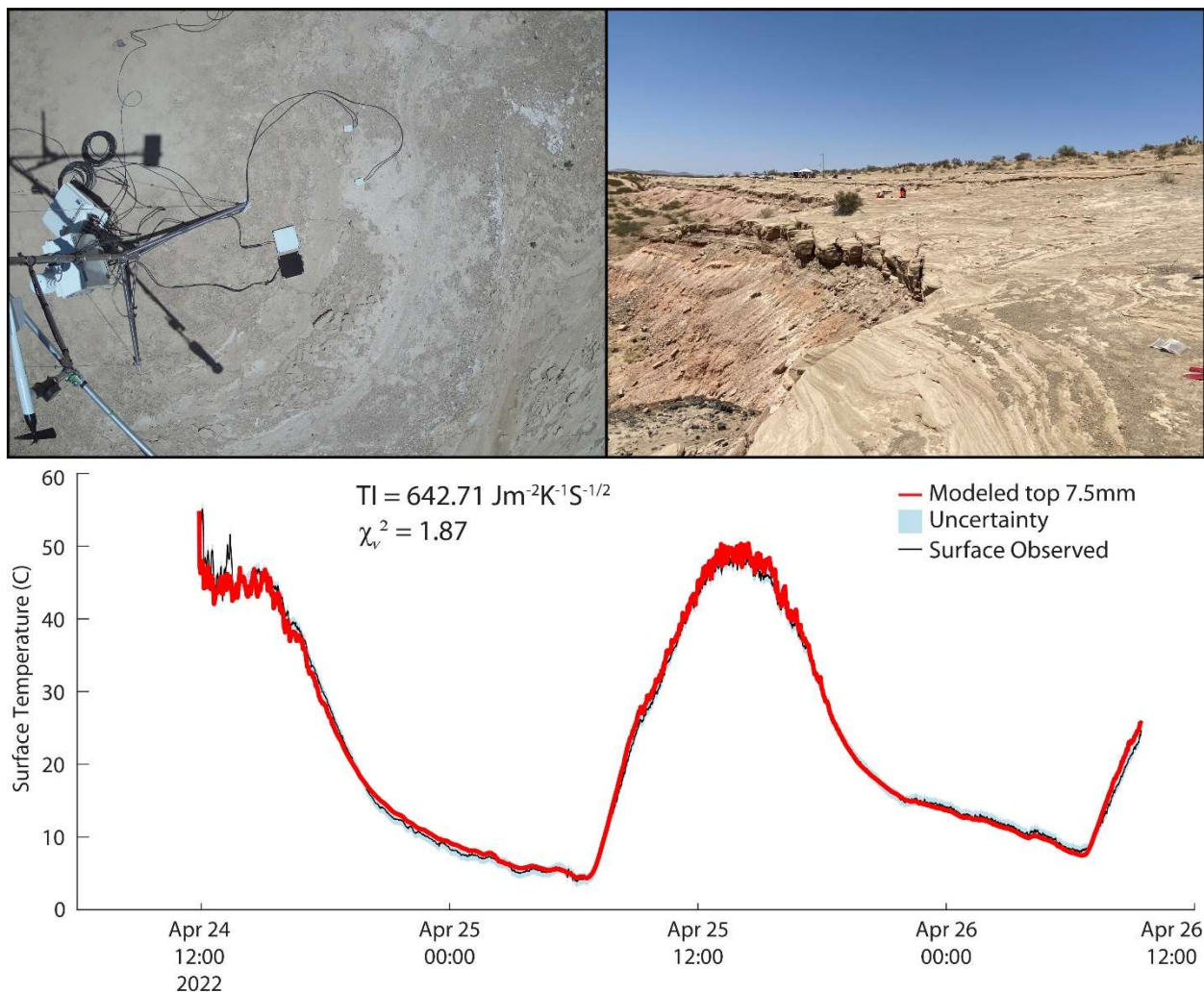


Figure 4-5. Context Images and thermal inertia fit at Hunt's Hole, NM. Black and white calibration targets are each 30 cm across.

At Hunt's Hole the remote setup was stationed atop a cohesive pyroclastic surge deposit. We captured an area of the deposit with scattered surficial sand ranging from none to a few cm thick. In addition, we collected hand-samples from a diverse set of materials within the immediate vicinity. These included unconsolidated fluvial and alluvial channel-fill, eolian sand, paleosols, and the surficial sediment atop an eroded basaltic lava flow that differed from other eolian sand in the area. The cohesionless and weakly lithified units that were able to be penetrated by the needle probe showed TIs ranging from $130\text{-}570 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ (Figure 4-5). The lowest of these

TIs were from the porous soils beneath the surge beds, while the highest was from the fluvial channel sediment closest to the floor of the crater. Measurements of the eolian sand ranged from 415-440 $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$, consistent with results for the eolian surface at Woodhouse Mesa. As discussed, for cohesive deposits, it was a challenge to achieve reliable Thermtest readings due to poor surface contact. However, using the remote setup, the surge beds showed the highest TIs of all measurements at the site (690-790 $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$). This result is consistent with the established notion that cementation plays a significant role in driving up bulk thermal conductivity (Piqueux and Christensen, 2009a).

4.5.1.3. Pahrump Playa

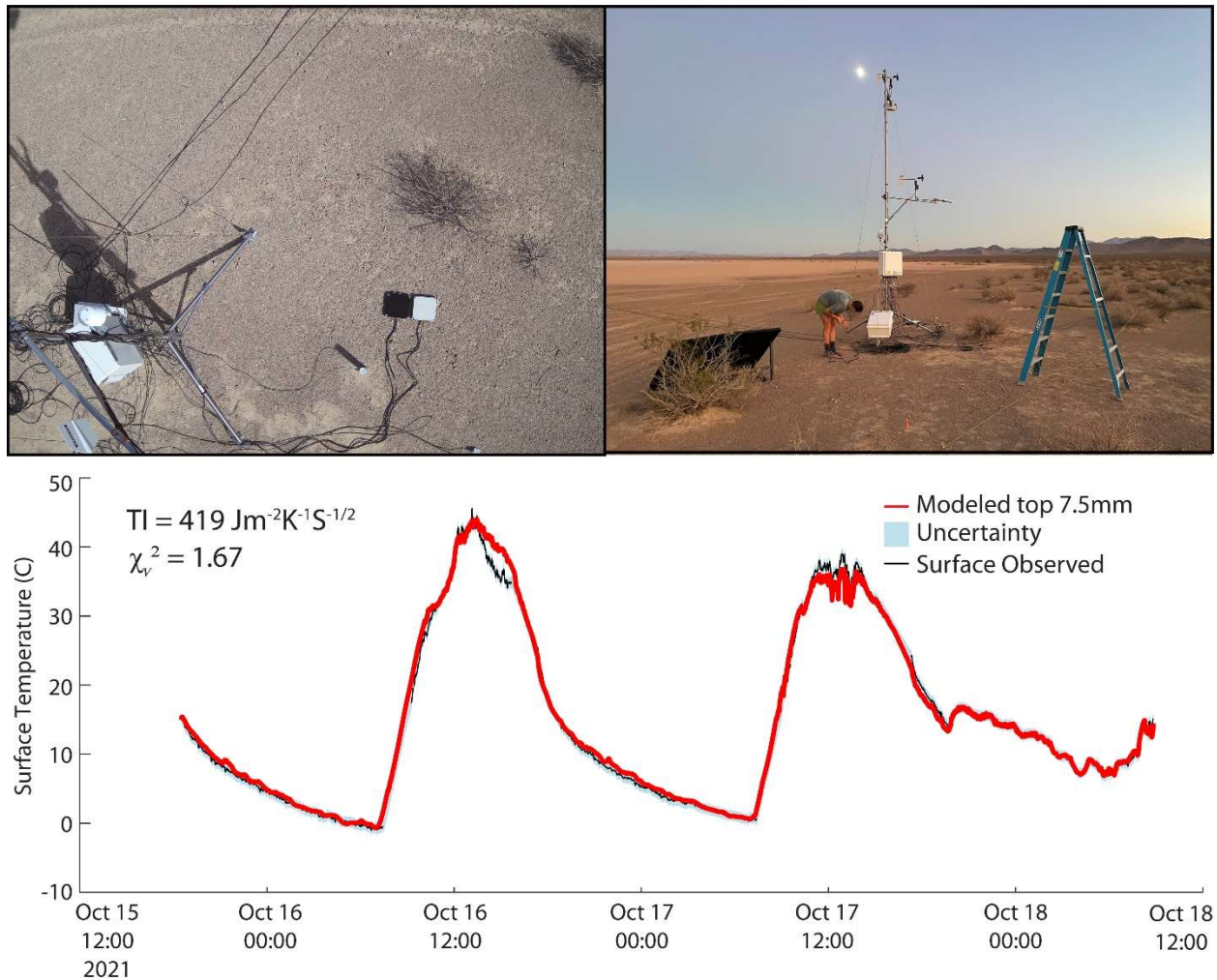


Figure 4-6. Context Images and thermal inertia fit at Pahrump Playa, NV. Black and white calibration targets are each 30 cm across.

The Pahrump Playa site hosted a single primary deposit type, desiccated lacustrine silt, with a slight variety in surface cover ranging from the same indurated fines as the subsurface, to cm-scale pebbles that were likely transported down slope from the adjacent mountain range. The cleanly exposed silt-bed showed TIs ranging from 410-495 $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$, derived from both tower and Thermtest measurements (Figure 4-6). The pebble-covered surface showed a slightly elevated TI of 517 $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$. Similar to the result from Black Point, it may be that this difference is explained by the mixture of two grain sizes, a large and fine component together, which appears to raise TI beyond that of the fine or coarse components alone.

