



**In-Scene Atmospheric Compensation of Thermal
Hyperspectral Imaging With Applications to
Simultaneous Shortwave Data Collection**

DISSERTATION

Cory T. Lane, Lieutenant Colonel, USAF
AFIT-ENP-DS-17-D-008

**DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY**

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

DISTRIBUTION STATEMENT A.
APPROVED FOR PUBLIC RELEASE; DISTRIBUTION IS UNLIMITED.

The views expressed in this document are those of the author and do not reflect the official policy or position of the United States Air Force, the United States Department of Defense or the United States Government. This material is declared a work of the U.S. Government and is not subject to copyright protection in the United States.

AFIT-ENP-DS-17-D-008

IN-SCENE ATMOSPHERIC COMPENSATION OF THERMAL
HYPERSPSPECTRAL IMAGING WITH APPLICATIONS TO SIMULTANEOUS
SHORTWAVE DATA COLLECTION

DISSERTATION

Presented to the Faculty
Graduate School of Engineering and Management
Air Force Institute of Technology
Air University
Air Education and Training Command
in Partial Fulfillment of the Requirements for the
Degree of Doctor of Philosophy in Applied Physics

Cory T. Lane, MS, MBA
Lieutenant Colonel, USAF

December 2017

DISTRIBUTION STATEMENT A.
APPROVED FOR PUBLIC RELEASE; DISTRIBUTION IS UNLIMITED.

IN-SCENE ATMOSPHERIC COMPENSATION OF THERMAL
HYPERSENSITRAL IMAGING WITH APPLICATIONS TO SIMULTANEOUS
SHORTWAVE DATA COLLECTION

Cory T. Lane, MS, MBA
Lieutenant Colonel, USAF

Committee Membership:

Kevin C. Gross, PhD
Chair

Benjamin F. Akers, PhD
Member

Steven T. Fiorino, PhD
Member

Allan W. Yarbrough, PhD
Member

ADEDEJI B. BADIRU, PhD
Dean, Graduate School of Engineering and Management

Abstract

Compensating for the effects of the Earth’s atmosphere is necessary to analyze hyperspectral remote sensing data of the Earth’s surface. A new algorithm, the Comprehensive Hyperspectral Atmospheric Effects Removal Method (CHAERM) is designed to provide in-scene atmospheric compensation of LWIR hyperspectral imagery with a priority on expediency suitable for operational contexts.

CHAERM’s methodology consists of a high-emissivity material screen, followed by a new method of decoupling the effects of continuum absorption and line absorption in the radiative transfer of the atmosphere. Spectral similarity is calculated in a way that allows rapid matching to the Global Atmospheric Profiles from Reanalysis Information (GAPRI) dataset, a large database of 4,846 meteorologically consistent atmospheric profiles. Additionally, the GAPRI database has been modified to account of surface elevation variability and different aerosol loading based on geography.

CHAERM’s capabilities are validated using simulated and real-world hyperspectral datasets. RMS residuals in retrievals of transmission and path radiance spectra have been shown to be consistently at or below 10% of the mean value in the band. A final tuning step, using nonlinear least squares minimization, can be used to reduce residual error by less than 5% while remaining bounded by realistic atmospheric states. CHAERM’s atmospheric state retrieval process is also suited for applications where the longwave atmospheric compensation of hyperspectral data can be used to inform the initial parameterization of a shortwave compensation method.

AFIT-ENP-DS-17-D-008

For Avery Grace...

Acknowledgements

With genuine sincerity, I would like to acknowledge all of the faculty and staff at the Air Force Institute of Technology. I was very late to join the Air Force's science and engineering community, so I have only recently been exposed to the incredible endeavors of the defense professionals that comprise it. As my time at AFIT draws to a close, I am humbled to have had the opportunity to pursue a defense-focused education at such an incredible institution.

I would like to extend my heartfelt gratitude to the members of my committee for their support and guidance. I am certainly grateful for my opportunity to learn from Dr. Akers and witness his phenomenal acumen for mathematics. I would also like to acknowledge the profound meteorological expertise of Dr. Fiorino and thank him for his willingness to fill many of the gaps in my weather background. I appreciate Dr. Yarborough's operationally minded perspective that helped to get me started in hyperspectral research at all. But most of all, I am truly grateful for the opportunity to work with and learn from Dr. Kevin Gross, who is one of the most amazing professionals, the most gifted researchers, and the most valuable mentors I've ever encountered in my Air Force career! Thank you all for such incredible support!

Cory T. Lane

Table of Contents

	Page
Abstract	iv
Acknowledgements	vi
List of Figures	x
List of Tables	xiv
List of Acronyms	xv
I. Introduction	1
1.1 Motivation	3
1.2 Objective	5
1.3 Limitations and Assumptions	6
1.4 Document Structure	8
II. Background	10
2.1 Hyperspectral Remote Sensing	10
2.2 Apparent Spectral Properties of Materials	14
2.3 Radiative Transfer Principles	18
2.3.1 Gaseous Absorption and Scattering	18
2.3.2 Beer-Lambert Law and Atmospheric Transmission	20
2.3.3 Schwarzschild Equation	22
2.4 Signal Propagation through the Atmosphere	23
2.4.1 Propagation of Shortwave Radiation	24
2.4.2 Propagation of Longwave Radiation	25
2.5 Units and Conversions	26
2.6 Approaches to Atmospheric Compensation	27
2.6.1 In-Scene AC	30
2.6.2 Model-Based AC	31
2.7 Existing Atmospheric Compensation Algorithms	33
2.7.1 Internal Average Reflectance / Empirical Line Method	34
2.7.2 Atmospheric Removal (ATREM) Algorithm	36
2.7.3 Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) Algorithm and FLAASH-IR	37
2.7.4 In-Scene Atmospheric Compensation (ISAC)	38
2.7.5 Quick Atmospheric Correction (QUAC)	41

