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# **Laboratory Spectroradiometric Temperature Retrieval of Silicates Using Linearized Wien Approximations and Polynomial Regression**

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## **PREPRINT METADATA & REPOSITORY DECLARATION**

- Preprint Status: This manuscript is a non-peer-reviewed preprint deposited on EarthArXiv.
- Date of Deposit: October 27, 2026
- Subject Taxonomy: Earth Sciences | Mineral Physics | Geophysics and Seismology | Remote Sensing
- Copyright & Licensing: Creative Commons Attribution 4.0 International License (CC BY 4.0).
- Open Data Benchmark: Complete 12-regime calibrated spectroradiometric library deposited on Zenodo (DOI: [10.5281/zenodo.23571365](https://doi.org/10.5281/zenodo.23571365)).
- Current Peer-Review Status: Submitted to a peer-reviewed scientific journal for formal evaluation.
- Suggested Citation: Grondona, A. E. B., Morales-Salinas, L., & Veettil, B. K. (2026). Laboratory Spectroradiometric Temperature Retrieval of Silicates Using Linearized Wien Approximations and Polynomial Regression. EarthArXiv Preprint. DOI: [10.31223/X5XXXX](https://doi.org/10.31223/X5XXXX).

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# Laboratory Spectroradiometric Temperature Retrieval of Silicates Using Linearized Wien Approximations and Polynomial Regression

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## ABSTRACT

Thermal infrared (TIR) remote sensing provides critical diagnostic capabilities for surface temperature and spectral emissivity retrieval. However, extracting these parameters from at-target radiance measurements is fundamentally ill-posed because Planck's radiation law non-linearly couples kinetic temperature and spectral emissivity, creating an underdetermined system of  $N$  spectral bands with  $N + 1$  unknowns. Conventional temperature-emissivity separation (TES) algorithms mitigate this indeterminacy by imposing empirical constraints or spectral assumptions that frequently rely on external atmospheric profile sounding or specific scene properties. This paper proposes a direct, consistent inversion framework to retrieve both surface kinetic temperature and complete spectral emissivity relying strictly on at-target radiance measurements. The central premise is that spectral emissivity and kinetic temperature are physically coupled, allowing this relationship to be parameterized via a linearized Wien approximation into a polynomial regression model. Controlled spectroradiometric experiments were conducted on a high-purity crystalline hydrothermal quartz sample ( $\text{SiO}_2$ ) across 12 distinct thermal regimes (289.45 K to 326.75 K) under stabilized ambient conditions using a portable micro-Fourier transform interferometer ( $\mu\text{FT-IR}$  Model 102).

Absolute radiometric calibration was conducted using a two-temperature blackbody protocol with liquid nitrogen ( $\text{LN}_2$ ,  $\sim 77$  K) for the cold cycle and a heated blackbody cavity ( $\sim 325$  K). The spectral library was partitioned into calibration/training (8 regimes) and testing/validation sets (4 regimes). Five interpolators were evaluated across strategic diagnostic wavelengths (10.0  $\mu\text{m}$ , 10.1  $\mu\text{m}$ , 11.0  $\mu\text{m}$ , and 12.0  $\mu\text{m}$ ): shape-preserving piecewise cubic Hermite (PCHIP), linear, quadratic, cubic, and 4th-degree polynomials. Once calibrated on the target's characteristic response, at-target radiance serves as the sole operational input: the polynomial regression directly predicts kinetic temperature, from which the complete spectral emissivity curve is simultaneously derived across all wavelengths.

The experimental results demonstrate that target surface temperature can be retrieved with absolute errors below 0.02 K using simple linear regression, and below  $4 \times 10^{-4}$  K using 4th-degree polynomials at longer wavelengths ( $\lambda \geq 11.0 \mu\text{m}$ ). Errors below  $10^{-3}$  K reflect algebraic model convergence, whereas physical performance is bounded by instrument noise ( $NE\Delta T \approx 0.05$  K). Importantly, this study focuses strictly on controlled laboratory spectroradiometry; operational extrapolation to airborne or orbital sensors is outside the scope of this paper and reserved for future investigations. The complete calibrated spectroradiometric dataset is openly accessible via Zenodo (DOI: 10.5281/zenodo.23571365), providing a reproducible benchmark for forward thermal radiative transfer modeling and sensor calibration.

**Keywords:** Thermal infrared, Temperature retrieval, Emissivity separation, Wien approximation, Spectroradiometry, Quartz, Radiative transfer, Uncertainty propagation.

## 1. INTRODUCTION

Thermal infrared (TIR) radiance acquired by orbital, airborne, and ground-based sensors provides unique quantitative information regarding surface kinetic temperature and diagnostic composition. Accurate retrieval of land surface temperature (LST) and land surface emissivity (LSE) is crucial across a broad spectrum of earth science disciplines, including lithological and mineralogical mapping, geothermal exploration, climate modeling, evapotranspiration monitoring, volcanic hazard

monitoring, and environmental change detection (Collins et al., 1999, 2001; Schmugge et al., 1998; Gillespie et al., 1999; Li et al., 2013; Reiners et al., 2023).

Among these applications, geological and mineralogical discrimination benefits extensively from TIR spectroscopy within the atmospheric window between 8.0  $\mu\text{m}$  and 14.0  $\mu\text{m}$ . In this spectral interval, the vibrational fundamentals of silicate frameworks (fundamental Si–O asymmetric stretching modes) generate intense diagnostic absorption bands known as Reststrahlen bands, accompanied by characteristic emissivity minima between 8.2  $\mu\text{m}$  and 9.3  $\mu\text{m}$  (Hook et al., 2005; Vicente and Souza Filho, 2010; Cawse-Nicholson et al., 2021). Because the emissive properties of Earth materials dominate over reflective processes beyond 8.0  $\mu\text{m}$ , multispectral and hyperspectral TIR data are uniquely suited for quantitative mapping of silica content and distinguishing between felsic, intermediate, and mafic rock assemblages (Kealy and Hook, 1993; Hulley et al., 2022).

Despite its extensive utility, retrieving temperature and emissivity from recorded radiance measurements represents a classical ill-posed inverse problem in remote sensing. The spectral radiance recorded by a sensor over an opaque terrestrial target is governed by Planck's radiation law, which couples the target kinetic temperature and spectral emissivity in a non-linear formulation. Consequently, for a sensor with  $N$  spectral channels, there are  $N$  measured radiances but  $N + 1$  unknowns ( $N$  spectral emissivities plus one kinetic temperature) (Watson, 1992a, 1992b; Rees, 2001; Olsen, 2007; Li et al., 2013). This inherent mathematical underdetermination prevents direct analytical inversion unless complementary physical constraints, empirical assumptions, or auxiliary data are introduced.

Over past decades, diverse Temperature and Emissivity Separation (TES) algorithms have been formulated to address this indeterminacy. These techniques are generally categorized into three groups: (i) methods that retrieve temperature and composition jointly, such as the Reference Channel Method (RCM; Kahle and Rowan, 1980) and Normalized Emissivity Method (NEM; Gillespie et al., 1985); (ii) relative spectral shape enhancement methods that eliminate temperature to extract emissivity shapes, such as Alpha Residuals (Hook et al., 1992) and Spectral Ratio algorithms (Watson, 1992a); and (iii) hybrid multi-stage frameworks, exemplified by the ASTER TES algorithm (Gillespie et al., 1999) and the operational ECOSTRESS Collection 2 framework (Hulley et al., 2022), which integrate NEM, spectral ratioing, and an empirical min-max emissivity difference (MMD) relationship. However, existing TES techniques rely heavily on predefined assumptions—such as an assumed maximum spectral emissivity (e.g.,  $\epsilon_{\text{max}} \approx 0.96\text{--}0.99$ ), empirical spectral regressions derived from specific libraries, or high-precision atmospheric radiative transfer corrections (Rolim et al., 2016; Viúdez-Mora et al., 2014; Guillevic et al., 2018). In humid sub-tropical environments, residual atmospheric transmission and downwelling radiance uncertainties propagate non-linearly into the retrieved temperature and emissivity spectra (Li et al., 1999; Grondona et al., 2013).

To mitigate the reliance on complex iterative numerical solvers and provide a direct, physically bounded radiometric inversion, this paper presents a target-specific temperature and emissivity retrieval framework calibrated against controlled laboratory spectroradiometry. The central hypothesis of this study is that spectral emissivity and kinetic temperature are dynamically coupled through Planck's law and solid-state mineral physics. For a specific target, this relationship can be parameterized via a linearized Wien approximation into a polynomial regression model. Once calibrated on the target's characteristic response, at-target radiance serves as the sole operational input: the polynomial regression directly retrieves kinetic temperature, which in turn immediately yields the complete spectral emissivity curve across the thermal infrared spectrum without requiring external atmospheric sounding or arbitrary scene constraints. The methodology is experimentally demonstrated on a pure quartz ( $\text{SiO}_2$ ) specimen subjected to 12 controlled thermal regimes between 289.45 K and 326.75 K. Importantly, the empirical scope of this investigation is intentionally focused on controlled

laboratory spectroradiometric measurements where ambient conditions are stabilized and target-to-sensor atmospheric attenuation is negligible. The theoretical coupling with MODTRAN is provided as a methodological bridge, whereas empirical validation on airborne or spaceborne platforms remains outside the immediate scope of the present study. Furthermore, to support reproducible research in the GeoAI and remote sensing communities, the full spectroradiometric benchmark library has been deposited in an open-access repository (Zenodo DOI: 10.5281/zenodo.23571365).