4.5.1.4. Sperry Wash

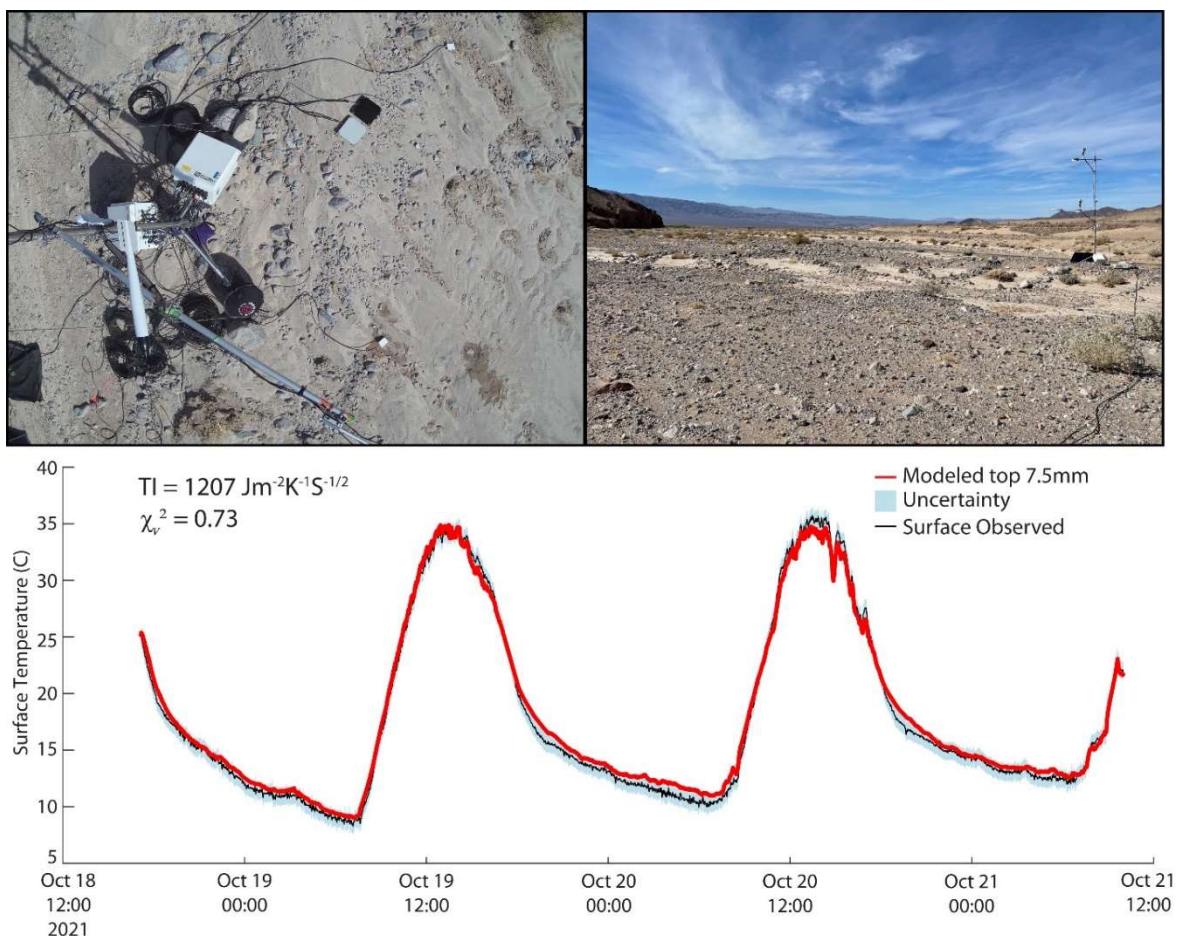


Figure 4-7. Context Images and thermal inertia fit at Sperry Wash, CA. Black and white calibration targets are each 30 cm across.

At Sperry Wash, a wide diversity of surface sediment was captured using both remote and *in situ* tools. The site covered ephemeral fluvial channels with regions of both well-sorted and poorly sorted facies. TIs of these units ranged from 400-1200 $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ (Figure 4-7). Poorly sorted surfaces with angular cobbles and silt hosted the highest mean TIs, while more homogeneous silt-to-sand sized soils fell on the lower end of the TI range. Results from UAV mapping of the broader site are discussed below.

4.5.1.5. Breiðamerkurjökull Glacier Fan

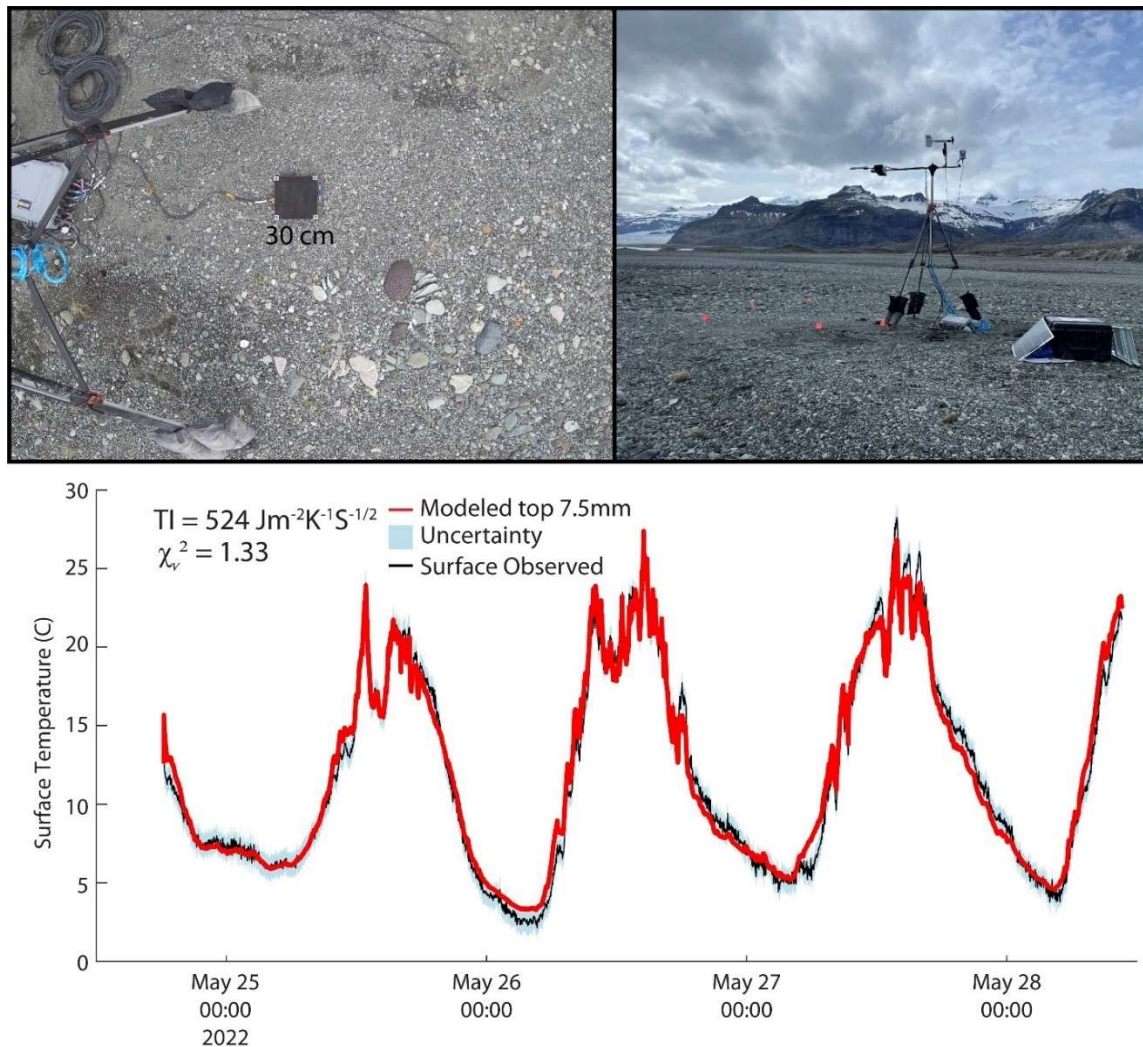


Figure 4-8. Context Images and thermal inertia fit at Breiðamerkurjökull, Iceland fan site.

At the fan site south of Breiðamerkurjökull Glacier, the surface and subsurface was a poorly sorted mixture of well-rounded clasts. While cobbles up to 10 cm were abundant, ~20 cm wide patches of dominantly sand-sized sediment were also captured beneath the tower. Upon measurement by hand, the sand patches showed TI values of 675-815 $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$. From the tower however, derived TI of the mixed-grain surface was upwards of 1350 $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$, similar to the value derived for the mixed surface at Sperry Wash (Figure 4-8). An individual cobble, embedded in the surface yielded a TI of 2099 $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$. Several cobbles that were perched atop the surface, rather than embedded within, were found to have much lower TIs (200-240 $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$). Like the cobbles at Black Point, it is not realistic to take these values as the TI of the cobbles alone, but in considering the sediment column as a whole and how the surface component contacts the subsurface, these values are more understandable. Thus, when observed remotely, the temperatures of perched clasts exposed to convective heat exchange appear significantly lower than an extensive bedrock unit composed of that same material. Similarly, patches of sand that show only moderate TIs when measured *in situ*, appear to have significantly higher TIs in remote observation if they cover or abut larger cobbles.