	Page
2.7.6 Summary of Atmospheric Compensation Algorithms	44
2.8 Spectral Similarity Metrics	45
III. Forward Modeling Methodology	47
3.1 Initializing MODTRAN’s radiative transfer calculations	47
3.2 ASTER Surface Material Spectra	48
3.3 World-wide Atmospheric Profile Data	49
3.3.1 GAPRI Database	49
3.3.2 TIGR Database	50
3.4 Use of LEEDR for visibility estimates	52
3.5 Incorporating surface elevation	55
3.5.1 Method #1: Hypsometric Adaptation to Altitude Data	57
3.5.2 Method #2: Truncation & Resampling Modification to Altitude Data	59
3.5.3 Validation of Adaptations with Real-world Data	60
3.6 Building Simulated Hyperspectral Data Sets	62
3.7 Real-world Sensor and Data Specifications	67
IV. Parameterizing the Atmospheric State	70
4.1 Inputs to Outputs Sensitivity Study	71
4.2 Exploration of Uniqueness in Inverse RT Computations	77
4.3 Functional Fitting of the Atmospheric State Variables	84
4.3.1 Creating the Functional Forms	84
4.3.2 Validating the Functional Fit Method	87
4.3.3 Tuning the Coefficients with Nonlinear Least Squares Optimization	88
V. Data-driven Atmospheric Compensation	93
5.1 High-emissivity Pixel Identification	94
5.2 Manifestations of Non-Unique Solutions with Simple Catalog Matching	95
5.3 The Combined Hyperspectral Atmospheric Effects Removal Method (CHAERM)	96
5.3.1 Decoupling the Line and Continuum Components of Transmission and Path Radiance	97
5.3.2 Obtaining $\mathbf{L}_0$	99
5.3.3 Compiling a Line Effects Catalog Using GAPRI	105
5.3.4 Identifying the best atmospheric compensation spectra	106

	Page
VI. Results and Analysis	108
6.1 Monochromatic AC with CHAERM.....	108
6.2 CHAERM with SEBASS Sensor Resolution	109
6.3 Aggregate Results	112
6.4 Noise Resilience	116
6.5 Real-World Data and the SEBASS Sensor	117
6.5.1 Collection Day #1.....	119
6.5.2 Real-World Collection #2 and #3	124
VII. Conclusion and Extensions	128
7.1 Summary of Substantive Contributions	128
7.1.1 Enhancement of the climatological databases	128
7.1.2 Demonstration of the anti-correlation of transmission and path radiance.....	129
7.1.3 Low-order parameterization of the atmospheric state.....	129
7.1.4 Data-driven atmospheric compensation	130
7.2 Application to Simultaneous VNIR/SWIR Remote Sensing	131
7.3 Extensions of this Research	132
Bibliography	134

List of Figures

Figure	Page
1 Sensing Scene Geometry Schematic	8
2 Panchromatic and Multispectral Imagery Examples	12
3 Hyperspectral Imager Design	12
4 Hyperspectral Image and Pixel	14
5 Spectral Variation of Land and Atmospheric in the LWIR	19
6 Scattering Size Parameter	20
7 Atmospheric Attenuation in the SWIR	23
8 Shortwave and Longwave Blackbody Radiation	25
9 Longwave Radiative Transfer Spectra	28
10 Planckian Emission at Terrestrial Temperatures	28
11 Distribution of Atmospheric Constituents	34
12 ISAC Scatterplot of $L(\lambda)$ vs. $B(\lambda, T)$	40
13 Endmember Spectra Used in QUAC	43
14 ASTER Emissivity Samples	50
15 Location of the GAPRI Atmospheric Profiles	51
16 Location of TIGR Atmospheric Profiles	52
17 TIGR and GAPRI Temperature Profiles	53
18 Geographic Effects on Visibility	55
19 Visibility Effect on Transmission	56
20 Temperature Profile Resampling	61
21 Comparison of Atmospheric Profile Resampling Methods	61
22 GAPRI Matches to Radiosonde Data (Denver, CO)	63

Figure		Page
23	TIGR Matches to Radiosonde Data (Denver, CO)	64
24	GAPRI Matches to Multiple CONUS Locations	65
25	Simulated At-Sensor Radiance	68
26	Comparison of Atmospheric Inputs and RT Outputs, Example 1	73
27	Comparison of Atmospheric Inputs and RT Outputs, Example 2	74
28	Temperature and Water Dependence on Line and Continuum Transmission	76
29	Temperature and Water Dependence on Line and Continuum Path Radiance	76
30	Similar At-Sensor Signals w/ Different Atmospheric Conditions	79
31	Similar At-Sensor Signals (including instrument response) w/ Different Atmospheric Conditions	81
32	Similar At-Sensor Signals (including instrument response) w/ Different Atmospheric Conditions	82
33	Brightness Temperature Differences with Variable Surface Temperatures	83
34	Functional Fitting of Water Content, Density, and Temperature	87
35	Forward-modeled TUD using Fit Functions, Example 1	89
36	Forward-modeled TUD using Fit Functions, Example 2	90
37	Forward-modeled TUD using Fit Functions and NLLS Tuning	92
38	Autonomous HE Pixel Selections	96
39	BB-catalog Matching Retrieval Results	97
40	Estimation of L_0 , Step 1	102