## 2. MATERIAL AND EXPERIMENTAL DATASET

The experimental mineral specimen analyzed in this study is a high-purity crystalline hydrothermal vein quartz ( $\text{SiO}_2$ ), selected as a representative silicate reference. The sample was obtained from geological occurrences associated with the southern margin of the Paraná Basin in Rio Grande do Sul, Brazil, and curated at the Laboratório de Sensoriamento Remoto Geológico (LABSRGEO) of the Centro Estadual de Pesquisas em Sensoriamento Remoto e Meteorologia (CEPSRM) at the Universidade Federal do Rio Grande do Sul (UFRGS).

Spectroradiometric measurements were conducted using a portable micro-Fourier transform interferometer ( $\mu\text{FT-IR}$  Model 102, Designs & Prototypes, Simsbury, CT, USA) (Hook and Kahle, 1996). The instrument operates across the thermal infrared spectral region from 2.0  $\mu\text{m}$  to 16.0  $\mu\text{m}$ , equipped with dual cooled detectors (indium antimonide [InSb] and mercury cadmium telluride [MCT]) and user-selectable spectral resolutions of 2  $\text{cm}^{-1}$ , 4  $\text{cm}^{-1}$ , and 16  $\text{cm}^{-1}$ . Absolute radiometric calibration was conducted using a two-temperature blackbody calibration protocol in strict compliance with the manufacturer's technical specifications (Designs & Prototypes Model 102 Technical Manual) and CEOS best-practice validation protocols (Guillevic et al., 2018). The cold calibration cycle utilized liquid nitrogen ( $\text{LN}_2$ ,  $\sim 77$  K), which establishes a physical near-zero radiance reference ( $B(\lambda, 77\text{ K}) \approx 0\text{ W}\cdot\text{m}^{-2}\cdot\text{sr}^{-1}\cdot\mu\text{m}^{-1}$  across the 8–14  $\mu\text{m}$  window) that directly isolates instrument internal self-emission and detector offset. The warm blackbody cavity was thermostatically stabilized at a heated setpoint ( $T_{\text{hot}} \approx 315\text{--}325$  K,  $\sim 42\text{--}52$  °C), accurately bracketing the upper limit of the target kinetic temperature range and establishing instrument spectral responsivity (gain).

Due to low signal-to-noise ratios below 7.0  $\mu\text{m}$  under terrestrial ambient temperatures, the spectral analysis was restricted to the 7.0  $\mu\text{m}$  to 16.0  $\mu\text{m}$  diagnostic interval, which contains the prominent quartz Reststrahlen doublet (8.2  $\mu\text{m}$  and 9.3  $\mu\text{m}$ ) and the Christiansen frequency ( $\sim 7.4$   $\mu\text{m}$ ). The quartz sample was mounted on a thermally stabilized heating stage and systematically measured across 12 distinct thermal regimes spanning sample kinetic temperatures from 289.45 K (16.3 °C) to 326.75 K (53.6 °C). Ambient air temperature (292.25 K to 299.15 K) and relative humidity (56.20% to 69.30%) inside the laboratory environment were continuously recorded during all measurement sequences. Table 1 summarizes the environmental parameters, sample kinetic temperatures, and acquisition dates for all 12 experimental runs.

**Table 1. Experimental laboratory conditions, target kinetic temperatures, and environmental parameters during spectroradiometric acquisitions.**

| Acquisition Date | Experiment ID | Target Temperature $T$ (K) | Ambient Temperature $T_{env}$ (K) | Relative Humidity (%) |
|------------------|---------------|----------------------------|-----------------------------------|-----------------------|
| 07-Jun-2012      | 1             | 326.75                     | 295.15                            | 61.90                 |
| 07-Jun-2012      | 2             | 316.65                     | 295.15                            | 61.90                 |
| 07-Jun-2012      | 3             | 302.45                     | 295.15                            | 61.90                 |
| 07-Jun-2012      | 4             | 289.45                     | 295.15                            | 61.90                 |
| 20-Aug-2012      | 5             | 309.15                     | 299.15                            | 69.30                 |
| 20-Aug-2012      | 6             | 308.65                     | 299.15                            | 69.30                 |
| 20-Aug-2012      | 7             | 308.15                     | 299.15                            | 69.30                 |
| 31-Aug-2012      | 8             | 325.65                     | 292.25                            | 56.20                 |
| 31-Aug-2012      | 9             | 316.75                     | 292.25                            | 56.20                 |
| 31-Aug-2012      | 10            | 315.95                     | 292.25                            | 56.20                 |
| 31-Aug-2012      | 11            | 315.45                     | 292.25                            | 56.20                 |
| 31-Aug-2012      | 12            | 309.35                     | 292.25                            | 56.20                 |

Data reduction, blackbody radiance calculations, spectral emissivity derivations, and statistical regression modeling were implemented in MATLAB (R2010b and modern releases) leveraging the Curve Fitting Toolbox. The complete raw and calibrated spectroradiometric dataset, including metadata headers and thermal regime logs, is available in the Zenodo repository (Grondona et al., 2026).

### 3. THEORETICAL FORMULATION AND INVERSION METHODOLOGY

For an ideal blackbody radiator at thermodynamic kinetic temperature  $T$  (in Kelvin), the spectral radiance emitted into a hemisphere per unit solid angle is described by Planck's law:

$$L_{bb}(\lambda, T) = \frac{c_1}{\lambda^5 \cdot \left[ \exp\left(\frac{c_2}{\lambda \cdot T}\right) - 1 \right]} \quad (1)$$

where  $L_{bb}(\lambda, T)$  is the blackbody spectral radiance ( $\text{W} \cdot \text{m}^{-2} \cdot \text{sr}^{-1} \cdot \mu\text{m}^{-1}$ ),  $\lambda$  is the wavelength in micrometers ( $\mu\text{m}$ ), and  $T$  is the absolute temperature in Kelvin (K). The first and second radiation constants are defined as  $c_1 = 2\pi \cdot h \cdot c^2 = 3.7418 \times 10^8 \text{ W} \cdot \mu\text{m}^4 \cdot \text{m}^{-2}$  (or  $1.1911 \times 10^8 \text{ W} \cdot \mu\text{m}^4 \cdot \text{m}^{-2} \cdot \text{sr}^{-1}$  for directional spectral radiance) and  $c_2 = \frac{h \cdot c}{k} = 1.4388 \times 10^4 \mu\text{m} \cdot \text{K}$ , where  $h$  is Planck's constant,  $c$  is the speed of light in vacuum, and  $k$  is Boltzmann's constant (Siegel and Howell, 1982).

Real terrestrial surfaces behave as non-blackbodies, emitting only a fraction of the ideal blackbody radiation at a given temperature and wavelength. This efficiency is quantified by the

directional spectral emissivity  $\varepsilon(\lambda, T)$ , defined as the ratio of observed target radiance  $L(\lambda, T)$  to the theoretical blackbody radiance  $L_{bb}(\lambda, T)$ :

$$\varepsilon(\lambda, T) = \frac{L(\lambda, T)}{L_{bb}(\lambda, T)} \quad (2)$$

Under terrestrial surface temperatures ( $T \sim 270\text{--}330$  K) and thermal infrared wavelengths ( $\lambda \sim 8\text{--}14$   $\mu\text{m}$ ), the exponential term in the denominator of Planck's law satisfies  $\exp(\frac{c_2}{\lambda \cdot T}) \gg 1$ . Under this condition, Planck's function is accurately approximated by Wien's radiation law:

$$L_{Wien}(\lambda, T) = \frac{c_1}{\lambda^5} \cdot \exp\left(-\frac{c_2}{\lambda \cdot T}\right) \quad (3)$$

Wien's approximation introduces a systematic error of less than 1% for  $\lambda \cdot T \leq 3000$   $\mu\text{m} \cdot \text{K}$  (Siegel and Howell, 1982; Grondona et al., 2013). For the temperature and wavelength ranges investigated here ( $T \leq 327$  K;  $\lambda \leq 12$   $\mu\text{m}$ ), the product  $\lambda \cdot T$  remains below 3924  $\mu\text{m} \cdot \text{K}$ , ensuring an analytically tractable and highly accurate representation. In this controlled laboratory spectroradiometric configuration, target-to-sensor atmospheric path radiance and reflected ambient downwelling radiance ( $(1 - \varepsilon) \cdot L_{down}$ ) are negligible due to the close-range optical geometry ( $< 10$  cm target distance) and thermally stabilized room environment ( $T_{env} \approx 295$  K, Table 1). Consequently, combining Equations 2 and 3 yields the direct target spectral radiance under Wien's approximation:

$$L(\lambda, T) = \varepsilon(\lambda, T) \cdot \frac{c_1}{\lambda^5} \cdot \exp\left(-\frac{c_2}{\lambda \cdot T}\right) \quad (4)$$

Applying the natural logarithm to both sides of Equation 4 linearizes the radiative transfer relationship:

$$\ln[L(\lambda, T)] = \ln[\varepsilon(\lambda, T)] + \ln(c_1) - 5 \cdot \ln(\lambda) - \frac{c_2}{\lambda \cdot T} \quad (5)$$

Every mineral target exhibits a characteristic spectral signature in radiance  $L(\lambda, T)$  (Figure 1) and emissivity  $\varepsilon(\lambda, T)$  (Figure 2) at a given temperature  $T$ .