4.5.1.6. Breiðamerkurjökull Glacier Margin

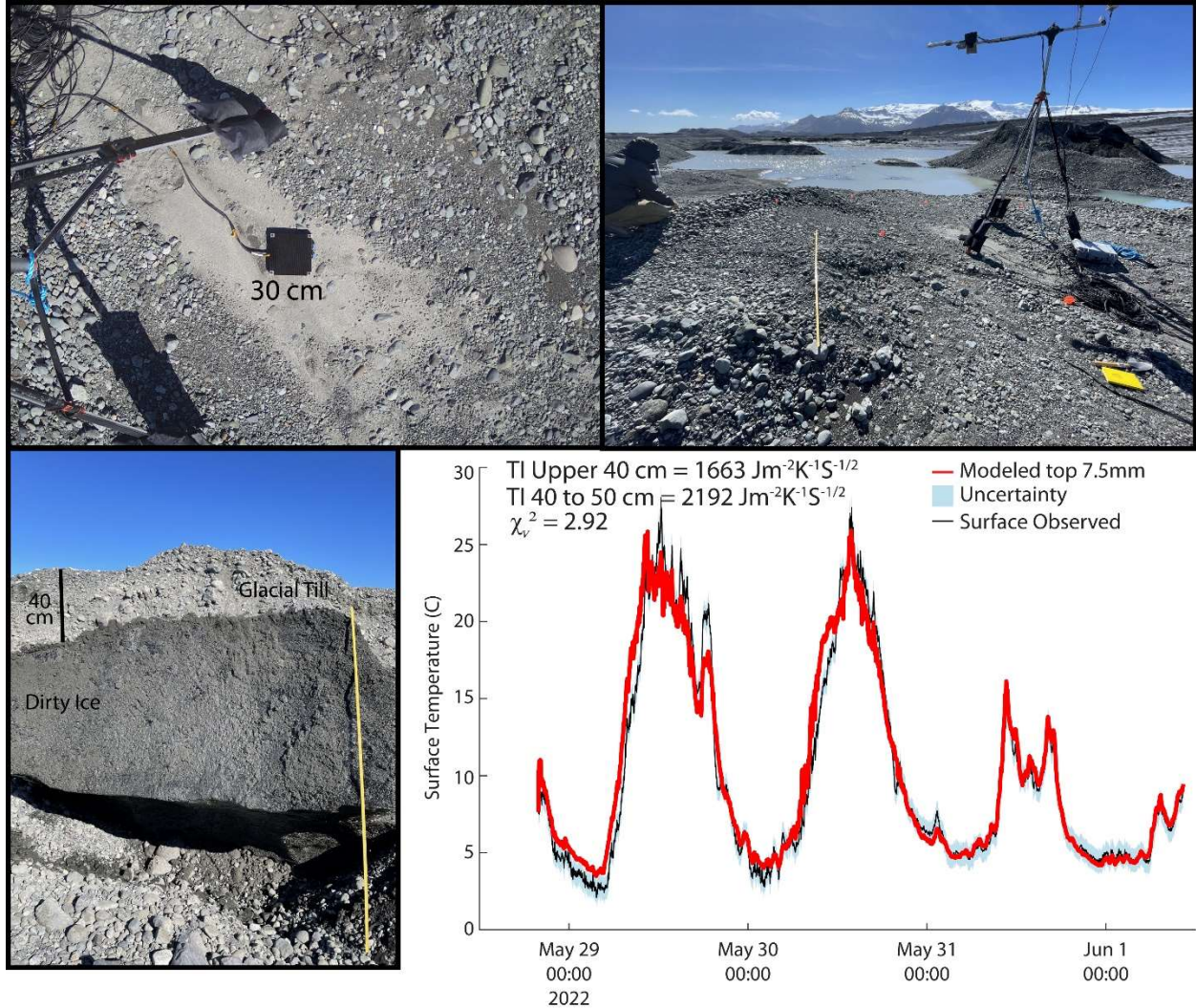


Figure 4-9. Context images and thermal inertia fit at Breiðamerkurjökull, Iceland glacier margin site.

At the terminal margin of Breiðamerkurjökull Glacier, we sampled a diversity of sedimentary deposits using both handheld tools and the tower measurements. Materials ranged from fine sediment atop the glacier itself, poorly sorted glacial till, a well-sorted lacustrine deposit, and lightly indurated fines within a fluvial channel. Of the materials measured by hand, the highest TI of $722 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ was from compacted and moderately sorted fine sand deposited atop an emerging esker, likely from vigorously flowing water. The lowest TIs of $\sim 270 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ were fine and well-sorted lacustrine deposits, likely formed in slack-water. Again, however, these *in*

situ TIs differ substantially from the tower-derived TIs, which ranged from 1242-1945 Jm⁻²K⁻¹s^{-1/2}, even over areas of dominantly fine surface sediment. We note that this range is somewhat higher than the observed TIs over fine sediment at the nearby fan site despite *in situ* values being similar if not lower.

One explanation is that this feature is a result of subsurface ice. We observed that the sediment beneath the tower was overlying a thick and fairly pure slab of ice beginning at ~40 cm depth. Typical ice hosts a TI of ~2000 Jm⁻²K⁻¹s^{-1/2} and the TI of ice-saturated sediment would be even higher. To test if subsurface heterogeneity might be influencing the thermal response, we ran the thermal model again for a region of mixed soil with large cobbles using a 2-layer approach and a boundary at 40 cm depth. In the 1-layer mode, this region was calculated to have a TI of 1945 Jm⁻²K⁻¹s^{-1/2} with a χ_v^2 of 4.82. In 2-layer mode, the top-layer TI was 1663 Jm⁻²K⁻¹s^{-1/2}, bottom TI was 2192 Jm⁻²K⁻¹s^{-1/2}, and χ_v^2 was 2.92 (Figure 4-9). If, in fact, the tower TI is encountering the effects of subsurface ice, it means that the controls on the thermal response observed over only three days extend beyond the anticipated diurnal skin depth of 14 cm (from DSD $= \sqrt{\left(\frac{\text{Seconds in a day}}{\pi} \cdot \frac{k}{\rho \cdot c_p}\right)}$ where $c_p = 1176$ J/kgK, $k = 1.64$ W/mK, and $\rho = 1864$ kg/m³), and that similar phenomena could be occurring in regions hosting buried ice on the surface of Mars (Piqueux et al., 2019).

4.5.1.7. Kīlauea

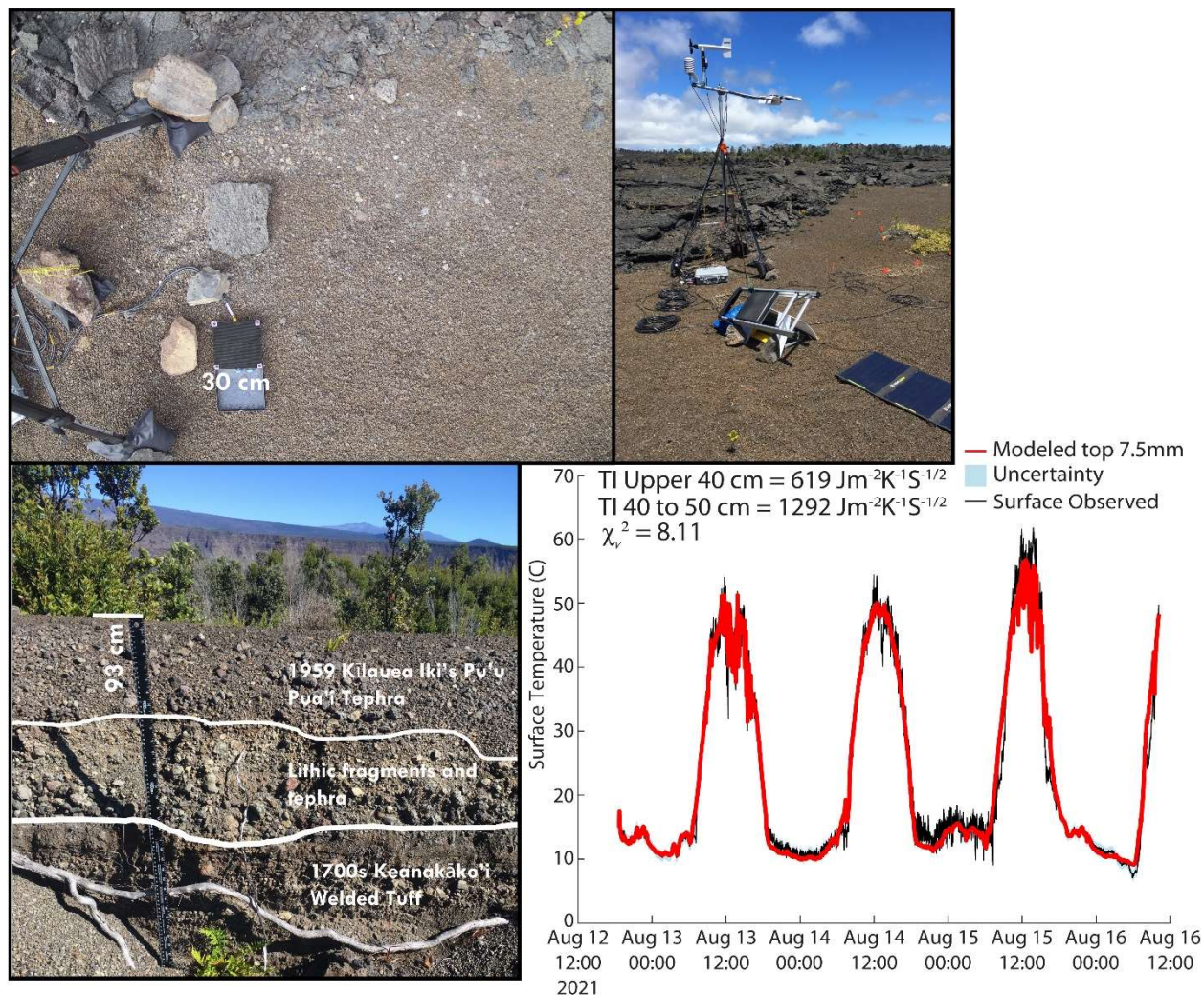


Figure 4-10. Context Images and thermal inertia fit at Kīlauea Volcano, HI showing subsurface layering.

At Kīlauea, we collected Thermtest and tower measurements at a site near Kēanākāko'i crater. We also collected Thermtest measurements of multiple sediment types at three other locations within the Hawai'i Volcanos National Park (Table 4-2). Hand measurements ranged from very low ($139 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ for mounds of Pele's hair) to moderate ($580 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$ for fine-grained lightly indurated material near the Halema'uma'u rim summit). Measurements of eolian bedforms yielded values from $332\text{--}495 \text{ Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$, consistent with previous results for eolian dunes.

Table 4-2. Additional sites at Kīlauea where Thermtest data was collected.

Site	Coordinates	Description of materials sampled
Kau Desert	19.35551N, -155.36427E	Eolian sand, indurated sand cohesive tephra, depression-filling fines
Halema'uma'u Summit	19.42028N, -155.29105E	Depression-filling fines, cohesive fines
Halina Pali Road	19.35278N, -155.28241E	Mat of Pele's hair, eolian sand, indurated sand

Thermtest measurements of the tephra at the Keanakāko'i indicated quite low k (<0.05 W/mK). However, model-derived k from the tower data initially indicated a much higher bulk k of 0.31 W/mK. From observations made in the field, it was noted that the soil grew increasingly dense, with higher lithic content with depth until 40cm, where the soil overlay a dense tuff unit (Figure 4-10). With this knowledge, the model was rerun in a two-layer format separated at 40 cm to probe whether distinguishing the thermophysical units would have an effect on fitting. χ^2 decreased somewhat after the change, and the two units were ultimately fit to have TIs of 619 and 1292 Jm⁻²K⁻¹s^{-1/2} for the upper and lower layers respectively (Figure 4-10). Those values are consistent with the observed unconsolidated tephra overlying a friable but cohesive tuff.