Figure		Page
41	Estimation of L_0 , Step 2	102
42	Comparison L_0 to Continuum Catalog Entry	104
43	L_0 vs. L Regression	104
44	Line Spectrum Estimates	105
45	CHAERM Process Flow Chart	107
46	Estimated Line Effects	110
47	Full Spectrum Retrievals	110
48	Retrieved Atmospheric State	111
49	Retrieved Emissivity Profiles Using CHAERM	111
50	Estimated Line Effects	113
51	Full Spectrum Retrievals with SEBASS Resolution	113
52	Retrieved Atmospheric State	114
53	Retrieved Emissivity Profiles Using CHAERM at SEBASS resolution	114
54	RMS Error	116
55	Noise Resilience Statistics, Transmission	117
56	Noise Resilience Statistics, Path Radiance	118
57	Estimated TUD Spectra from HSI Scene	119
58	Real-world Imagery of HSI Scene	120
59	HE Pixel Assessments	122
60	Regression Results using Real-World Data	122
61	Line Effects Spectra using Real-World Data	123
62	Associated Atmospheric State from CHAERM Analysis	123
63	Derived TUD from CHAERM Analysis	124

Figure		Page
64	Derived TUD from ISAC Analysis	125
65	Computed Emissivity Spectra of HE Material, Day 1	125
66	Computed Emissivity Spectra of HE Material, Day 2	126
67	Computed Emissivity Spectra of HE Material, Day 3	126

List of Tables

Table		Page
1	Temperature and Line Transmission Statistics	75
2	Atmospheric Function Fit Coefficient Statistics	87
3	Summary of Match Consistency	115

List of Acronyms

AC	Atmospheric Compensation
AGL	Above Ground Level
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
ATREM	ATmospheric REMoval
BRDF	Bidirection Reflectance Distribution Function
ED	Euclidean Distance
ENVI	Environment for Visual Images
FLAASH	Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes
FOV	Field of View
FPA	Focal Plane Array
GAPRI	Global Atmospheric Profiles from Reanalysis Information
HSI	Hyperspectral Imaging
IFOV	Instantaneous Field of View
LUT	Look Up Table
LUT	Look Up Table
MODTRAN	MODerate Resolution Atmospheric TRANsmission
MSL	Mean Sea Level
SA	Spectral Angle

SNR	Signal to Noise Ratio
TES	Temperature Emissivity Separation
TES	Temperature-Emissivity Separation
TIGR	Thermodynamic Initial Guess Retrieval
tp5	MODTRAN Tape 5 file
tp6	MODTRAN Tape 6 file
TUD	Transmission, Upwelling, and Downwelling Atmospheric Spectra

IN-SCENE ATMOSPHERIC COMPENSATION OF THERMAL HYPERSPECTRAL IMAGING WITH APPLICATIONS TO SIMULTANEOUS SHORTWAVE DATA COLLECTION

I. Introduction

Remote sensing is a large enterprise that can be described as any field in which information about an object is obtained without making physical contact with it [1, 2]. In the scientific communities, remote sensors are used to extract information about a target, often the Earth's surface, by analyzing the energy that surface materials reflect or emit. This is often accomplished with a downward-looking sensor placed on an aircraft or satellite [3, 4, 5]. Currently, there are hundreds of these types of sensors collecting data all around the Earth, supporting numerous scientific communities, including geology, forestry, agriculture, oceanography, meteorology, and mineralogy [6]. These technologies are also integral to many non-scientific pursuits, especially those involving intelligence gathering, reconnaissance, and remote surveillance [7].

The chronology of remote sensing tells the story of a continually advancing technological frontier. The first operational employment of a remote sensor occurred in the mid-1800s, when a camera mounted to a tethered balloon was used for topographic mapping of the Earth's surface [8]. Some seventy years later, cameras mounted on aircraft were routinely taking pictures of enemy forces as World War I was fought. By the conclusion of the Second World War, remote sensors had been developed for other-than-daytime scenarios by using the infrared and microwave portions of the electromagnetic spectrum [8].

Until the 1960s, remote sensing primarily used broadband sensors. Because they aggregate energy over large portions of the electromagnetic spectrum, broadband sensors typically have good signal-to-noise characteristics. For many years, the technological improvements primarily resulted in increased spatial resolution, allowing more detail to be captured in the image. However, because increasing spatial resolution usually comes as the result of a larger aperture, which was certainly true in the early and mid-1900s, the sensors themselves were forced to also become larger and larger. As became apparent to scientists and engineers in the 1960s, ever increasing aperture sizes were not pragmatic, being both difficult and expensive to engineer, launch, operate, and maintain.

With spatial resolution improvements having reached something of a technological asymptote, investigating how spectral (i.e., wavelength dependent) information might be employed in remote sensing applications emerged as the new frontier [6]. This technology was pursued earnestly, and by the early 1970s, sensors had been developed that could simultaneously measure radiation in multiple discrete spectral channels (equivalently, spectral bands).

The early successes of multispectral imaging systems were a catalyst in the remote sensing community that spurred continued research in spectral remote sensing capabilities, particularly seeking to increase spectral resolution. In the early 1980s, scientists at the NASA Jet Propulsion Laboratory (JPL) successfully developed the first multispectral system [9] with sufficient spectral resolution that it was distinguished as hyperspectral imaging (HSI). The capabilities of hyperspectral sensors quickly advanced, leading to sensors capable of measuring radiation in hundreds of narrow, discrete spectral channels. Today, a typical hyperspectral imager may have more than 200 spectral channels and a spatial array with more than 300,000 pixels.

1.1 Motivation

An HSI system’s capabilities make unique contributions to remote sensing that are not possible with conventional broadband imaging. When placed on an aircraft, small, or large satellite, these sensors generate data at an incredible rate, with some recording more than 4 terabytes of data per day [5]. Thus, as efficiencies in the hyperspectral processing chain are discovered that lead to faster computing solutions, the impact to the community can be significant [10].