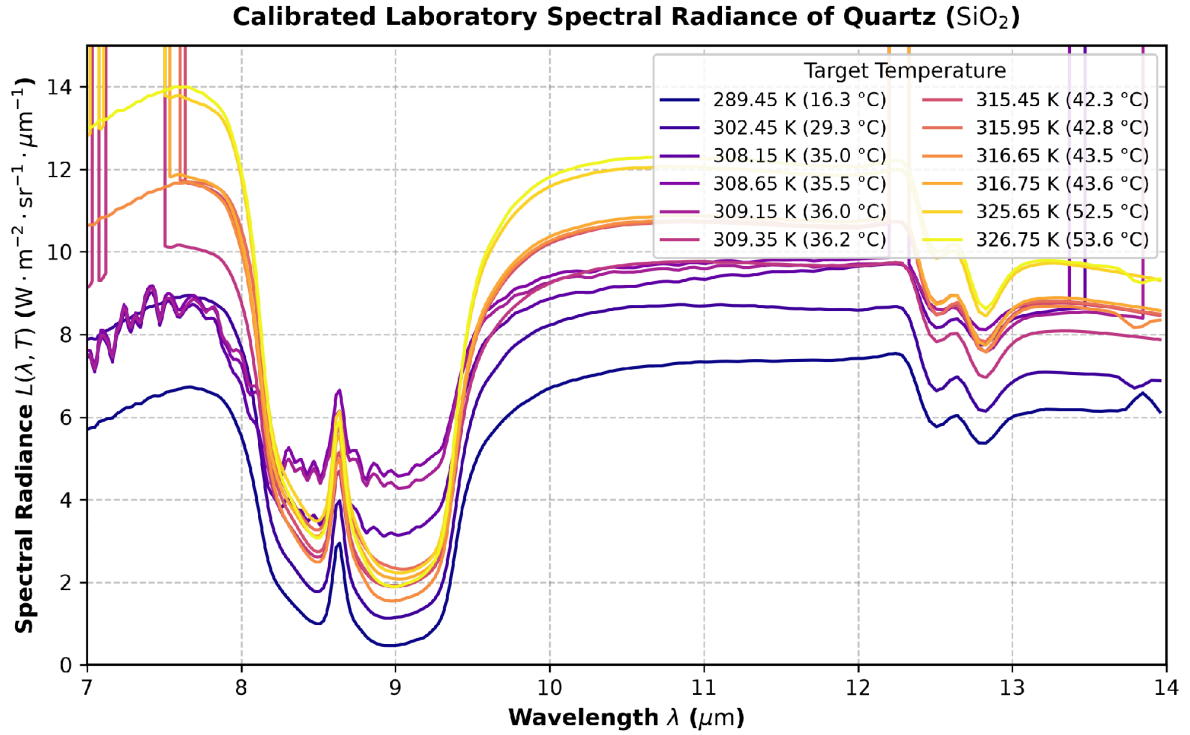


Figure 1. Calibrated laboratory thermal infrared spectral radiance curves of the hydrothermal quartz specimen measured across 12 controlled thermal regimes (289.45 K to 326.75 K).

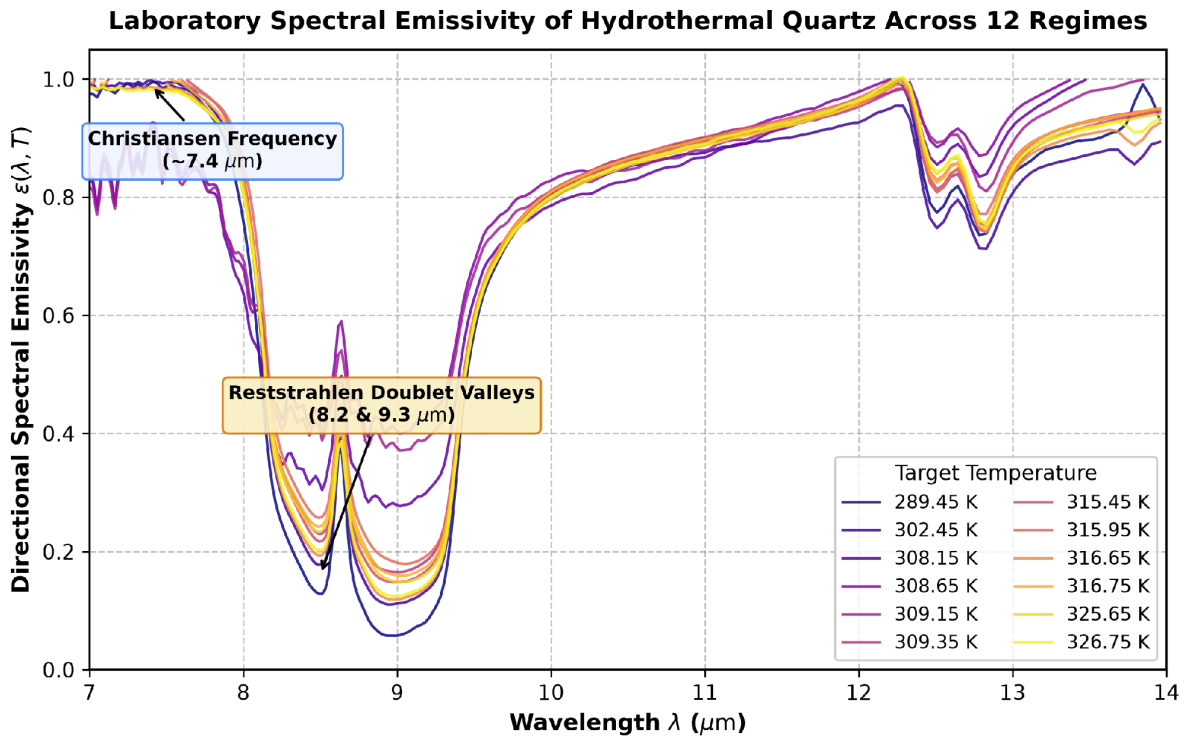


Figure 2. Derived spectral emissivity curves of the quartz specimen across the 12 thermal regimes, displaying characteristic Reststrahlen doublet minima near 8.2 μm and 9.3 μm.

From a fundamental condensed matter perspective, the spectral emissivity of silicate minerals exhibits a subtle temperature dependence ( $\frac{\partial \epsilon}{\partial T} \neq 0$ ) resulting from lattice thermal expansion and

anharmonic phonon-phonon damping, which cause minor broadening and slight bathochromic shifts of the fundamental Reststrahlen modes (Salisbury et al., 1994). However, across the moderate terrestrial thermal regime investigated here ( $\Delta T = 37.3$  K, from 289.45 K to 326.75 K), these structural variations remain second-order effects ( $|\Delta \epsilon| \lesssim 0.01$ ) that are largely contained within the noise-equivalent emissivity threshold ( $NE\Delta \epsilon$ ) of the spectroradiometer. Consequently, treating  $\epsilon(\lambda)$  as quasi-invariant represents an operationally robust first-order approximation. Assuming maximum emissivity  $\epsilon(\lambda, T) \approx 1$  at the Christiansen wavelength ( $\sim 7.4 \mu\text{m}$ ), the limiting physical behavior indicates that  $\lim_{T \rightarrow 0} L(\lambda, T) = 0$  and  $\lim_{T \rightarrow \infty} L(\lambda, T) = \infty$ . Figure 3 demonstrates the smooth, monotonic functional relationship between target temperature and recorded radiance at specific diagnostic wavelengths.