At this site, we also used tower measurements to derive TI for more cohesive rocks directly. A 20 cm wide block of the Keanakāko'i tuff was placed at the surface within the scene. Its derived TI was 1283 Jm⁻²K⁻¹s^{-1/2}, in very good alignment with the lower layer TI derived for the soil. Additionally, a portion of a pahoehoe lava flow that overlies the clastic tephra was captured. This moderately low-density basalt (~2000 kg/m³) had a derived TI of 1080 Jm⁻²K⁻¹s^{-1/2}.

4.5.2. Grain Properties

From our measurements of grain properties (Figure 4-3), several trends emerge in support of theory and previous empirical observations (Figure 4-11). For example, eolian sediment showed on average a standard deviation of 1.45 ϕ and skewness of -0.034, while fluvial sediment

showed a standard deviation of 1.92ϕ and skewness of -0.016 , indicating stronger sorting in the eolian settings. Also, fluvial sediment was the most well-rounded with a mean roundness of 0.70 (out of 1), while pyroclastic materials were the least rounded at 0.55 , consistent with trends in exposure to mechanical weathering.

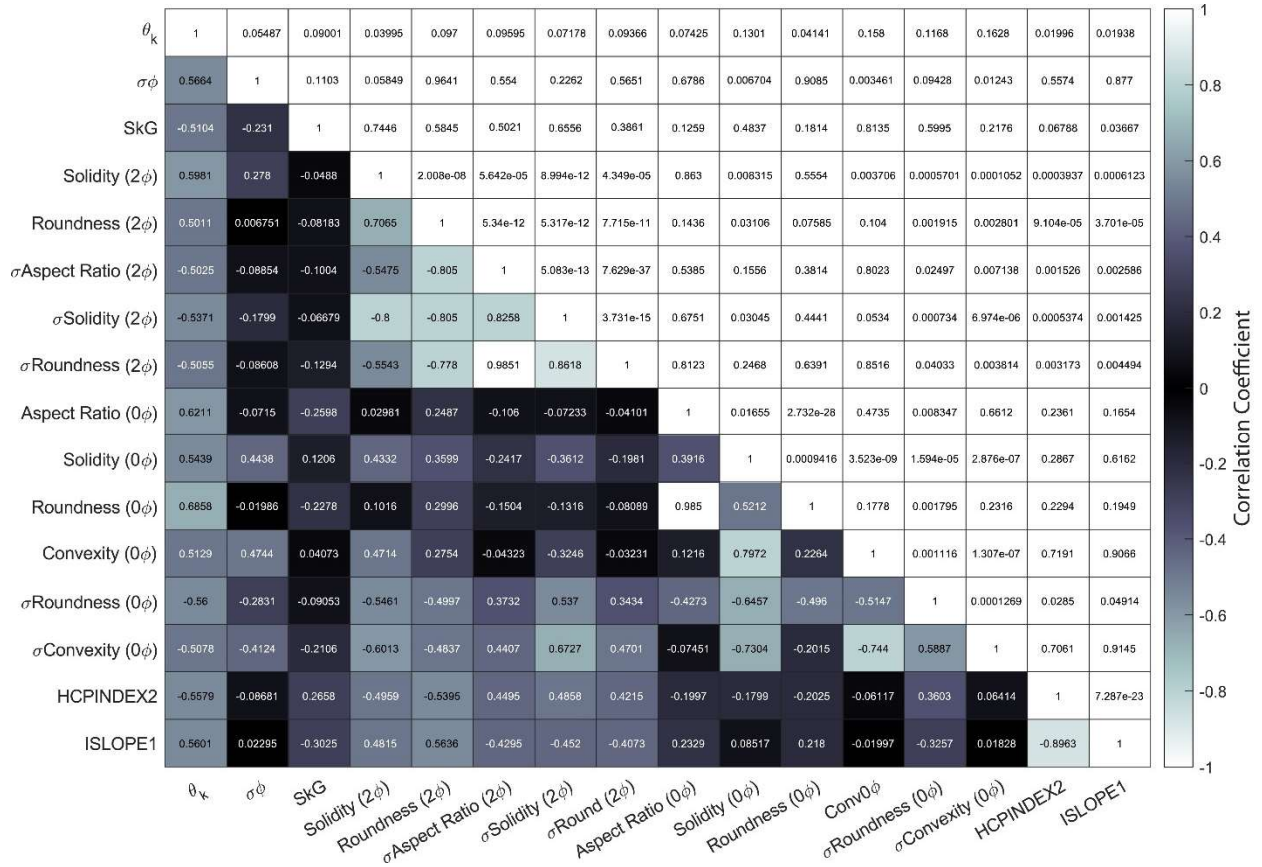


Figure 4-11. Correlation coefficients (bottom left triangle) and p-values (top right triangle) for all variables with >0.5 correlation with θ_k .

4.5.3. Spectral Properties

The Woodhouse Mesa, Iceland, Black Point and Kīlauea sites were primarily basaltic or amorphous with characteristic olivine and pyroxene features dominating the spectral shape (Figures 4-12 and 4-13). Quartz was identified as a primary component from spectra of Sperry Wash and Hunt's Hole, and phyllosilicate dominates at Pahrump Playa. Nonetheless, there was litho-

logic heterogeneity present within each site and several spectral-thermophysical relationships emerged amongst and between sites.

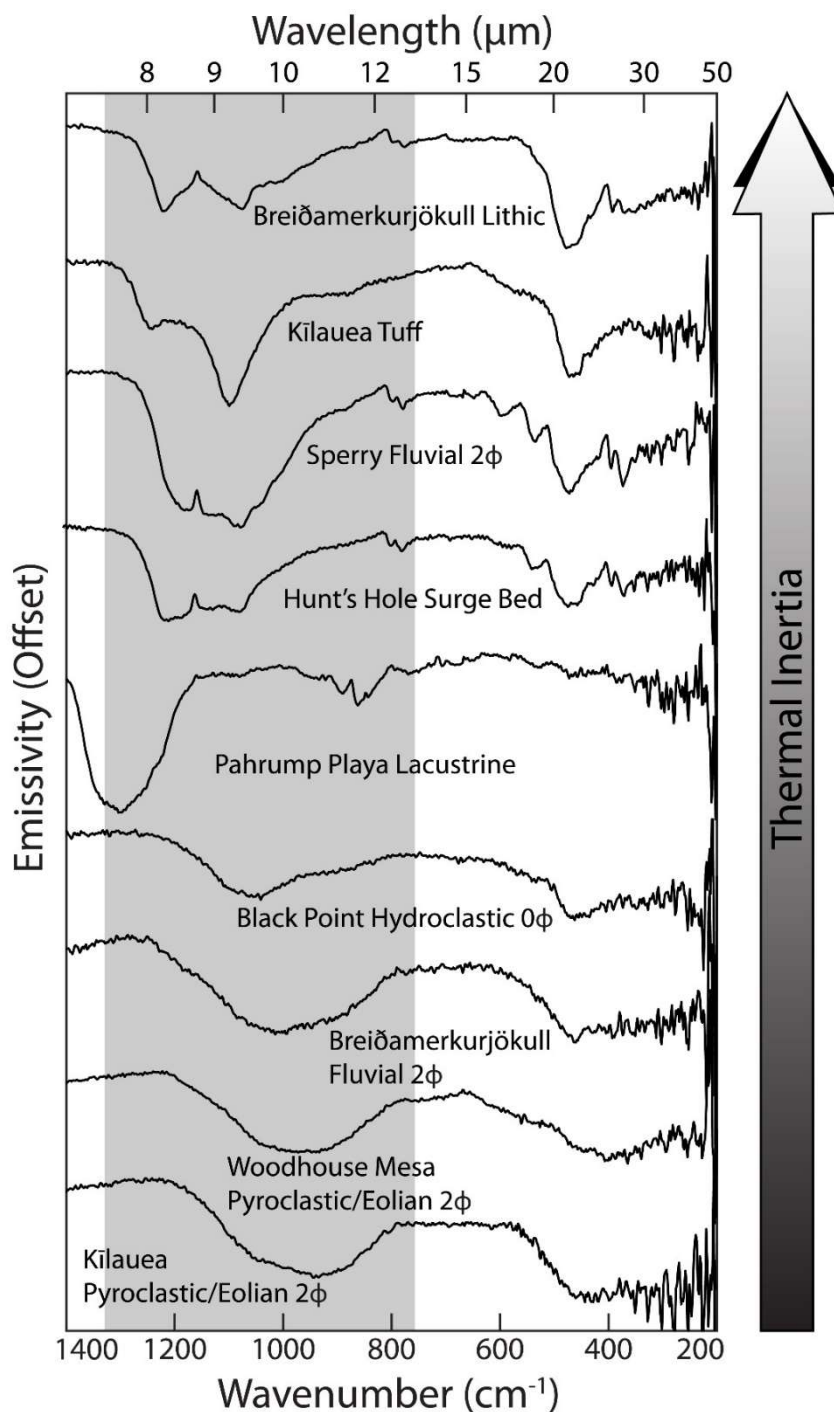


Figure 4-12. Infrared emission spectra of select samples from each site arranged by increasing sample site thermal inertia. The thermal imagery band (7.5-13.5 μm) is highlighted and approximately aligns with the region considered for the Reststrahlen feature weighted absorption center (7-15 μm).

Emissivities (Figure 4-12) in the infrared camera's thermal band range (7.5-13.5 μm) extended from 0.91 to 0.99, with the basaltic sites all near 0.97 and the more felsic sites showing lower values. Reflectance spectra (Figure 4-13) showed mean reflectances over 0.35-2.5 μm ranging from 0.03 for tephra at Black Point to 0.57 for the surge beds at Hunt's Hole. When comparing the emission WAC to reflectance parameters, measures of mafic silicate minerals (OLINDEX3, LCPINDEX2, HCPINDEX2) and amorphous silica (MIN2250) showed a positive correlation with WAC, while some indicators of mineral hydration (BD1900_2, BD1400) showed a negative correlation (Figure 4-14). This result is consistent with previous studies showing that the WAC (in μm) is higher for mafic rocks with lower silica content than felsic rocks hosting higher silica content (Smith et al., 2013). Emission spectra did not show a significant relationship with TI.