Airborne and spaceborne hyperspectral sensor data is used to identify and classify surface materials and to detect and track changes to the Earth’s surface. To accomplish this effectively, a thorough accounting of the atmospheric effects on the propagating signal must be accomplished. However, radiative transfer processes in the Earth’s atmosphere can be challenging to estimate and model from both a theoretical and practical standpoint. As a result, atmospheric compensation (AC) has become its own field of study in support of hyperspectral data analysis. The research presented here is focused on developing an advanced and efficient atmospheric compensation technique appropriate for use in an operational setting where “real-time” analysis is a priority.

The fundamentals of atmospheric compensation of airborne and space-borne remote sensing are rooted in understanding and describing the atmospheric state. The atmospheric state encompasses the physical characteristics and chemical composition of the atmosphere along a specific path between the sensor and the target. A well described state includes the gas concentrations of all constituents, the temperature and pressure profile, the water content and its distribution, and the aerosol distribution. The unique combination of these state variables dictate the physics of the radiative transfer in the atmosphere. A purpose of the compensation process is to remove the effects of atmospheric absorption and scattering from the

surface-leaving signal, while maintaining the spectral features of the surface material(s) [9, 11, 12].

In practice, it is virtually impossible to accurately measure or estimate all of these parameters. This is not particularly problematic for broadband remote sensing in the visible, where unless the line of sight is particularly hazy, the atmosphere has minimal impact on the propagating signal. When taking data outside of the visible band, however, the atmosphere significantly influences the propagating signal, regardless of the prevailing visibility [8, 13]. Because most hyperspectral sensors measure energy outside of the visible band, a proper accounting of the atmospheric effects is a requisite step before drawing any quantitative conclusions about the characteristics of the surface [14, 15, 16].

Most users and developers of AC algorithms operate in a trade space that requires decisions to be made about computational efficiencies at the expense of absolute accuracy [9]. As the spectral resolution of new HSI sensors continues to increase, the computational expense required to calculate the radiative transfer also increases [17]. In the scientific community, where processing time may not be a factor, the atmospheric radiative transfer processes can certainly be modeled in painstaking detail, often using line-by-line radiative transfer codes or high-resolution band models. But in other user communities, especially surveillance and intelligence, computational expediency that leads to functional accuracy is often a higher priority than high-fidelity modeling.

To this end, AC methods with a premium on speed generally avoid performing the line-by-line computations associated with high-fidelity radiative transfer modeling. Instead, they employ alternate approaches that often do not rely upon external or *a priori* information. These in-scene or data-driven methods typically invoke simplifying assumptions about the radiation transport computations.

Unfortunately, these assumptions can be difficult to satisfy completely, and thus, in-scene approaches are often limited to operate only in specific spectral bands or only when certain scene materials are known to be present. Though the capabilities are constantly evolving in the community, there are presently few methods that are accurate, computationally efficient, and are independent from *a priori* information [18].

A continually developing understanding of the atmosphere, more robust access to *in situ* atmospheric data, and advancing sensor technologies have ensured the continued relevance and necessity of atmospheric compensation research. Hyperspectral remote sensing is evolving, but advances in the sensor technology must also be followed by continual improvements in the atmospheric compensation of the data. Otherwise, HSI data analysis will effectively reach a technological asymptote.

1.2 Objective

The purpose of atmospheric compensation is to remove the effects of the atmosphere on the propagating signal so that only the surface-leaving radiance remains. The interest of this research lies at the nexus where operational necessity meets scientific fidelity. Fundamentally, it seeks to develop an in-scene atmospheric compensation method for LWIR remote sensing that relies only on the data obtained by the sensor and exploits the phenomenology of the underlying physical processes governing the radiative transfer. This research further seeks to provide an algorithm that is robust enough to support operational requirements with as little pre-processing initialization (e.g., *a priori* information about the atmospheric state) and as little post-processing latency as possible.

Although the method in this research utilizes the data collected in the LWIR, it

is intended to facilitate the AC of simultaneously collected VNIR/SWIR data through the estimation of atmospheric temperature and water content profiles. Interest in simultaneous dual-band data is a relatively new research avenue because HSI data have historically only been collected in the shortwave or in the longwave regions of the spectrum. However, new HSI sensor platforms are launching with the capability to obtain simultaneous longwave and shortwave data, and the capability to inform the atmospheric compensation using the data obtained from both bands is a natural next step for AC [19, 20].

1.3 Limitations and Assumptions

Many atmospheric compensation research projects have been conducted seeking to advance the field of HSI. As other researchers have shown, there are many real-world complexities applicable to the complete atmospheric compensation of hyperspectral imagery. Because the specific aims of this research pertain to a data-driven technique, some complex processes have been neglected. The following list summarizes the scope of the research and identifies its assumptions and limitations. When required, the impact of incorporating these assumptions will be addressed in the subsequent sections of this document.

- In this research, the VNIR/SWIR (or shortwave) region of the electromagnetic spectrum is defined by the wavelengths from $0.4\ \mu\text{m}$ to $2.5\ \mu\text{m}$. The LWIR (longwave) region includes the wavelengths between $8.0\ \mu\text{m}$ and $14.0\ \mu\text{m}$. This research does not utilize data obtained in the midwave infrared (MWIR) region of the spectrum, defined here as $2.5\ \mu\text{m}$ to $8.0\ \mu\text{m}$. Due to the more complex radiative transfer considerations in this region and the large spectral region between $5 - 8\ \mu\text{m}$ where the atmosphere is rendered opaque due to water vapor absorption, MWIR data is not often used in remote sensing

applications of the Earth’s surface [2, 21].