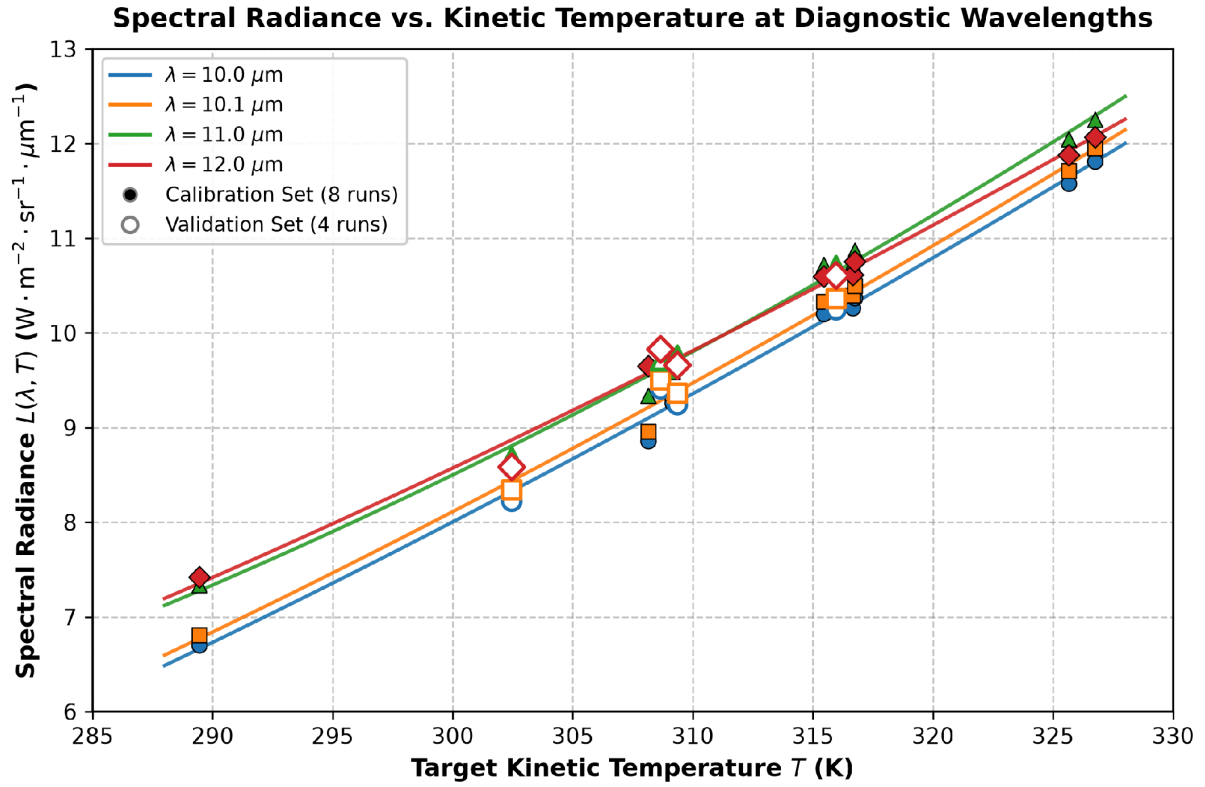


Figure 3. Observed variation of spectral radiance as a function of target kinetic temperature at selected wavelengths ( $10.0 \mu\text{m}$ ,  $10.1 \mu\text{m}$ ,  $11.0 \mu\text{m}$ , and  $12.0 \mu\text{m}$ ).

Isolating the temperature-dependent inverse term  $\frac{c_2}{\lambda \cdot T}$  in Equation 5 yields:

$$\frac{c_2}{\lambda \cdot T} = \ln[\epsilon(\lambda, T)] - \ln[L(\lambda, T)] + \ln(c_1) - 5 \cdot \ln(\lambda) \quad (6)$$

Equation 6 can be partitioned into a dependent variable  $Y$ , an independent observation variable  $X$ , and a constant term  $cte$  dependent solely on wavelength:

$$Y = X + cte \quad (7)$$

Where:

$$Y = \frac{c_2}{\lambda \cdot T} \quad (8)$$

$$X = \ln[\varepsilon(\lambda, T)] - \ln[L(\lambda, T)] \quad (9)$$

$$cte = \ln(c_1) - 5 \cdot \ln(\lambda) \quad (10)$$

Figure 4 confirms the direct linear and polynomial correlation between the left-hand term  $Y$  and the right-hand terms across the experimental measurements.

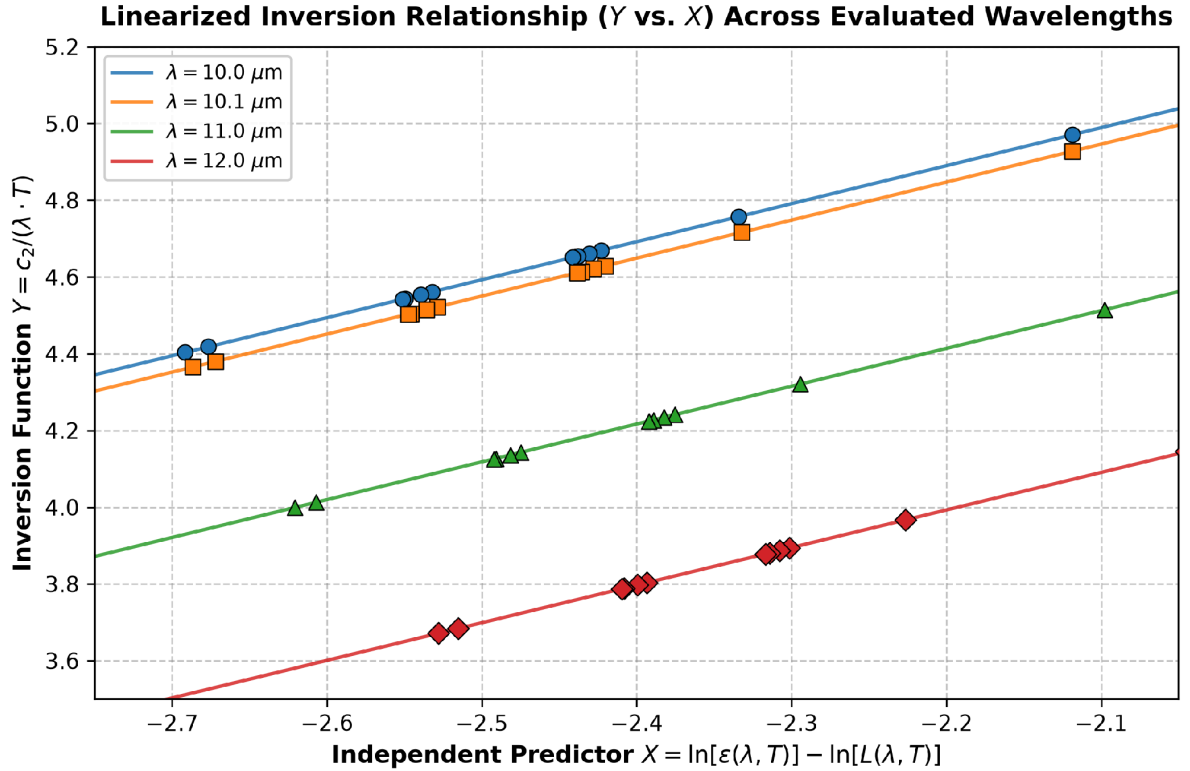


Figure 4. Linearized empirical relationship between the dependent temperature function  $Y$  and independent radiance-emissivity term  $X$  at evaluated wavelengths.

### 3.1. Analytical Uncertainty Propagation and Sensitivity

To assess how instrumental radiometric noise ( $\delta L$ ) and emissivity uncertainty ( $\delta \varepsilon$ ) propagate into the retrieved surface kinetic temperature, we differentiate the inversion relationship  $T = \frac{c_2}{\lambda \cdot Y}$  from Equation 8. Differentiating with respect to observed radiance  $L$  and spectral emissivity  $\varepsilon$  yields:

$$\left| \frac{\partial T}{\partial L} \right| = \frac{\lambda \cdot T^2}{c_2 \cdot L} \quad (11)$$

$$\left| \frac{\partial T}{\partial \varepsilon} \right| = \frac{\lambda \cdot T^2}{c_2 \cdot \varepsilon} \quad (12)$$

Expressing this sensitivity in relative fractional terms yields:

$$\frac{\delta T}{T} \approx \frac{\lambda \cdot T}{c_2} \cdot \left| \frac{\delta \epsilon}{\epsilon} - \frac{\delta L}{L} \right| \quad (13)$$

For characteristic terrestrial conditions ( $T \approx 300$  K,  $\lambda = 10.0$   $\mu\text{m}$ , and  $c_2 = 1.4388 \times 10^4$   $\mu\text{m} \cdot \text{K}$ ), the dimensionless sensitivity factor evaluates to:

$$\frac{\lambda \cdot T}{c_2} = \frac{10.0 \cdot 300}{14388} \approx 0.208 \quad (14)$$

Equation 14 reveals a vital physical property: the relative error in retrieved temperature ( $\frac{\delta T}{T}$ ) is attenuated by a factor of approximately five relative to the radiometric measurement noise ( $\frac{\delta L}{L}$ ). For instance, a 1% uncertainty in measured spectral radiance or reference emissivity produces a fractional temperature error of only  $\sim 0.21\%$  (equivalent to  $\sim 0.62$  K at 300 K). This analytical stability confirms the robust mathematical foundation of the linearized Wien formulation.