The albedo proxy, R1330, showed a positive correlation with aspect ratio and roundness of the 2 ϕ grain fractions but not of the 0 ϕ fractions. As previously noted, at 2 ϕ , as opposed to 0 ϕ , the grains seemed to be dominantly composed of single minerals and amorphous material. One explanation for the albedo-rounding trend is the tendency of high albedo minerals like quartz and feldspar to be rounded after weathering as opposed to the lower albedo amphibole, pyroxene, and basaltic glass.

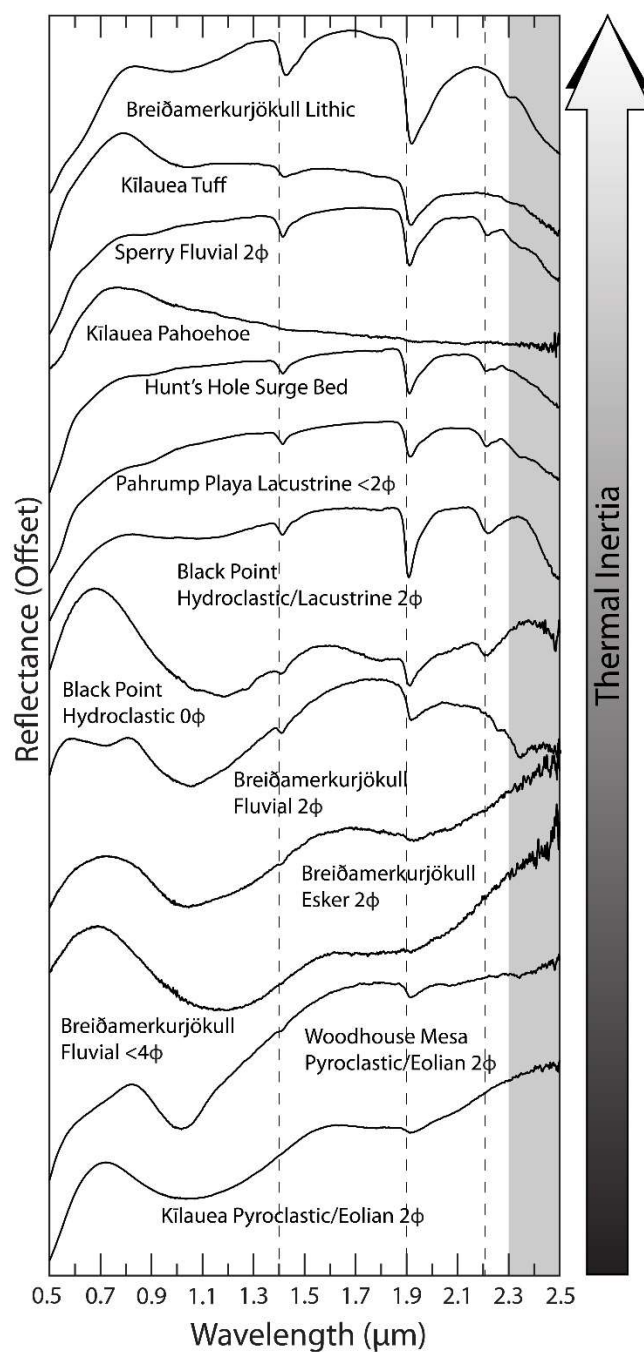


Figure 4-13. Visible and near-infrared reflectance spectra of select samples from each site arranged by increasing sample site thermal inertia. Absorptions indicative of mineral hydration (1.4, 1.9 and ~ 2.2 μm) are noted with dashed lines. The 2.3 μm dropoff, quantified with the D2300 parameter, is highlighted.

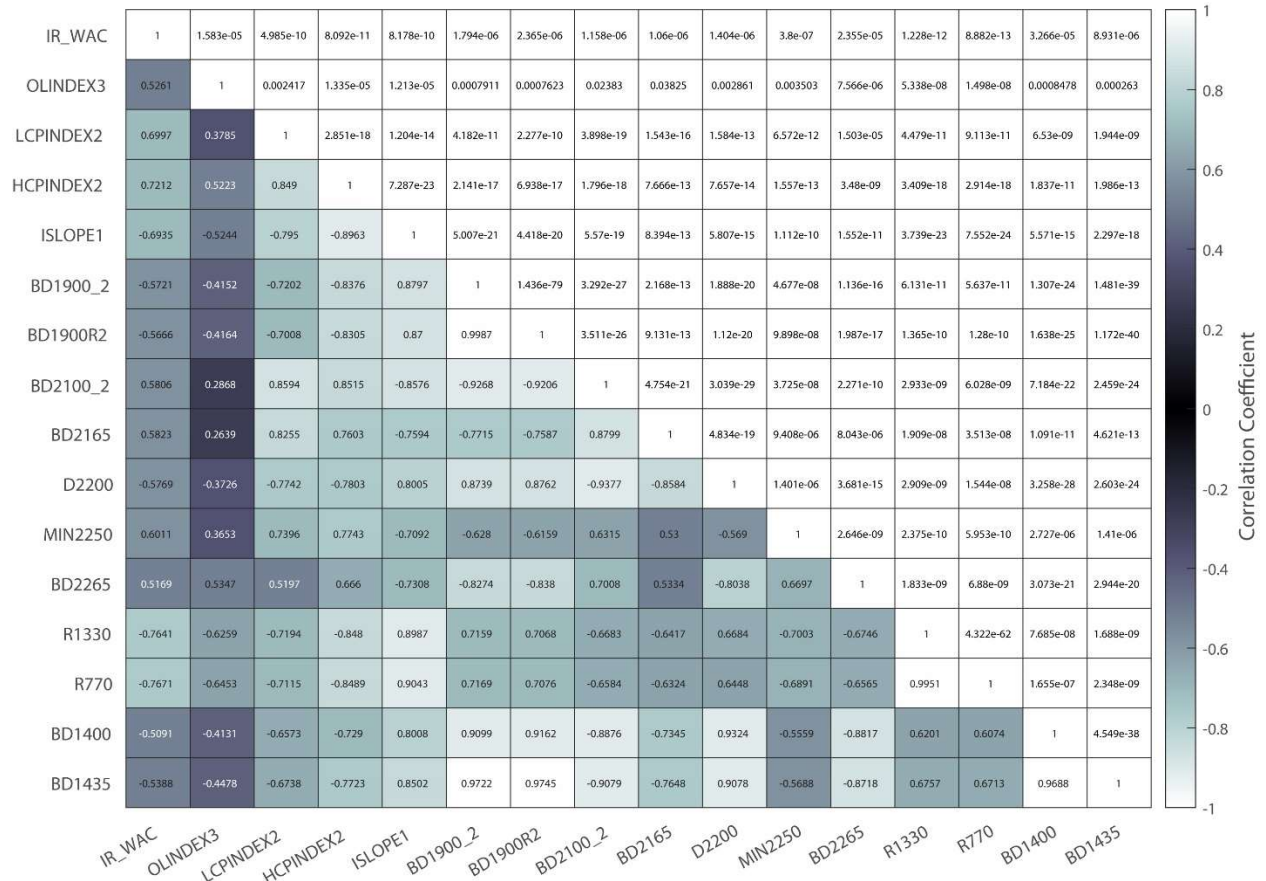


Figure 4-14. Correlation coefficients (bottom left triangle) and p-values (top right triangle) for all variables with >0.5 correlation with the infrared emission spectra's weighted absorption center (WAC).

4.6. DISCUSSION

4.6.1. Grain Properties

Correlation analysis revealed several potential trends in the controls on TI. Presley and Christensen, 2010b posited that grain shape plays a role in thermophysics primarily by controlling the regolith density. In a similar vein, the fitting parameter θ_k seems to be at least partially controlled by grain size and shape (Figure 4-11). Positive correlations with solidity, roundness, and aspect ratio, and negative correlations with skewness and standard deviations of grain size, solidity, roundness, and aspect ratio indicate that the soil's capacity for holding water as it per-

tains to thermal conductivity (likely similar to porosity) increases in well-rounded and well-sorted soils. In poorly sorted soils and/or those with angular or oblong grains, more of the pore space is filled, decreasing the capacity for water. We did not, however, find significant correlations to median grain size with other measured properties, suggesting that the manner in which grains are mixed together is more significant for water capacity than their sizes alone.

Given the relationship between model-derived θ_k and numerous grain size and shape parameters, it seems that TI and the other fitting parameters might be used together to classify sediment type. To explore the potential for this tool to predict grain properties, we used a linear regression model trained with our dataset to predict sorting ($\sigma\phi$) (Figure 4-15) and 0ϕ grain roundness (Figure 4-16) from UAV-derived TI, θ_k , m , and albedo at Sperry Wash. The result was a model R^2_{adj} of 0.80 for the training data and predicted maps hosting $\sigma\phi$ ranging from 1.3 to 3.9 (5-95% quantile interval) and 0ϕ grain roundness ranging from 0.69-0.82 (5-95% quantile interval). These values align relatively closely with measured $\sigma\phi$ of 0.65-3.08 and 0ϕ grain roundnesses of 0.66-0.78 for the five samples collected from Sperry Wash.