- Due to the scarcity of LWIR HSI datasets, this research conducts much of its analysis using simulated hyperspectral data. Version 5.3 of the Moderate Resolution Atmospheric Transmission program (MODTRAN) [22] has been used to forward model the atmospheric effects on propagating radiation in order to create simulated hyperspectral data cubes. MODTRAN’s computations of the transmittance function, path radiance spectra, and downwelling spectra for a given atmospheric state are assumed to be accurate.
- The simulated hyperspectral data used in this study makes no attempt to represent actual material distributions on the Earth’s surface (i.e., a landscape). Instead, each pixel of the simulated cube represents the signal from a single surface material that fills the instantaneous field of view (IFOV) of a generic remote sensing instrument. However, the signals do represent realistic materials because the emissivity spectra for each surface material in the simulated scene was obtained from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) spectral database [23].
- With regard to the viewing geometry of both the synthetic and real-world data, the following limitations are imposed: no off-nadir viewing geometries are considered, the propagation path within the sensor’s field of view (FOV) is constant, and the atmospheric state associated with each hyperspectral data cube is assumed to be invariant throughout all pixels in the image.
- With regard to the ground surfaces being imaged, this research effort makes the following assumptions: the surface is assumed to be flat with respect to the viewing geometry of the sensor, the materials are assumed to be Lambertian, and the all pixels in the sensor’s field of view (FOV) are assumed

to be at the same elevation. No bidirectional reflectance distribution functions (BRDF) have been incorporated, and no efforts have been made to simulate or to address the effects of specular reflection. Finally, no attempts were made to simulate the effects of adjacency.

- The atmospheric state is assumed to be cloud free along the line of sight, and no consideration of the radiative effects of clouds is included in the atmospheric compensation process.

These assumptions, although expansive, are not uncommon in the initial development and validation of an atmospheric compensation model. The schematic in Figure 1 depicts a typical scene geometry applicable to this research.

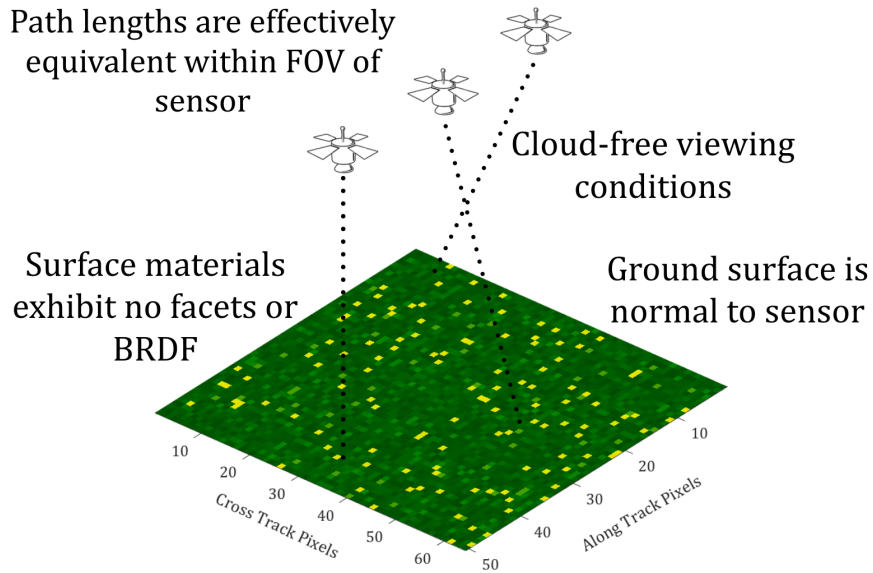


Figure 1. Typical scene geometry for hyperspectral remote sensing simulations in this research.

1.4 Document Structure

In the development of this research, some important foundations to HSI modeling were modified and adapted, and each is worthy of discussion. As such,

whole chapters will be dedicated to the foundational “stepping stones” before the actual AC algorithm is discussed. Chapter 2, though, will properly introduce relevant background and theoretical material by providing a succinct description of hyperspectral remote sensors, an in depth treatment of radiative transfer fundamentals, and a summary discussion of other existing atmospheric compensation algorithms. Chapter 3 will investigate the specifics of the forward modeling methodology that was used in this research to transfer atmospheric state variables into radiative transfer variables. This will discuss in some detail modifications that have been made to existing climatological databases and the justifications for those adaptations. Chapter 4 provides a comprehensive discussion of how the atmospheric state can be parameterized into “low-dimensional” representations that are easy to manipulate for tuning purposes while still enforcing physical constraints. Additionally, this chapter will investigate the specific challenges besetting the development of any in-scene atmospheric compensation method, specifically focusing on the anti-correlation between transmission losses and path radiance emission that contributes to non-unique solutions. Finally, then Chapter 5 will describe the Comprehensive Hyperspectral Atmospheric Effects Removal Method (CHAERM), a new algorithm by which in-scene atmospheric compensation can be accomplished that utilizes the adapted databases discussed in Chapter 3 while mitigating the pitfalls elucidated in Chapter 4. Chapter 6 will demonstrate CHAERM’s performance using simulated and real-world hyperspectral datasets. A comparison of CHAERM will be made to the in-scene atmospheric compensation method of Young, et al. [14] discussed at length in Chapter 2. Chapter 7, then, will provide several avenues for subsequent research.

II. Background

This chapter introduces foundational concepts pertaining to HSI and this research. Sections 2.1 through 2.4 discuss the science and engineering principles relevant to HSI including: a description of a nominal hyperspectral sensor and energy dispersion; a discussion of the apparent spectral properties of materials; a brief treatment of the physics of the radiative transfer of the Earth’s atmosphere; and a summary of shortwave and longwave propagation processes of the Earth’s atmosphere. Sections 2.6 and 2.7 of this chapter introduce the foundational aspects of model-based and data-driven atmospheric compensation methods and summarize existing algorithms to show a progression in the approaches to AC over the years. Although CHAERM is specifically designed for LWIR data, some discussion of VNIR/SWIR radiative transfer and atmospheric compensation are included in the chapter for completeness. As will be shown, one of the benefits of CHAERM is the estimation of tunable atmospheric state, which could certainly be leveraged to facilitate shortwave AC for temporally coincident data.