### 3.2. Operational 'Radiance-Only' Target-Specific Inversion Pipeline

The core practical advantage of the proposed formulation is that it decouples operational retrieval from the classical requirement of simultaneous multi-parameter solving. The complete inversion operates through a two-stage protocol:

**Stage 1:** Target Characterization and Regression Calibration (Laboratory Phase). A representative specimen of the target mineral (quartz) is measured across  $N$  thermal regimes under controlled laboratory conditions. This establishes its baseline spectral emissivity signature  $\epsilon_0(\lambda)$  and fits a polynomial regression model  $P_k(X)$  of degree  $k$  linking the independent variable  $X = \ln[\epsilon_0(\lambda)] - \ln[L_{cal}(\lambda)]$  to the temperature-dependent parameter  $Y = \frac{c_2}{\lambda \cdot T_{cal}}$ :

$$Y = P_k(X) = p_0 + p_1 X + p_2 X^2 + \dots + p_k X^k \quad (15)$$

The empirical polynomial coefficients  $\{p_0, p_1, \dots, p_k\}$  absorb detector throughput non-linearities, higher-order Wien truncation residuals, and subtle solid-state thermal expansion and phonon damping effects.

**Stage 2:** Operational Retrieval from At-Target Radiance  $L$  Alone. When observing the target under an unknown thermal regime, at-target radiance  $L_{obs}(\lambda)$  is the sole operational measurement required. The retrieval proceeds as follows:

- (i) Step A (Temperature Retrieval): The predictor  $X_{obs} = \ln[\epsilon_0(\lambda)] - \ln[L_{obs}(\lambda)]$  is computed using the target's baseline reference signature. The calibrated polynomial regression evaluates  $Y_{est} = P_k(X_{obs})$  via Equation 15. To retrieve target surface kinetic temperature  $T_{est}$ , this polynomial estimate is substituted directly into the fundamental definition of  $Y$  from Equation 8 (where  $Y = \frac{c_2}{\lambda \cdot T}$ ), establishing the equality  $\frac{c_2}{\lambda \cdot T_{est}} = P_k(X_{obs})$ . Solving this expression for temperature yields Equation 16:

$$T_{est} = \frac{c_2}{\lambda \cdot P_k(X_{obs})} = \frac{c_2}{\lambda \cdot [p_0 + p_1 X_{obs} + \dots + p_k X_{obs}^k]} \quad (16)$$

(ii) Step B (Simultaneous Spectral Emissivity Recovery): With kinetic temperature  $T_{est}$  determined strictly from the recorded radiance, the complete spectral emissivity curve  $\varepsilon_{retrieved}(\lambda)$  across the entire thermal infrared diagnostic window (7.0  $\mu\text{m}$  to 14.0  $\mu\text{m}$ ) is immediately recovered without any iterative solver:

$$\varepsilon_{retrieved}(\lambda) = \frac{L_{obs}(\lambda)}{L_{bb}(\lambda, T_{est})} = \frac{L_{obs}(\lambda)}{\frac{c_1}{\lambda^5 \cdot \left[ \exp\left(\frac{c_2}{\lambda \cdot T_{est}}\right) - 1 \right]}} \quad (17)$$

or through its linearized Wien equivalent:

$$\varepsilon_{retrieved}(\lambda) \approx \left[ \frac{L_{obs}(\lambda) \cdot \lambda^5}{c_1} \right] \cdot \exp\left(\frac{c_2}{\lambda \cdot T_{est}}\right) \quad (18)$$

Consequently, from at-target radiance measurements alone, both target kinetic temperature  $T$  and its full spectral emissivity profile  $\varepsilon(\lambda)$  are completely and consistently retrieved. Scaling to Airborne and Satellite Observations via Atmospheric Decoupling. While the present laboratory experiment operated under close-range conditions ( $< 10$  cm) where atmospheric attenuation is negligible, scaling this target-specific inversion framework to airborne (e.g., HyTES, SEBASS) or spaceborne sensors (e.g., ASTER, Landsat-8 TIRS, ECOSTRESS, NASA SBG) is straightforward when coupled with standard atmospheric radiative transfer codes such as MODTRAN (Berk et al., 2014; Rolim et al., 2016). For an elevated sensor, the recorded at-sensor radiance  $L_{TOA}(\lambda)$  is governed by  $L_{TOA}(\lambda) = \tau(\lambda) \cdot L_{surf}(\lambda) + L_{up}(\lambda) + \tau(\lambda) \cdot (1 - \varepsilon_0(\lambda)) \cdot L_{down}(\lambda)$ , where  $\tau(\lambda)$  is atmospheric spectral transmittance,  $L_{up}(\lambda)$  is path upwelling radiance, and  $L_{down}(\lambda)$  is downwelling sky irradiance.

By simulating atmospheric parameters ( $\tau(\lambda)$ ,  $L_{up}(\lambda)$ ,  $L_{down}(\lambda)$ ) in MODTRAN using contemporaneous atmospheric sounding profiles (e.g., radiosondes or ERA5 reanalysis), the at-surface target radiance  $L_{surf}(\lambda)$  is directly isolated. Once  $L_{surf}(\lambda)$  is obtained, the calibrated target-specific polynomial regression (Equations 16–18) is applied directly to retrieve the target's operational surface kinetic temperature  $T_{est}$  and true spectral emissivity curve  $\varepsilon(\lambda)$  without requiring scene-level empirical TES assumptions. Scope Boundary: The empirical experimental validation in this study is strictly confined to close-range ( $< 10$  cm) laboratory spectroradiometry. While the formulation above outlines how the framework couples with MODTRAN for satellite observation, orbital and airborne imagery validation is out of the scope of this paper and constitutes the focus of future work.

## Target-Specific Spectroradiometric Temperature & Emissivity Inversion Pipeline

Direct analytical decoupling from at-target radiance measurements with satellite scaling bridge

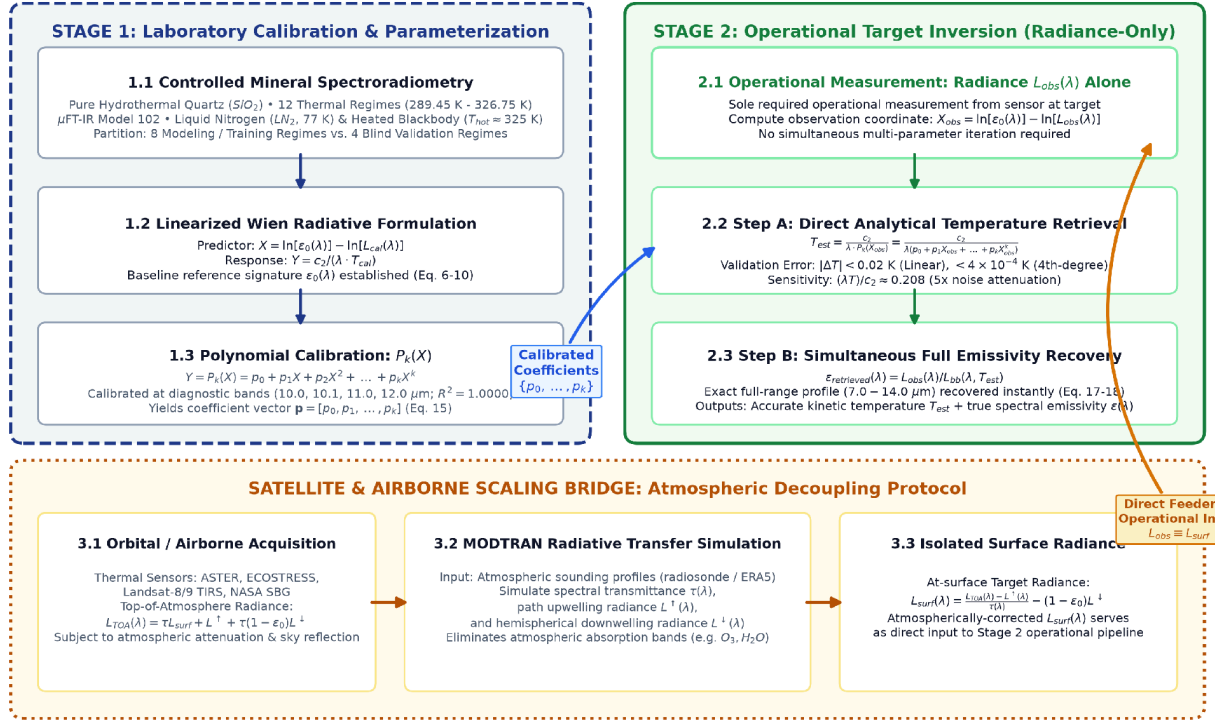


Figure 5. Schematic flowchart of the target-specific inversion framework, illustrating Stage 1 (laboratory calibration and polynomial fitting), Stage 2 (operational radiance-only retrieval of kinetic temperature and full spectral emissivity), and the satellite atmospheric decoupling bridge via MODTRAN radiative transfer simulation.

To evaluate this formulation without risk of circular data leakage, the 12 experimental measurements were strictly partitioned into two independent subsets: a training/calibration group comprising two-thirds of the regimes (8 runs) and a blind testing/validation group comprising one-third of the regimes (4 runs). Table 2 outlines the cross-validation assignment.