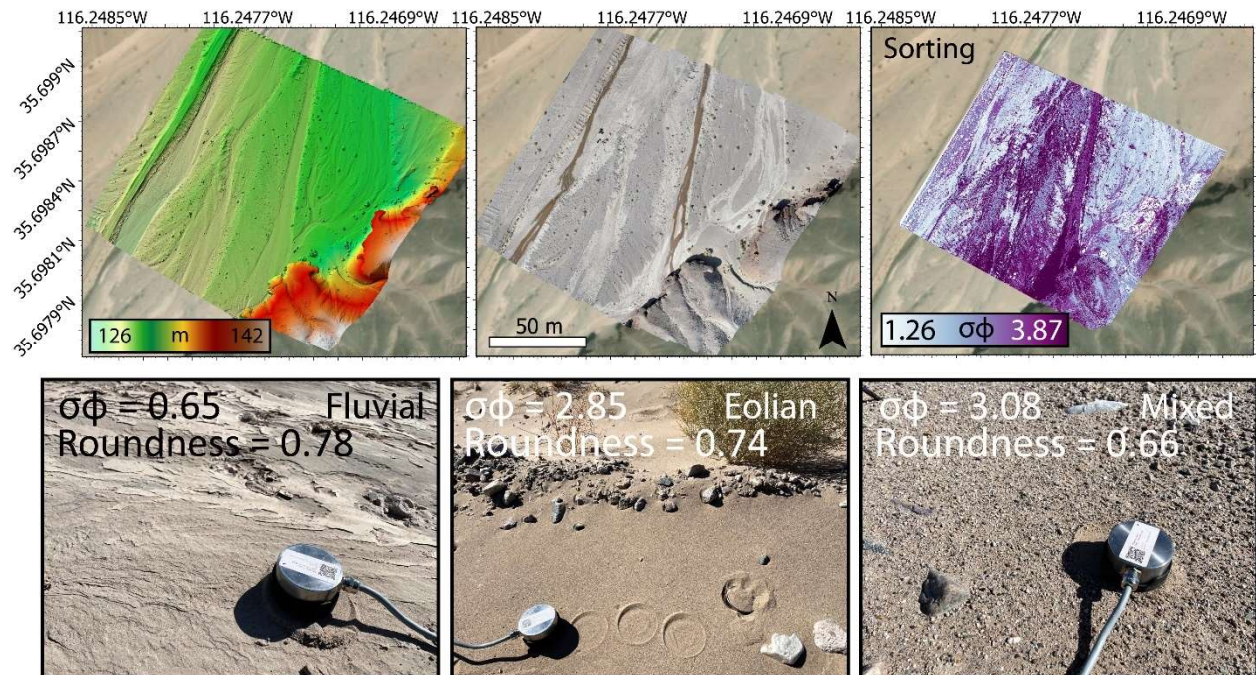


Figure 4-15. Sorting prediction results (top right) from Sperry Wash estimating the spread in grain size ($\sigma\phi$) where lower values indicate more sorting. Hillshade-elevation map and visible imagery of the site are shown for reference. Examples of the measured $\sigma\phi$ and roundness for three surface units, with the TPS-EFF probe for scale, are shown in the bottom row. The backward stepwise regression model for $\sigma\phi$ is $-0.27 + 7.7 \cdot 10^{-3} \cdot TI + 0.44 \cdot \theta_k + 1.7 \cdot m - 17 \cdot Albedo - 7.5 \cdot 10^{-3} \cdot TI \cdot m + 7.9 \cdot \theta_k \cdot Albedo + 12 \cdot m \cdot Albedo$.

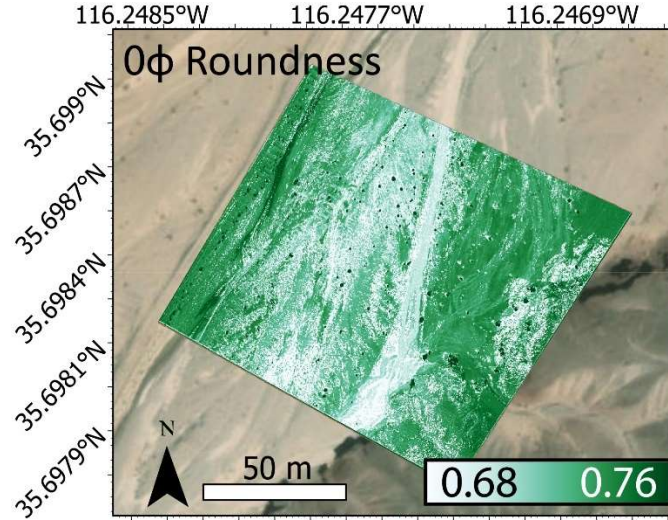


Figure 4-16. 0ϕ grain roundness prediction results from Sperry Wash. The backward stepwise regression model for the 0ϕ grain roundness is $0.538 + 1.66 \cdot 10^{-4} \cdot TI + 0.107 \cdot \theta_k + 0.1488 \cdot m + 2.76 \cdot 10^{-2} \cdot Albedo - 1.51 \cdot 10^{-4} \cdot TI \cdot m - 0.128 \cdot \theta_k \cdot m + 6.50 \cdot 10^{-2} \cdot \theta_k \cdot Albedo$.

4.6.2. Spectral Properties

An interesting trend to emerge from correlation analysis of spectral parameters was the positive correlation between the D2300 and BD640_2 parameters and TI (Figure 4-17). At the same time, MIN2200 and BD2190 showed negative correlations with TI. D2300 is indicative of the presence of Fe and Mg silicate hydration or hydroxylation. In some circumstances this might mean the samples with elevated D2300 had greater mineral hydration and/or clay content, however, MIN2200 is a separate measure of silicate hydroxylation and BD2190 a separate measure of clay content, albeit not all clays have the same spectral features. Additionally, BD640_2 suggests the presence of microcrystalline ferric minerals. Given these four relationships, we suggest the most likely explanation is that D2300 and BD640_2 are, in part, tracking the presence of non-clay cementing phases (Clark et al., 1990 Farrand et al., 2018), which we know from model-

ing have a significant role in affecting heat transfer by acting as a thermal bridge between larger grains (Piqueux and Christensen, 2009a).

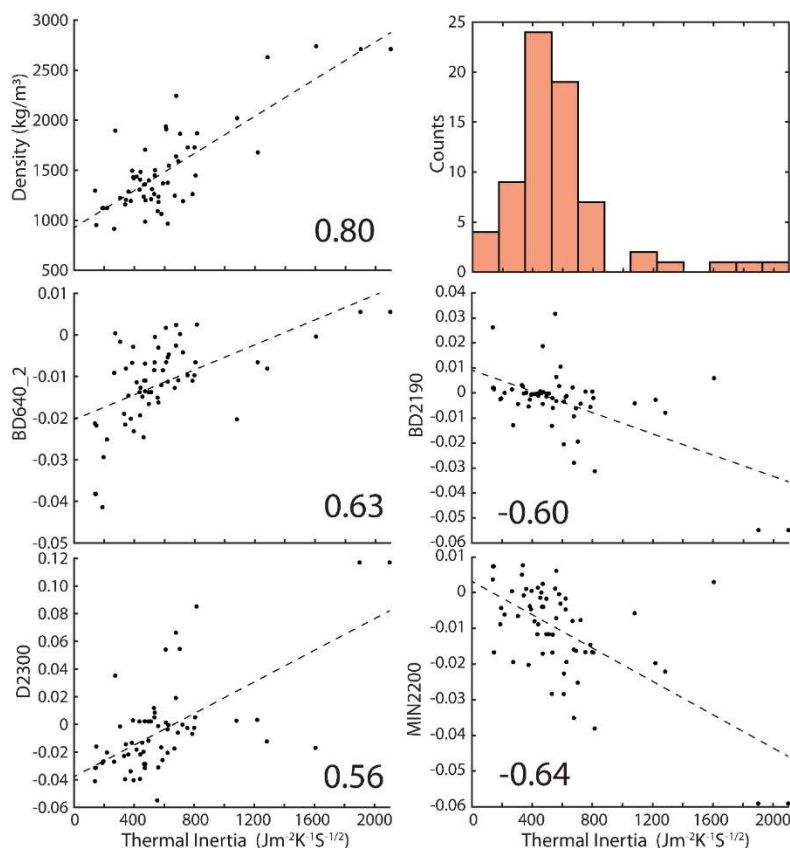


Figure 4-17. Histogram of thermal inertia and scatter plots of all variables with greater than 0.5 absolute correlation with thermal inertia showing correlation coefficients. *BD640_2*: follows the 0.64 μm band depth of some ferric minerals. *D2300*: follows the 2.3 μm dropoff typical of hydroxylated Fe, Mg silicates. *BD2190*: follows the 2.19 μm Al-OH band depth. *MIN2200*: follows the 2.16 μm and 2.21 μm Si-OH band depths.

4.6.3. Application to Mars

On Mars, sediment surfaces hosting a fine-grained lightly cementing component, such as the ‘Rocknest’ site in Gale crater, typically also host higher TIs than surficial sediment missing that component, such as the ‘Bagnold Dunes’ site (Edwards et al., 2018; Ehlmann et al., 2017). In other contexts on Mars, 2.3 μm features have been associated with deposits of fluvio-lacustrine origins (Ehlmann and Edwards, 2014; Mustard et al., 2008), and remote sensing work in Arabia Terra has also observed a subtle D2300-TI relationship (Koeppel et al., 2021). There,

surfaces hosting elevated D2300 also appear to host higher crater densities than adjacent units, an indicator of enhanced cohesion. From these observations, we suggest that D2300 and TI might be used together to differentiate fluvial and eolian sediment. To test the utility of the relationships observed in our dataset for classifying surfaces on Mars, we interrogated data from a previously studied area of Sera crater on Mars where there is some diversity in TI and D2300 over multiple sedimentary surface units (Figure 4-18).

We used THEMIS-derived TI, daytime THEMIS emissivity, and CRISM MTR products to classify surface units according to an SVM-ECOC (Falco et al., 2020; Pal, 2009) approach, trained on our Earth-analog data after calibrating TI to Mars. The classification loss by resubstitution was 0.26, indicating classification confidence was high for $\frac{3}{4}$ of the training data – and it appears that the majority of misclassification was between eolian and pyroclastic and between lacustrine and fluvial classes, for which spectral distinctions can often be uncertain. When applying this type of model in the context of classification, the interpretive leap from grain properties to depositional context is embedded in the model, however after some minor interpretation, the results are compelling.

The model returned three distinct surface types, which we name Class I, II and III. From the terrestrial dataset Class I is associated with eolian environments, Class II with fluvial, and Class III with pyroclastic. As viewed in CTX and HiRISE imagery (Figure 4-18), Class I is exclusively confined to major dark-toned bedforms, which is consistent with the type of eolian distribution that formed Class I deposits in the predictive dataset. Class II was associated with the fractured floor of Sera crater, which has previously also been assessed be of likely aqueous origin (Figure 2-2 Chapter 2; Koeppel et al., 2021). The dominant class was Class III, which included Sera crater’s layered deposits and seemingly dusty surfaces, as viewed in CTX and

HiRISE imagery. Because our terrestrial dataset did not include surfaces hosting the same style of dust cover that is found on Mars, the model selected the closest spectral and thermophysical match. The similarity between dust on Mars and pyroclastic material on Earth is consistent with models that suggest much of Mars' dust and airfall sediment has volcanoclastic origins (Bell et al., 1993; Hynek et al., 2003). Additionally, the inclusion of layered deposits in Class III, if taken to be dust-free, is consistent with proposed volcanoclastic origins for the layered deposits in Arabia Terra (Hynek and Di Achille, 2017).