2.1 Hyperspectral Remote Sensing

A conventional, broadband imaging system, which is decidedly not hyperspectral, integrates incident radiation over a large enough spectral channel to achieve an appropriate signal-to-noise ratio (SNR) [24]. The most routine example of this takes all of the electromagnetic radiation arriving at a sensor’s aperture and focuses onto the sensor’s focal plane, creating a spatially resolved panchromatic image that conveys the intensity of light as a function of location.

Multispectral imaging systems extend the broadband concept and collect data in some number of discrete spectral bands that can be several hundred nanometers

wide. These bands (or bins) are typically selected to be in the highly transmissive spectral regions of the atmosphere, so that good SNR statistics are maintained. Perhaps the most prolific multispectral imagers are those designed to create true-color imagery in the visible band, which collect data in red, green, and blue (RGB) channels. Multispectral data offers more information content than panchromatic data in that it permits quantitative analysis of the spectral component of the received signal. As a result, MSI provides more information about the inherent spectral characteristics of the image constituents than is possible with a panchromatic image because comparisons can be made among the discrete channels [1]. Illustrative examples of panchromatic and multispectral imagery are provided in Fig. 2.

Hyperspectral imaging represents the extension of the MSI capability to achieve higher spectral resolution using more and narrower spectral channels. A recent study using short-wave hyperspectral data to estimate land surface radiation clearly demonstrated an increased accuracy when using hyperspectral data over multispectral data [25]. The downside of measuring data in narrow spectral bands is reduced SNR, and hyperspectral imagers, particularly in the LWIR, often rely upon large spatial footprints to compensate for the reduction in integrated power in the spectral channel. This is one of the motivations behind recent interest in fusing dual-band (i.e., VNIR/SWIR and LWIR) data [26].

The design of a multi or hyperspectral imager is similar to a traditional camera except for a notable difference in the dispersion of light. Because a panchromatic camera measures no spectral data, both dimensions of its 2-D focal plane array (FPA) are spatial dimensions. As is shown in Fig. 2a, the 2-D image is simply the intensity of the integrated radiation recorded on the FPA. In an HSI system, remote sensing is combined with spectroscopy, so the image chain must include a dispersing



(a) Panchromatic Image



(b) Multispectral RGB Image

Figure 2. Examples of Panchromatic and Multispectral Imagery [24]

element. The schematic in Fig. 3 details the process. First, the incident energy from the scene is passed through an entrance slit to limit the FOV in the dispersion direction and mitigate chromatic aberration [24]. The radiation is then collimated, dispersed by a prism or diffraction grating, and focused as a function of wavelength on the spectral axis of the FPA. Typically hundreds of pixels are used in the spectral dimension to ensure the channels remain narrow over a some bandwidth [4, 24, 27]. For the sake of completeness, it should be noted that another common approach to be able to measure energy along a spectral dimension is to use a Fourier transform spectrometer and interferometry [24, 28].

In the case of either instrument, the contiguous pixels along in one dimension of

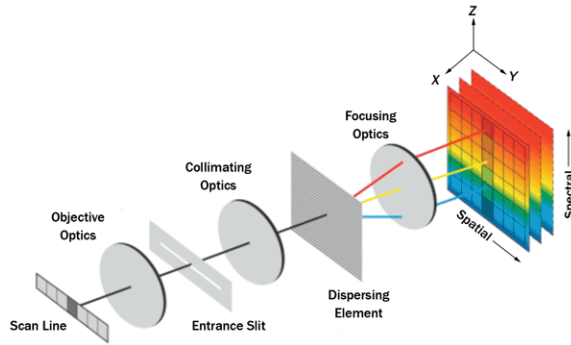


Figure 3. Schematic indicating the components of a dispersive hyperspectral imager [29].

the FPA record the spectrally resolved radiance, the second dimension of the of the FPA records spatial information at a given wavelength of light, and a data cube is then formed by recording spatial-spectral FPA data while the platform transits or the sensor slews. This concept of the HSI data cube is illustrated in Fig. 4, which shows the spatial dimensions of the scene and the additional spectral data obtained on a per pixel basis.

The specific design of a hyperspectral imager’s optical system and the characteristics of its FPA determine the instrument’s spatial and spectral resolution. Today’s hyperspectral sensors routinely achieve spatial resolution on the order of meters with spectral resolution of 5 nm in the VNIR/SWIR and at or better than 30 nm in the LWIR [2, 21, 30]. The pixels on an FPA record digital counts. These values are converted to radiance through a radiometric calibration process that is unique to each instrument [5, 24].

It is the ability to create a nearly continuous spectrum that effectively distinguishes HSI technology from MSI. For example, the Moderate-Resolution Imaging Spectroradiometer (MODIS) is a multispectral sensor that covers the spectral region between $0.4 - 14.4 \mu\text{m}$ with 36 discrete channels [31], while the NASA-JPL hyperspectral Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), a hyperspectral imager, covers the band between $0.4 - 2.5 \mu\text{m}$ with 224 contiguous channels [32].