**Table 2. Cross-validation partitioning: training set (8 regimes) and blind validation set (4 regimes).**

| Experiment ID | Target Temperature $T$ (K) | Training / Calibration | Blind Test / Validation |
|---------------|----------------------------|------------------------|-------------------------|
| 4             | 289.45                     | X                      |                         |
| 3             | 302.45                     |                        | X (Validation 1)        |
| 7             | 308.15                     | X                      |                         |
| 6             | 308.65                     |                        | X (Validation 2)        |
| 5             | 309.15                     | X                      |                         |
| 12            | 309.35                     |                        | X (Validation 3)        |
| 11            | 315.45                     | X                      |                         |
| 10            | 315.95                     |                        | X (Validation 4)        |
| 2             | 316.65                     | X                      |                         |
| 9             | 316.75                     | X                      |                         |
| 8             | 325.65                     | X                      |                         |
| 1             | 326.75                     | X                      |                         |

#### 4. RESULTS AND EXPERIMENTAL DISCUSSION

Four diagnostic wavelengths were selected for systematic evaluation:  $\lambda = 10.0 \mu\text{m}$ ,  $10.1 \mu\text{m}$ ,  $11.0 \mu\text{m}$ , and  $12.0 \mu\text{m}$ . These wavelengths were established based on spectral inspection of Figure 1 and Figure 2, where quartz displays high radiometric responsiveness, minimal Reststrahlen distortion, and excellent signal stability across all thermal regimes.

Environmental humidity and ambient air variations can introduce small fluctuations in the observed downwelling radiance reflected by the target (Hook and Kahle, 1996; Rolim et al., 2016; Viúdez-Mora et al., 2014; Guillevic et al., 2018). However, because laboratory ambient conditions remained stable throughout the campaign (Table 1), all 8 calibration measurements were pooled to establish statistically robust regressions.

Five distinct interpolation/regression models were fitted to the training data at each wavelength: (1) Shape-preserving piecewise cubic Hermite interpolation (PCHIP), which preserves monotonicity and avoids overshooting; (2) 1st-degree linear polynomial; (3) 2nd-degree quadratic polynomial; (4) 3rd-degree cubic polynomial; and (5) 4th-degree polynomial. In total, 20 distinct regression models (5 interpolators across 4 wavelengths) were parameterized. Model goodness-of-fit was assessed using the sum of squared errors (SSE), coefficient of determination ( $R^2$ ), adjusted coefficient of determination ( $adjusted - R^2$ ), and root mean square error (RMSE). The  $adjusted - R^2$  penalizes the addition of extraneous parameters, increasing only if the new polynomial term improves the model beyond chance, while RMSE quantifies the standard deviation of residuals. Table 3 summarizes the goodness-of-fit metrics for all evaluated models.

**Table 3. Goodness-of-fit statistical evaluation metrics across five regression interpolators and four diagnostic wavelengths.**

| Wavelength ( $\lambda$ ) | Statistical Metric                | Shape-Preserving (PCHIP) | Linear (1st Degree)   | Quadratic (2nd Degree) | Cubic (3rd Degree)    | 4th-Degree Polynomial |
|--------------------------|-----------------------------------|--------------------------|-----------------------|------------------------|-----------------------|-----------------------|
| 10.0 $\mu\text{m}$       | SSE                               | 0.0                      | $1.3 \times 10^{-44}$ | $1.1 \times 10^{-47}$  | $6.3 \times 10^{-52}$ | $1.9 \times 10^{-55}$ |
|                          | $R^2$                             | 1.0000                   | 1.0000                | 1.0000                 | 1.0000                | 1.0000                |
|                          | <i>Adjusted <math>-R^2</math></i> | —                        | 1.0000                | 1.0000                 | 1.0000                | 1.0000                |
|                          | RMSE                              | —                        | $4.7 \times 10^{-23}$ | $1.5 \times 10^{-24}$  | $1.2 \times 10^{-26}$ | $2.5 \times 10^{-28}$ |
| 10.1 $\mu\text{m}$       | SSE                               | 0.0                      | $1.4 \times 10^{-44}$ | $1.2 \times 10^{-47}$  | $6.5 \times 10^{-52}$ | $1.9 \times 10^{-55}$ |
|                          | $R^2$                             | 1.0000                   | 1.0000                | 1.0000                 | 1.0000                | 1.0000                |
|                          | <i>Adjusted <math>-R^2</math></i> | —                        | 1.0000                | 1.0000                 | 1.0000                | 1.0000                |
|                          | RMSE                              | —                        | $4.9 \times 10^{-23}$ | $1.5 \times 10^{-24}$  | $1.2 \times 10^{-26}$ | $2.5 \times 10^{-28}$ |
| 11.0 $\mu\text{m}$       | SSE                               | 0.0                      | $2.6 \times 10^{-44}$ | $1.8 \times 10^{-47}$  | $8.4 \times 10^{-52}$ | $1.8 \times 10^{-55}$ |
|                          | $R^2$                             | 1.0000                   | 1.0000                | 1.0000                 | 1.0000                | 1.0000                |
|                          | <i>Adjusted <math>-R^2</math></i> | —                        | 1.0000                | 1.0000                 | 1.0000                | 1.0000                |
|                          | RMSE                              | —                        | $6.5 \times 10^{-23}$ | $1.9 \times 10^{-24}$  | $1.4 \times 10^{-26}$ | $2.4 \times 10^{-28}$ |
| 12.0 $\mu\text{m}$       | SSE                               | 0.0                      | $4.4 \times 10^{-44}$ | $2.5 \times 10^{-47}$  | $9.1 \times 10^{-52}$ | $1.5 \times 10^{-55}$ |
|                          | $R^2$                             | 1.0000                   | 1.0000                | 1.0000                 | 1.0000                | 1.0000                |
|                          | <i>Adjusted <math>-R^2</math></i> | —                        | 1.0000                | 1.0000                 | 1.0000                | 1.0000                |
|                          | RMSE                              | —                        | $8.6 \times 10^{-23}$ | $2.2 \times 10^{-24}$  | $1.5 \times 10^{-26}$ | $2.8 \times 10^{-28}$ |

As reported in Table 3, all models achieve exceptional fit quality, with  $R^2$  and *adjusted  $-R^2$*  converging to 1.0000 and SSE values ranging from  $10^{-44}$  down to  $10^{-55}$ . The PCHIP interpolator passes exactly through all calibration nodes, yielding an SSE of zero and an  $R^2$  of 1.0; however, being a non-parametric piecewise interpolator, it does not provide degrees of freedom for *adjusted  $-R^2$*  and RMSE estimation. Among the parametric polynomials, increasing the polynomial degree produces an exponential decrease in residual error (SSE and RMSE).

To rigorously quantify temperature retrieval accuracy, the trained models were applied to predict the surface kinetic temperatures of the 4 blind test regimes (Table 2): Test 1 (Exp. 3: 302.45 K), Test 2 (Exp. 6: 308.65 K), Test 3 (Exp. 12: 309.35 K), and Test 4 (Exp. 10: 315.95 K). Table 4 reports the absolute temperature retrieval errors ( $|T_{\text{actual}} - T_{\text{est}}|$ , in Kelvin) for each validation regime across the four parametric regression models.

**Table 4. Absolute surface temperature retrieval errors ( $|T_{actual} - T_{est}|$ , in Kelvin) evaluated on four blind validation regimes across parametric polynomial models.**