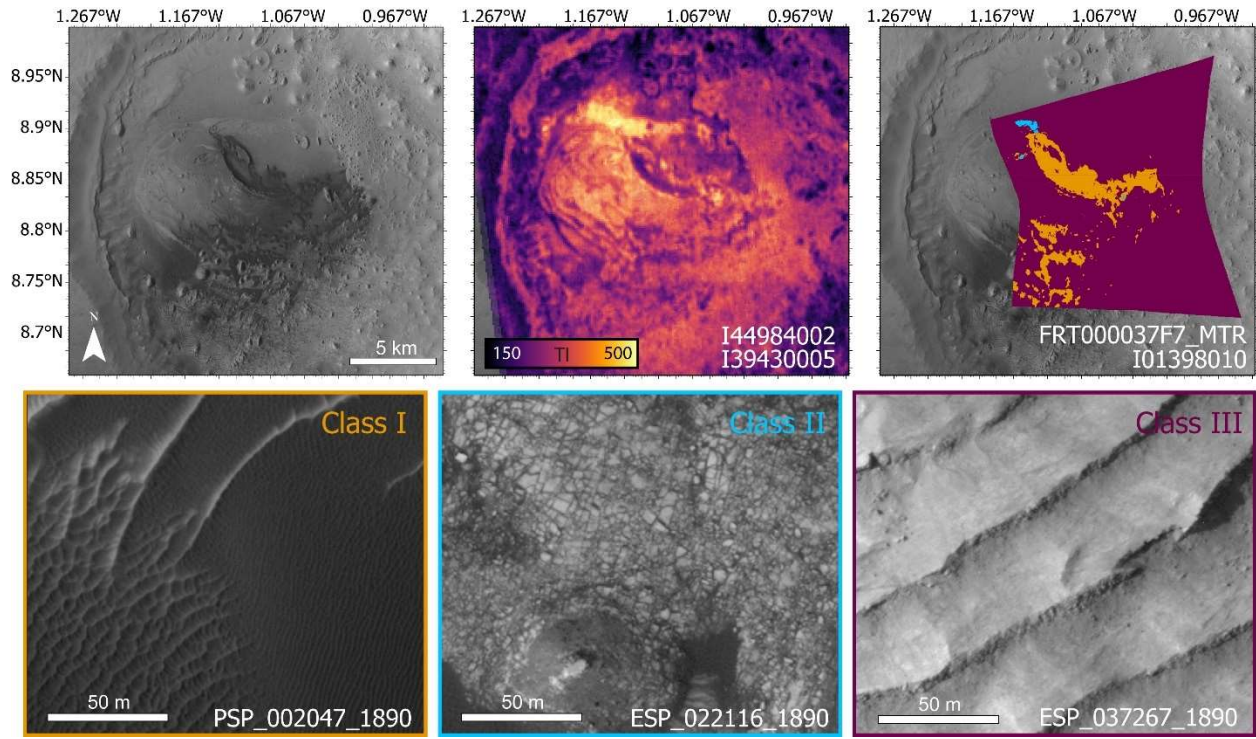


Figure 4-18. Classification results (top right) from Sera crater overlain on the CTX global mosaic (Dickson et al., 2018). Among the terrestrial data used for model training, Class I (orange) is associated with eolian material, Class II (blue) is associated fluvial settings, and Class III (maroon) is associated with pyroclastic environments. Model inputs included thermal inertia (in $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-1/2}$) from nighttime THEMIS imagery (I44984002 and I39430005), emission spectra from daytime THEMIS imagery (I01398010), and band parameters from CRISM imagery (FRT00037F7_MTR). HiRISE imagery exemplifying each of the classified surfaces is shown in the bottom row.

4.7. CONCLUSION

We collected thermophysical data from eight field analog regions on Earth representing a diverse suite of materials relevant to surfaces on Mars. We used thermophysical data from those sites to further tune our parametrization of a surface energy balance model (Chapter 3). The model calculates bulk dry soil thermal conductivity, and we demonstrated that it can be directly translated to Mars by accounting for soil moisture and atmospheric effects on conductivity and evaporative cooling. Moreover, for the first time, we were able to use paired thermophysical and spectral properties measured exclusively in materials on Earth to successfully make predictions for surface materials on Mars from remote sensing data. By establishing this mechanism for interpreting the Martian surface, we open the door to further thermophysical comparisons of surface materials on the two worlds.

Another useful outcome of this work is the demonstrated relationship between model-derived soil water capacity and grain size and shape. More homogenous, well-sorted and well-rounded soils are modeled to be able to carry more water, perhaps due to higher porosity, thus limiting the effects of small amounts of water on thermal conductivity. Given that soil water capacity is a model-fit parameter, it should be possible to use remote sensing data in tandem with the model to make predictions for either 1) grain parameters when water content is known or estimated, or 2) water content when grain parameters are known or estimated. To demonstrate this tool, we used aerial data in tandem with the model to predict grain sorting and roundness at one of our terrestrial field sites.

In addition to grain distribution, we also uncovered a unique relationship between TI and spectral features indicative of cementing or grain-coating minerals. The fact that this relationship stands out far more than any grain property confirms an important finding about the controls on

TI in surficial sediment, which was previously discussed only in the context of models (Piqueux and Christensen, 2009a; Presley et al., 2009). In the absence of water or ice, grain size and shape likely play a minor role compared to the role of cementing minerals in clastic sediment. Again, using the relationships between TI and visible near-infrared spectral parameters, it is possible to make predictions about surface materials in a dry state that can indicate their origins.

By controlling for the unique environmental conditions present on Earth, we were able to derive thermophysical properties, translate TI to its value on Mars, and begin to study the nuanced controls present in natural depositional settings as they apply to Mars. This work empirically highlights key controls on TI in natural sediment and it sets the stage for further investigations of trends that may prove to be pivotal tools for analysis of the Martian surface.

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4.9. APENDIX 4A

The full dataset from this work can be accessed at <https://doi.org/10.5281/zenodo.7847705>

CHAPTER 5

CONCLUSION

The last three chapters have presented efforts to disentangle the thermophysical properties of clastic deposits and improve our ability to uncover the depositional and climactic histories recorded in sediments on Mars. In Chapter 2, a study of a captivating and widespread set of deposits on Mars' surface was detailed. New remote sensing analysis tools were introduced for use in tandem with infrared imagery that provide pivotal context and supporting evidence for thermophysical interpretations. Those observational parameters, and the realization of their utility in deciphering thermal inertia, provided a basis for embarking on an extensive experimental campaign to quantify some of the key correlations between thermal inertia and traits that are beneficial to interpreting rock and sediment origins.

In Chapter 3, a new approach for deriving thermal inertia on Earth was detailed, and in Chapter 4, that approach was used to generate an unprecedented dataset of thermal inertia and spectral and physical properties for a diverse range of sediment types relevant to Mars' surface. A multivariate analysis approach was used to analyze the relationships in that data, and to the author's surprise and delight several of those insights relate directly to results highlighted in the Mars remote sensing work of Chapter 2.

The many combinations of features inherent to natural sediment challenge thermophysical interpretation. However, through remote sensing data analysis, field experiments, and modeling, multiple novel insights have emerged. We now have a better understanding of the nature of heat transfer in natural sediments and of tools that can be used to interrogate the origins of sediments as they pertain to worlds past. It is the author's hope that in the coming years, the scien-

tific community will be able to use and expand on these efforts to uncover new and fascinating insights from Earth and Mars.

APPENDIX 6A

TESTING METHODS FOR DETECTION OF UNFAMILIAR LIFE IN MARTIAN REGOLITH

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6.1. INTRODUCTION

Mission related efforts to detect extant life on Mars' surface, such as the Viking lander experiments (Klein, 1978), have thus far focused on organic chemical tracers and gaseous by-products of active biotic processes. Yet, despite the multiple experiments conducted on Mars' surface, consensus on the evidence for extant life remains missing (Benner et al., 2000). Scientists and philosophers have speculated on the possibility that Martian life takes a form that is chemically unfamiliar to us and to the design of those early experiments (e.g., Cleland, 2012; McKay, 2004). As such, a method of detecting extant life that does not require organic chemistries may be a useful complement to the more conventional approaches on future missions to Mars' surface.

In this exploratory work, we investigate and compare the viability of two easily coopted lander payloads for detecting biotic activity in Martian soils which do not rely on C-O-H chemistries. We present and discuss results from initial sensitivity tests of cellular metabolism using the non-toxic redox tracer dye Alamar Blue (resazurin, ThermoFisher) (O'Brien et al., 2000;

Rampersad, 2012) and infrared thermography (Kluge et al., 2013) in an inoculated Mars regolith simulant (Cannon et al., 2019).

6.2. METHODS

6.2.2. Alamar Blue (*resazurin*)

Alamar Blue experiments were conducted in sealed jars filled with mixtures of biologically active and Mars simulant soils in a factor-of-ten dilution series. Upon reduction, non-fluorescent resazurin becomes highly fluorescent resorufin. After mixing samples with Alamar Blue, fluorescence was measured using a plate reader and qualitatively confirmed using a confocal fluorescence microscope. As points of comparison, we also measured CO₂ at the beginning and end of the experiment. In both experiments, we controlled for grain-size, water content and basaltic provenance in order to limit sample variability.

6.2.3. Infrared Thermography (IRT).

Eight mixtures of Mars simulant and active soil were placed on a partitioned sampling tray. After mixing 1.5 mL of distilled water into each sample and heating the samples in a 45 °C oven for 8 hours, the tray was placed in a 30 °C dark chamber with a downfacing infrared (7.5-13.5 µm) imager overhead for 6 hours. Pixel values converted to temperature provide a time series.

6.3. RESULTS AND DISCUSSION

Reconnaissance testing using Alamar Blue solution suggests that biotically-triggered fluorescence can be detected (Figure 6A-1) with similar sensitivity as traditional gas exchange monitoring, although future testing with less dilute mixtures will improve interpretations.