The simultaneously obtained shortwave and longwave HSI data that is the focus of this research naturally follows from the development of sensors with increasingly narrow spectral channels (i.e., better spectral resolution). Unfortunately, as channel width decreases, so does the magnitude of the signal, and achieving sufficient SNR can be operationally challenging. One solution for high-resolution hyperspectral imaging is to use a larger spatial footprint, allowing more surface-leaving energy to

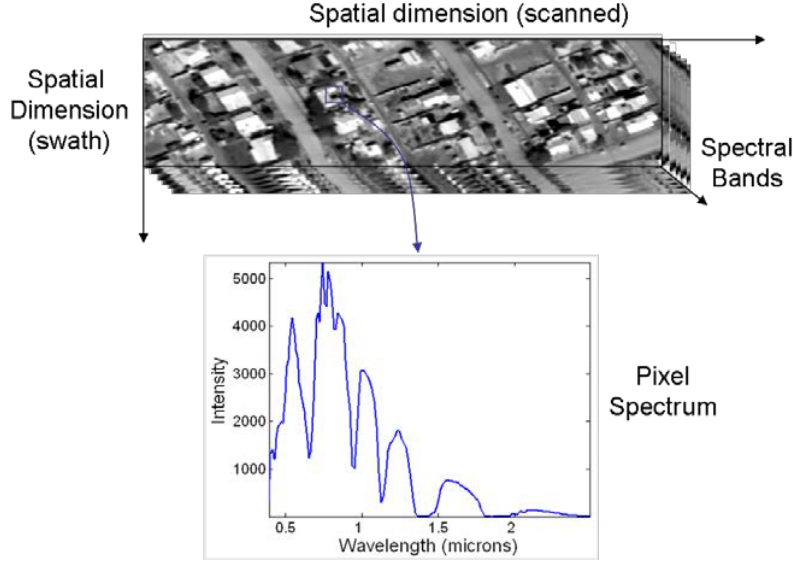


Figure 4. Illustrative example of hyperspectral image cube in the VNIR/SWIR including the radiance spectrum of a single pixel [24].

enter the sensor. This, of course, increases the likelihood of material mixing within a pixel and may frustrate small object searches. Thus, recent studies have begun looking at the advantage of acquiring spatially and temporally coincident data in both the VNIR/SWIR and LWIR. Coupling longwave data to coincident shortwave data helps to overcome SNR throughput problems that are particularly problematic for high-resolution LWIR sensors [21, 26].

2.2 Apparent Spectral Properties of Materials

The only way to determine quantitatively an object's fundamental apparent spectral properties (i.e., reflectance or emissivity) is to measure spectral radiance [24], which is why HSI's capabilities surpass those of conventional broadband visible imaging for material identification and classification [5, 6, 33]. The spectral characteristics of a reflectance or emissivity spectrum pertain to its overall shape and the spectral location and depths of any absorption features, and it uniquely describes an imaged material in a scene [5, 14, 24, 34, 35]. But it must be

accurately derived because the spectral characteristics of the surface-leaving signal are always, and often significantly, affected by atmospheric effects. This means the measured radiance spectrum alone is often cannot be used to reliably identify scene materials.

The spectral properties of matter, whether its phase be solid, liquid, gas, or plasma, is the result of its interaction with electromagnetic radiation at the atomic scale. These processes are fundamentally described by quantum mechanics. The apparent spectral properties measured by a hyperspectral include reflectance, transmission, and absorption and are related to a material's chemical composition, its structure, and its physical dimensions [24]. At a material interface, energy conservation requires that incident electromagnetic radiation be reflected at the material's surface, be absorbed by the material, or be transmitted through the material. Mathematically, this is represented by the sum of three unitless quantities

$$\rho(\lambda) + \alpha(\lambda) + \tau(\lambda) = 1 \quad (1)$$

where $\rho(\lambda)$ is spectral reflectance, $\alpha(\lambda)$ is spectral absorptivity, and $\tau(\lambda)$ is spectral transmittance. Each of these quantities describes a percentage of the total radiation, thus each must be equal to or greater than zero and less than or equal to one.

Ignoring any directional effects, the reflectance of a smooth surface is defined by $\rho(\lambda) = \pi \frac{L(\lambda)}{E(\lambda)}$, the ratio between the radiance $L(\lambda)$ reflected off of a surface and the spectral irradiance $E(\lambda)$ generated by all direct and indirect sources that is incident upon it. The factor of π in this expression relates radiance to irradiance under the assumption that the entire hemisphere is in view and uniformly irradiates the surface. Some materials do not uniformly reflect energy in all directions, meaning the viewing geometry must be considered [16, 24]. These material characteristics are not considered in this research.

Kirchhoff's Law is commonly invoked to relate absorptivity and emissivity in Eq. 1. If a material is in thermodynamic equilibrium, then by Kirchhoff's Law $\alpha(\lambda) = \varepsilon(\lambda)$, and the fundamental relationship between emissivity and reflectivity is given by

$$\rho(\lambda) = 1 - \varepsilon(\lambda) \quad (2)$$

assuming the surface is opaque (i.e., $\tau(\lambda) \approx 0$). The first principles definition of emissivity requires Planck's function, which describes blackbody radiation at a given temperature as a function of wavelength. The spectrum of a blackbody radiator is

$$B(\lambda, T) = \frac{2hc^2}{\lambda^5(e^{hc/k_b\lambda T} - 1)} \quad (3)$$

where $B(\lambda, T)$ is expressed in units of $\frac{W}{m^2 \mu m sr}$, $c = 2.998 \times 10^8 m/s$, $h = 6.626 \times 10^{-34} J s$, and $k_b = 1.381 \times 10^{-23} J/K$. Spectral emissivity is then defined as $\varepsilon(\lambda) = \frac{L(\lambda, T)}{B(\lambda, T)}$, the ratio of a material's emitted radiation to the emitted radiation of an ideal blackbody at the same temperature. Although, like reflectivity, emissivity is a directional phenomenon, it is not uncommon to neglect any directional dependence on the emitted radiation of a surface material. This is referred to as a Lambertian approximation. Field measurements have shown that for sensor viewing angles less than 30° , most naturally occurring surface materials at terrestrial temperatures (i.e., $200 - 300 K$) behave as Lambertian emitters [36]. Therefore, this approximation is consistent with the capabilities of a nadir-viewing sensor, whose fields of view typically are $\sim 10^\circ$.