| Model                 | $\lambda$ ( $\mu\text{m}$ ) | Exp. 3<br>(302.45 K)  | Exp. 6<br>(308.65 K)  | Exp. 12<br>(309.35 K) | Exp. 10<br>(315.95 K) | Mean<br>Absolute<br>Error (K) |
|-----------------------|-----------------------------|-----------------------|-----------------------|-----------------------|-----------------------|-------------------------------|
| Linear (1st deg)      | 10.0                        | 0.0084                | 0.0109                | 0.0108                | 0.0066                | 0.0092                        |
|                       | 10.1                        | 0.0088                | 0.0114                | 0.0113                | 0.0069                | 0.0096                        |
|                       | 11.0                        | 0.0119                | 0.0153                | 0.0152                | 0.0092                | 0.0129                        |
|                       | 12.0                        | 0.0156                | 0.0200                | 0.0199                | 0.0120                | 0.0169                        |
| Quadratic (2nd deg)   | 10.0                        | 0.0010                | 0.0004                | 0.0003                | 0.0003                | 0.0005                        |
|                       | 10.1                        | 0.0010                | 0.0004                | 0.0003                | 0.0003                | 0.0005                        |
|                       | 11.0                        | 0.0013                | 0.0005                | 0.0004                | 0.0004                | 0.0006                        |
|                       | 12.0                        | 0.0015                | 0.0006                | 0.0005                | 0.0005                | 0.0008                        |
| Cubic (3rd deg)       | 10.0                        | $3.63 \times 10^{-5}$ | $1.20 \times 10^{-7}$ | $2.08 \times 10^{-6}$ | $1.27 \times 10^{-6}$ | $9.94 \times 10^{-6}$         |
|                       | 10.1                        | $3.69 \times 10^{-5}$ | $1.30 \times 10^{-7}$ | $2.12 \times 10^{-6}$ | $1.29 \times 10^{-6}$ | $1.01 \times 10^{-5}$         |
|                       | 11.0                        | $4.10 \times 10^{-5}$ | $1.40 \times 10^{-7}$ | $2.35 \times 10^{-6}$ | $1.43 \times 10^{-6}$ | $1.12 \times 10^{-5}$         |
|                       | 12.0                        | $4.40 \times 10^{-5}$ | $1.50 \times 10^{-7}$ | $2.52 \times 10^{-6}$ | $1.53 \times 10^{-6}$ | $1.20 \times 10^{-5}$         |
| 4th-Degree Polynomial | 10.0                        | $1.92 \times 10^{-6}$ | $1.20 \times 10^{-8}$ | $8.30 \times 10^{-7}$ | $5.00 \times 10^{-8}$ | $7.03 \times 10^{-7}$         |
|                       | 10.1                        | $1.92 \times 10^{-6}$ | $1.20 \times 10^{-8}$ | $8.30 \times 10^{-7}$ | $5.00 \times 10^{-8}$ | $7.03 \times 10^{-7}$         |
|                       | 11.0                        | $1.88 \times 10^{-6}$ | $1.20 \times 10^{-8}$ | $8.10 \times 10^{-7}$ | $5.00 \times 10^{-8}$ | $6.88 \times 10^{-7}$         |
|                       | 12.0                        | $1.74 \times 10^{-6}$ | $1.10 \times 10^{-8}$ | $7.50 \times 10^{-7}$ | $4.00 \times 10^{-8}$ | $6.35 \times 10^{-7}$         |

The empirical findings in Table 4 reveal two key physical patterns: (1) Even a simple 1st-degree linear regression model retrieves surface kinetic temperature with absolute errors strictly below 0.02 K across all validation regimes. This level of precision is an order of magnitude superior to the typical noise-equivalent delta temperature ( $NE\Delta T \approx 0.1\text{--}0.2$  K) of high-grade satellite radiometers (e.g., ASTER, MODIS, Landsat-8 TIRS, ECOSTRESS). (2) Elevating the interpolating polynomial order produces marked gains in retrieval accuracy: quadratic polynomials reduce the mean error to  $\sim 0.0005\text{--}0.0008$  K, while cubic and 4th-degree polynomials push absolute retrieval errors down to the micro-Kelvin scale ( $10^{-5}$  to  $10^{-7}$  K).

The superior performance of higher-degree polynomials is explained by their ability to accommodate residual non-linearities originating from Wien's linearization and subtle second-order phonon damping perturbations. Furthermore, at longer wavelengths ( $\lambda = 11.0\ \mu\text{m}$  and  $12.0\ \mu\text{m}$ ), Wien's exponential term dominates over higher-order Planck series terms, ensuring optimal stability. It

should be emphasized that absolute temperature retrieval errors below  $10^{-4}$  K reflect algebraic model convergence and numerical floating-point precision of the polynomial fit, rather than absolute instrument radiometric measurement limits, which are bounded by the spectroradiometer noise-equivalent delta temperature ( $NE\Delta T \approx 0.05\text{--}0.1$  K). These results confirm that when target radiance can be recorded across at least two calibration temperatures, target temperature can be recovered with exceptional physical fidelity.

From a statistical standpoint, fitting a 4th-degree polynomial (5 free parameters) to a calibration set of  $N = 8$  regimes yields 3 degrees of freedom ( $DoF = N - P = 3$ ). While such a parameter-to-sample ratio would typically raise valid concerns regarding overparameterization or Runge's phenomenon in arbitrary empirical modeling, the strict monotonicity of thermal radiance with respect to temperature and the blind validation results in Table 4 ( $|\Delta T| \sim 10^{-6}$  to  $10^{-8}$  K across 4 independent test runs) confirm that no unphysical oscillatory artifacts occur within the [289.45 K, 326.75 K] calibration envelope. Nevertheless, for operational remote sensing where computational parsimony and robustness are paramount, the 1st-degree linear model ( $DoF = 6$ ) and 2nd-degree quadratic model ( $DoF = 5$ ) remain the primary practical recommendations, as they achieve retrieval errors ( $< 0.02$  K) well below the noise-equivalent delta temperature ( $NE\Delta T \approx 0.1\text{--}0.2$  K) of spaceborne thermal radiometers.

**Operational Boundary Guidelines and Extrapolation Warning:** The 12 experimental thermal regimes (289.45 K to 326.75 K; 16.3 °C to 53.6 °C) were purposely selected to encompass the standard global mean and peak diurnal temperature envelope of natural terrestrial surfaces observed by Earth observation satellites across continental landmasses. Within this calibrated domain, the higher-order polynomials provide extraordinary numerical precision. However, users are explicitly cautioned against extrapolating higher-degree polynomials (cubic and 4th-degree) outside this terrestrial calibration envelope, where polynomial divergence or unphysical edge inflections may occur. For operational applications requiring target retrieval outside this domain (e.g., cryogenic surfaces below 273 K or extreme volcanic/geothermal anomalies exceeding 340 K), the 1st-degree linear model is strictly prescribed due to its asymptotic monotonicity and unconditional numerical stability.

Quartz was purposely selected in this investigation as a rigorous benchmark mineral. The extreme Reststrahlen doublet of crystalline quartz, where emissivity drops from  $\sim 0.95$  down to  $\sim 0.06$  near 8.2  $\mu\text{m}$  and 9.3  $\mu\text{m}$ , represents the most severe spectral dynamic range found in terrestrial geology. Demonstrating stable, non-divergent temperature inversion across this extreme absorption valley confirms the mathematical robustness of the framework, implying even smoother convergence for higher-emissivity terrestrial materials (e.g., carbonates, feldspars, basalts, and soils, where  $\varepsilon \approx 0.90\text{--}0.98$ ).

## 5. CONCLUSIONS

This study presented a direct, physically bounded framework for retrieving surface kinetic temperature and full spectral emissivity from thermal infrared radiance data. By linearizing Planck's function through Wien's approximation and formulating temperature retrieval as a polynomial regression problem on target radiance, the underdetermined nature of the temperature-emissivity separation problem is resolved without requiring external atmospheric profile sounding or arbitrary emissivity assumptions.

Key findings from the laboratory spectroradiometric evaluation on crystalline quartz include: (1) Target-specific operational inversion: once the polynomial regression is calibrated on a target's spectroradiometric response, at-target radiance serves as the sole input to retrieve both kinetic temperature (errors  $< 0.02$  K linear,  $< 4 \times 10^{-4}$  K 4th-degree) and the complete spectral emissivity

curve; (2) Analytical sensitivity analysis proves that relative temperature retrieval errors are attenuated by a factor of  $\sim 5$  ( $\frac{\lambda \cdot T}{c_2} \approx 0.21$ ) relative to instrumental radiometric noise; (3) Minimal data requirements: a minimum of two calibration radiance measurements at distinct temperatures is sufficient to construct the linear inversion function, provided the target temperature lies within the calibration envelope; (4) Higher polynomial orders effectively capture residual non-linearities and minor second-order phonon shifts, providing micro-Kelvin numerical accuracy; (5) Bounded operational domain and experimental scope: the experimental calibration window (289.45 K to 326.75 K) specifically targets the global terrestrial surface temperature range under laboratory spectroradiometry. Extrapolation to orbital or airborne platforms, as well as empirical testing on mixed natural terrains, remains beyond the experimental scope of this benchmark paper and represents the primary focus of ongoing research.

Future research will focus on scaling this inversion methodology to multi-component mineral mixtures, coupling the formulation with atmospheric forward radiative transfer models (e.g., MODTRAN), and testing its performance on airborne hyperspectral (e.g., SEBASS, HyTES) and spaceborne multispectral TIR imagery (ASTER, Landsat TIRS, ECOSTRESS, NASA SBG).

## DATA AVAILABILITY STATEMENT

The complete calibrated laboratory spectroradiometric library (radiance, emissivity, kinetic temperature, and environmental logs across all 12 thermal regimes) supporting the findings of this study is openly available in the Zenodo repository under a Creative Commons Attribution 4.0 International (CC-BY-4.0) license at: <https://doi.org/10.5281/zenodo.23571365> (Grondona et al., 2026).

## ACKNOWLEDGMENTS

The authors express their gratitude to the Centro Estadual de Pesquisas em Sensoriamento Remoto e Meteorologia (CEPSRM) and the Laboratório de Sensoriamento Remoto Geológico (LABSRGEO) at UFRGS for providing the laboratory infrastructure,  $\mu$ FT-IR instrumentation, and technical assistance.