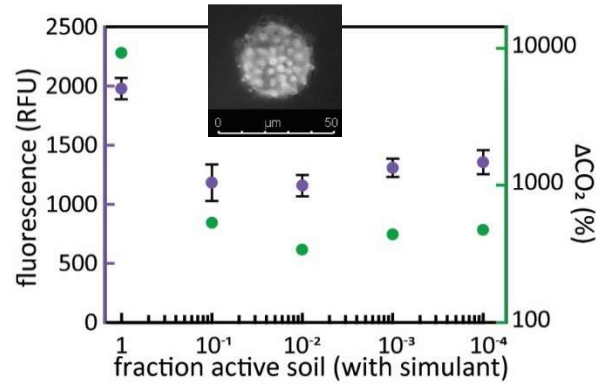


Figure 6A-1. Alamar Blue-activated fluorescence (excitation, Texas Red filter at BP 560/40) and ΔCO_2 in soil samples diluted with Mars simulant. Uncertainty on ΔCO_2 measurements is smaller than the marker sizes.

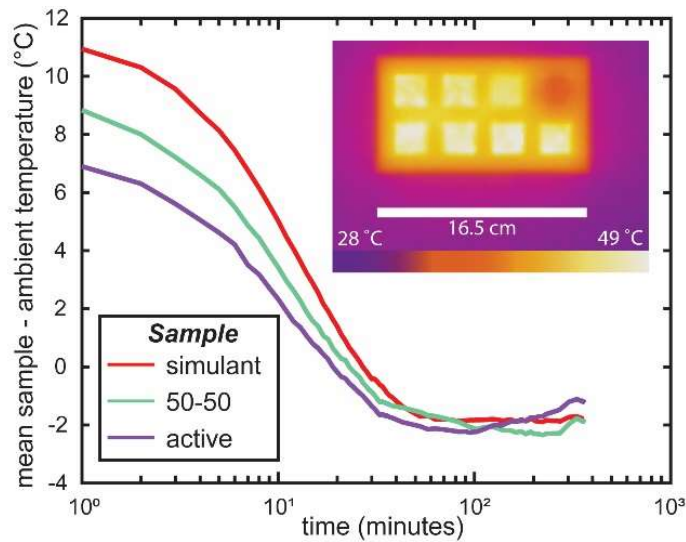


Figure 6A-2. IRT-derived temperature evolution of 3 of 8 samples. Maximum uncertainty is ± 0.5 °C.

IRT experiments (Figure 6A-2) show that samples with larger fractions of active soil show lower temperatures after heating and higher temperatures at ambient (~ 30 °C) thermal equilibrium. If the temperature variation is a result of biotic activity, initially lower temperatures may result from cellular fluid retention, while the eventual warming may result from metabolic reactions (Russell and Cook, 1995).

This and prior works indicate that both Alamar Blue and IRT have the potential to be use-

ful, non-destructive tools for the detection of extant life in Martian regolith. Further investigations will provide better constraints on the sensitivity of these tools to the variety of possible forms of life that may exist on Mars.

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APPENDIX 7A

REVIEW OF LOCATIONS WHERE *IN SITU* THERMOPHYSICAL OBSERVATIONS HAVE BEEN COLLECTED ON MARS

Sample Location	Inferred Formation Setting	Cohesion, kPa (Friction angle, °) [Density, kg/m ³]	Grain/Bed/deposit Morphology – Visual features	Mineralogy	TI [Jm ⁻² K ⁻¹ s ^{-½}]
Burns Formation, Endurance crater ^{1,2,3}	Dune, sand sheet, interdune, and playa facies. Evaporite conditions during deposition or alteration.	[<2000]	Well-sorted coarse to medium grained sand and local mudstones. Cross-bedding, ripple cross-lamination. Ca-Mg-Fe-sulfate cements; 2° fabric selective porosity; hematitic concretions; nodules; cement overgrowths; soft sediment deformation	Sulfate-cemented basalt	400–1100
Stimson Formation, Gale crater ^{1,4}	Dry aeolian sandstone of crescentic dune field.	Lithified	M-scale planar/trough cross-bedded, medium-coarse-grained (bimodal) sandstone. Concretion-rich (20-30mm) facies. Silica-rich alteration halos along fractures.	Basaltic with Si-rich alteration	700
Murray Formation, Gale crater ^{4,5}	Redox stratified lake deposit interspersed fluvio-deltaic sandstone.	Lithified	Thickly to thinly laminated mudstones. Interspersed medium-coarse, moderately well sorted, cross-bedded sandstones and sandstone clinoforms; local conglomerate. Desiccation. Dendritic concretions. Silica-rich alteration halos along fractures. Post-lithification Ca-sulfate veins.	K-rich basalt, redox stratified. Ca-sulfate veins. Jarosite. Si-rich alteration	650
Bagnold Dunes, Gale crater ⁶	Aeolian bed-forms	Cohesionless	0.1-0.35 mm grains	Basaltic/Palagonite	170-180
Endurance crater, Bed-forms ^{7,6}	Aeolian bed-forms	Cohesionless	0.130 mm grains	Basaltic/Palagonite	200
Laguna Hollow (Gusev) ⁷	Aeolian bed-forms	Cohesionless	<0.21 mm grains	Basaltic/Palagonite	150
Gusev Plains Soil ⁷	Aeolian bed-forms	Cohesionless	~0.21 mm agglomerates of grains	Basaltic/Palagonite	200
Serpent/Saber Bedform (Gusev) ⁷	Aeolian bed-forms	Cohesionless	Trimodal: 1– 2 mm, 0.250 – 0.500 mm, <0.210 mm grains	Basaltic/Palagonite	250
Meridiani Plains Soil ⁷	Evaporitic spherules in aeolian bed-forms	Cohesionless	Bimodal: 0.6– 6 mm set in very fine sand <0.125 mm grains	Hematite spherules in Palagonite dust	100-150
Bradbury Group, Gale crater ^{8,1,4}	Braided fluvial-delta with interspersed lacustrine deposition and aeolian facies	Lithified	Interbedded conglomerates, sandstones and mudstones. Cross-bedding. Pre-filling cements, filled and hollow nodules, subaqueous shrinkage cracks, raised ridges/veins. Vuggy porosity, sedimentary dike, extensive networks of Ca-sulfate veins	K-rich Basalt Ca-sulfate veins. Redox stratified	1700
Matijevic formation ^{1,3}	impact or volcanic proximal	Lithified [~2000]	2-4 mm Lapilli + coarse to very coarse sand. Ca-sulfate veins. Alu-	High Si and P Basaltic source	620–1100

	airfall deposit		minous clay-bearing “boxwork”	with Ca-Sulfate and Al-clay veins	
Shoemaker formation ^{1,3}	impact breccia; suevite	Lithified [~2000]	Massive polymict clast-rich to clast-poor breccias. Ca-sulfate veins	Basalt with Fe-clay alteration and ca-sulfate veins	620–1100
Grasberg formation ^{1,3}	low energy, possibly distal airfall	Weakly lithified [~2000]	Very fine sand to mudstone. Local laminations. upper 0.5m light-toned. Ca-sulfate veins.	Low Mg Basalt with ca-sulfate veins	620–1100
Home Plate ^{1,3}	Lower: explosive volcanoclastic Upper: aeolian-reworked pyroclastic surge deposit	1000–10000 (40–60) [2600–2800]	Poorly sorted clasts with well-sorted sandstone. 2–2000 mm. Bedded to massive, poorly sorted clastics (incorporating a bomb sag). Upper: moderately- to well-sorted, cross-bedded sandstones.	High Mg and P Basalt	1200–2500
Opaline Silica Deposits ^{1,3}	Hydrothermal or hot spring/geyser silica sinter or	Lithified	Nodular mm-scale digitate. Scattered outcrops of opaline silica	Altered basaltic silica	620–1100
Peace Class Rocks ^{1,3}	N/A	Lithified	Mm- to cm-scale bedded, poorly sorted pebbly sandstone	Ultramafic with hydrated Mg-Ca sulfate cements	620–1100
Viking Lander Site I ^{3,9,5}	Drift material	1.6±1.2 or 0–3.7 (18±2.4) [1150±150]	<0.2 mm grains	Basaltic/Palagonite	40–125 (inferred from lab)
Viking Lander Site I ^{3,9,5}	Blocky soil	5.1±2.7 or 2.2–10.6 (30.8±2.4) [1600±400]	0.05–3 mm	Basaltic/Palagonite	368–410 (inferred from lab)
Viking Lander Site I/II ^{3,9,5}	Rocks	1000–10000 (40–60) [2600]	> 1 cm, cobbles and blocks	Basaltic/Palagonite	1200–2500 (inferred from lab)
Viking Lander Site II ^{3,9,5}	Crusty/cloddy soil	1.1±0.8 or 0–3.2 (34.5±4.7) [1400±200]	0.005–0.5 mm	Basaltic/Palagonite	200–326 (inferred from lab)
Pathfinder site ^{3,9,5}	Drift material	0.18–0.53 (15.133.1) [1066–1269]	<0.2 mm grains	Basaltic/Palagonite	40–125 (inferred from lab)
Pathfinder site ^{3,9,5}	Wind ripples	0–1 (34.8–37.7) [1100–1300]	0.06–0.2 mm	Basaltic/Palagonite	60–200 (inferred from lab)
Pathfinder site ^{3,9,5}	Cloddy material	–0.34–0.57 (31.4–42.2) [2000–2200]	~0.05–~3 mm	Basaltic/Palagonite	200–326 (inferred from lab)
Phoenix Lander site ¹⁰	Ice-cemented soil	0.2–1.2 (38)	0.07–0.08 mm	H ₂ O Ice-cemented soil	200–350
Insight site ¹¹	Duricrust	0.05–1.9 (30–50)	Mixed dust, sand, and pebbles	Basaltic/Palagonite	160–230

Table A7-1. Sediment and sedimentary rocks on Mars which have been used as ground truths for remote TI derivations. Adapted from (McLennan et al., 2019). See (McLennan et al., 2019) for more complete descriptions of sediment and lists of sources. ¹(McLennan et al., 2019) ²(Grotzinger et al., 2005) ³(Golombek et al., 2008) ⁴(Vasavada et al., 2017) ⁵(Grotzinger et al., 2015) ⁶(Edwards et al., 2018) ⁷(Ferguson et al., 2006a) ⁹*Herkenhoff et al.*, 2009 ¹⁰(Michael T. Mellon et al., 2009) ¹¹(Golombek et al., 2020) ⁸(Edgar et al., 2018; Mangold et al., 2016; Williams et al., 2013)

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