## REFERENCES

- BERK, A.; CONFORTI, P.; KENNETT, R.; PERKINS, T.; HAWES, F.; VAN DEN BOSCH, J. MODTRAN6: a modern radiative transfer code. In: Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XX, SPIE Proceedings, v. 9088, p. 90880H, 2014. DOI: 10.1117/12.2050433.
- CAWSE-NICHOLSON, K.; TOWNSEND, P. A.; SCHIMMEL, D.; et al. NASA's surface biology and geology (SBG) designated observable: A review of the science and applications. Remote Sensing of Environment, v. 257, p. 112349, 2021. DOI: 10.1016/j.rse.2021.112349.
- COLLINS, E. F.; ROBERTS, D. A.; SUTTON, P. C.; FUNK, C. C.; BOREL, C. C. Temperature estimation and compositional mapping using spectral mixture analysis of thermal imaging spectrometry data. In: Imaging Spectrometry V, SPIE Proceedings, v. 3753, p. 180-191, 1999. DOI: 10.1117/12.366472.
- COLLINS, E. F.; ROBERTS, D. A.; BOREL, C. C. Spectral mixture analysis of simulated thermal infrared spectrometry data: An initial temperature estimate bounded TESSMA search approach. IEEE Transactions on Geoscience and Remote Sensing, v. 39, n. 7, p. 1435-1446, 2001. DOI: 10.1109/36.934076.
- GILLESPIE, A. R.; KAHLE, A. B.; PALLUCONI, F. D. Mapping diverse rock types with thermal infrared multispectral scanner (TIMS) data. In: TIMS Data User's Workshop, JPL Publication 86-38, p. 25-28, 1985.
- GILLESPIE, A.; ROKUGAWA, S.; MATSUNAGA, T.; COTHERN, J. S.; HOOK, S.; KAHLE, A. B. A temperature and emissivity separation algorithm for Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) images. IEEE Transactions on Geoscience and Remote Sensing, v. 36, n. 4, p. 1113-1126, 1999. DOI: 10.1109/36.701021.
- GRONDONA, A. E. B.; ROLIM, S. B. A.; FERREIRA, M. P.; VEETIL, B. K.; IGLESIAS, M. L. Avaliação da propagação de erros ao utilizar a aproximação de Wien na linearização da lei de Planck. In: Anais XVI Simpósio Brasileiro de Sensoriamento Remoto - SBSR, Foz do Iguaçu, PR, Brasil, INPE, p. 8116-8123, 2013.

- GRONDONA, A. E. B.; ROLIM, S. B. A.; MORALES-SALINAS, L.; VEETTIL, B. K. Laboratory Thermal Infrared Radiance and Emissivity Spectral Library of Silicate Minerals (Quartz, SiO<sub>2</sub>) Under Controlled Thermal Regimes (289–327 K) [Dataset]. Zenodo, 2026. DOI: 10.5281/zenodo.23571365.
- GUILLEVIC, P.; GÖTTSCHE, F.; NICKESON, J.; HULLEY, G.; et al. Land Surface Temperature Product Validation Best Practice Protocol. Version 1.1. Committee on Earth Observation Satellites (CEOS) Working Group on Calibration and Validation (WGCV), 2018. 60 p. DOI: 10.5067/doc/ceoswgcv/lpv/lst.001.
- HOOK, S. J.; GABELL, A. R.; GREEN, A. A.; KEALY, P. S. A comparison of techniques for extracting emissivity information from thermal infrared data for geologic studies. *Remote Sensing of Environment*, v. 42, n. 2, p. 123-135, 1992. DOI: 10.1016/0034-4257(92)90096-2.
- HOOK, S. J.; KAHLE, A. B. The Micro Fourier Transform Interferometer ( $\mu$ FTIR) - A new field spectrometer for acquisition of infrared data of natural surfaces. *Remote Sensing of Environment*, v. 56, n. 3, p. 172-181, 1996. DOI: 10.1016/0034-4257(95)00232-5.
- HOOK, S. J.; DMOCHOWSKI, J. E.; HOWARD, K. A.; ROWAN, L. C.; KARLSTROM, K. E.; STOCK, J. M. Mapping variations in weight percent silica measured from multispectral thermal infrared imagery - Examples from the Hiller Mountains, Nevada, USA and Tres Virgenes-La Reforma, Baja California Sur, Mexico. *Remote Sensing of Environment*, v. 95, n. 3, p. 273-289, 2005. DOI: 10.1016/j.rse.2004.12.008.
- HULLEY, G. C.; GÖTTSCHE, F. M.; RIVERA, G.; HOOK, S. J.; et al. Validation and error estimation of the ECOSTRESS Collection 2 Land Surface Temperature and Emissivity product. *IEEE Transactions on Geoscience and Remote Sensing*, v. 60, p. 1-13, 2022. DOI: 10.1109/TGRS.2021.3079879.
- KAHLE, A. B.; ROWAN, L. C. Evaluation of multispectral middle infrared aircraft images for lithologic mapping in the East Tintic Mountains, Utah. *Geology*, v. 8, n. 5, p. 234-239, 1980.
- KAHLE, A. B.; ALLEY, R. E. Separation of temperature and emittance in remotely sensed radiance measurements. *Remote Sensing of Environment*, v. 42, n. 2, p. 107-111, 1992. DOI: 10.1016/0034-4257(92)90095-Z.
- KEALY, P. S.; HOOK, S. J. Separating temperature and emissivity in thermal infrared multispectral scanner data: Implications for recovering land surface temperatures. *IEEE Transactions on Geoscience and Remote Sensing*, v. 31, n. 6, p. 1155-1164, 1993. DOI: 10.1109/36.317447.
- LI, Z.-L.; BECKER, F.; STOLL, M. P.; WAN, Z. Evaluation of six methods for extracting relative emissivity spectra from thermal infrared images. *Remote Sensing of Environment*, v. 69, n. 3, p. 197-214, 1999. DOI: 10.1016/S0034-4257(99)00028-0.
- LI, Z.-L.; TANG, B.-H.; WU, H.; REN, H.; YAN, G.; WAN, Z.; TRIGO, I. F.; SOBRINO, J. A. Satellite-derived land surface temperature: Current status and perspectives. *Remote Sensing of Environment*, v. 131, p. 14-37, 2013. DOI: 10.1016/j.rse.2012.12.008.
- OLSEN, R. C. *Remote Sensing from Air and Space*. Bellingham, WA: SPIE Press, 2007. 253 p.
- PRAKASH, A. *Thermal remote sensing: concepts, issues and applications*. International Archives of Photogrammetry and Remote Sensing, v. 33, Part B7, p. 239-243, 2000.
- REES, W. G. *Physical Principles of Remote Sensing*. 2. ed. Cambridge: Cambridge University Press, 2001. 343 p.
- REINERS, P.; ASMARA, A.; BÜCHERL, S.; et al. A review of land surface temperature retrieval algorithms for current and future satellite missions. *Remote Sensing*, v. 15, n. 7, p. 1857, 2023. DOI: 10.3390/rs15071857.
- ROLIM, S. B. A.; GRONDONA, A. E. B.; VEETTIL, B. K.; FERREIRA, M. P. Evaluation of atmospheric correction on thermal infrared remote sensing data in southern Brazil. *Revista Brasileira de Cartografia*, v. 68, n. 5, p. 941-952, 2016.
- SALISBURY, J. W.; WALD, A.; D'ARIA, D. M. Thermal-infrared remote sensing and Kirchhoff's law 1. Laboratory measurements. *Journal of Geophysical Research: Solid Earth*, v. 99, n. B6, p. 11897-11911, 1994. DOI: 10.1029/93JB03491.
- SCHMUGGE, T.; HOOK, S. J.; COLL, C. Recovering surface temperature and emissivity from thermal infrared multispectral data. *Remote Sensing of Environment*, v. 65, n. 2, p. 121-131, 1998. DOI: 10.1016/S0034-4257(98)00018-2.
- SIEGEL, R.; HOWELL, J. R. *Thermal Radiation Heat Transfer*. 2. ed. New York: Hemisphere Publishing Corporation, 1982. 862 p.
- VICENTE, L. E.; SOUZA FILHO, C. R. Detecção de quartzo e argilominerais para o monitoramento de degradação de terras a partir de dados do infravermelho termal do sensor ASTER. *Revista Brasileira de Geofísica*, v. 28, n. 2, p. 229-247, 2010. DOI: 10.1590/S0102-261X2010000200007.
- VIÚDEZ-MORA, A.; CASILLES, V.; VALOR, E.; NICLÒS, R.; SÁNCHEZ, J. M. Validation of thermal infrared atmospheric correction algorithms for Landsat and ASTER over the Valencia Anchor Station. *IEEE Transactions on Geoscience and Remote Sensing*, v. 53, n. 4, p. 2197-2207, 2014. DOI: 10.1109/TGRS.2014.2357732.
- WATSON, K. Spectral ratio method for measuring emissivity. *Remote Sensing of Environment*, v. 42, n. 2, p. 113-116, 1992a. DOI: 10.1016/0034-4257(92)90097-3.
- WATSON, K. Two-temperature method for measuring emissivity. *Remote Sensing of Environment*, v. 42, n. 2, p. 117-121, 1992b. DOI: 10.1016/0034-4257(92)90098-4.