Emissivity is unique to a material, and many naturally occurring materials are good emitters of longwave radiation. However, it is worth noting that an airborne remote sensor may not observe an entirely homogenous, isothermal material in its IFOV. More often, deriving the surface emissivity in a hyperspectral scene

represents an ensemble emissivity, $\epsilon_r(\lambda) = \sum_{k=1}^N a_k \epsilon_k(\lambda)$, where a_k represents each of the k material’s normalized relative abundance [37]. Target detection algorithms entertain decoupling individual endmembers from the ensemble. To validate the atmospheric compensation technique applied in this research, care will be exercised to ensure homogeneous pixels are used, for which ground-truth emissivity spectra have been obtained and validated.

An AC algorithm transforms at-sensor radiance to the surface-leaving radiance generated by the solid or liquid materials on the surface, which also contains the material’s emissivity “fingerprint.” Because solid materials and liquids are broadband absorbers, their emission spectra exhibit spectral smoothness (assuming LTE). This characteristic is attributed to the short excited state lifetimes of non-gas-phase matter [38, 39]. Generally speaking, therefore, a derived emissivity spectrum should be a smoothly varying function of wavelength.

Local thermodynamic equilibrium also appropriately describes the Earth’s atmosphere below ~ 60 km because the frequency of molecular collisions dominates radiative transitions between the gases and the electromagnetic radiation field [40, 41, 42]. This means the gases in the atmosphere radiate energy in proportion to the absorptivity spectra of the constituents and the temperature of the gas. Gaseous absorption is a spectrally narrow phenomenon, and the transmission spectrum of the atmosphere contains these absorption features from all of the constituents which comprise it. In the event of an incomplete or inaccurate atmospheric compensation attempt, narrow spectral artifacts will likely remain in the derived emissivity spectra of the surface. This is often be exploited in both a quantitative and qualitative sense to assess the accuracy of an AC method [15, 34, 38, 43]. Fig. 5 depicts surface feature and atmospheric gas spectra between $8 - 12 \mu\text{m}$, clearly showing how solid-phase and gas-phase absorption

features are easily discernible based on the scales of their variation.

2.3 Radiative Transfer Principles

Radiative transfer describes the physical phenomena of energy transfer through a medium. This section describes the radiative transfer concepts applicable to the Earth’s atmosphere that are relevant to remote sensing and atmospheric compensation.

2.3.1 Gaseous Absorption and Scattering.

Absorption and scattering are two phenomena associated with the interaction of electromagnetic radiation and matter. To what extent electromagnetic radiation is absorbed by a gas atom or molecule, if it is absorbed at all, is ultimately a quantum mechanical phenomena, and detailed treatment is not necessary here. Instead, it will suffice to say that if the complex index of refraction of a medium has a nonzero imaginary component, then incident electromagnetic radiation will be attenuated as it propagates. The phenomena can be described by an absorption coefficient β_a , which is related to the imaginary part of a material’s index of refraction n_i by $\beta_a = \frac{4\pi n_i}{\lambda}$. The absorption coefficient describes the rate of attenuation per unit distance for a given wavelength [40, 41].

Scattering is the second mechanism that accounts for radiation’s interaction with matter, but it does not represent an energy exchange like absorption. Scattering phenomena are responsible for redirecting radiation, so its effect can be responsible for adding energy to the measured radiance or removing it. Scattering is fundamentally difficult to model and predict, but in general, it is the size of the particles in relation to the wavelength of the radiation that determines the significance of the scattering interaction [40].

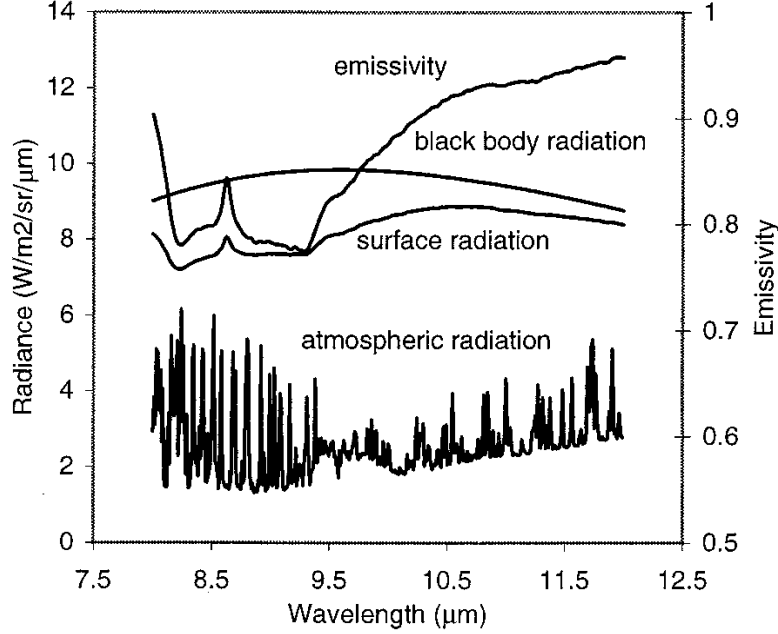


Figure 5. A LWIR land surface radiance and emissivity spectra compared to an atmosphere spectra. Solid materials do not exhibit the degree of high spectral variability seen in gaseous absorption, thus high-frequency features in a retrieved spectra is indicative incomplete atmospheric compensation [15].

There are two types of scattering processes dominant in the Earth's atmosphere. The first, Rayleigh scattering, occurs when VNIR/SWIR radiation interacts with gas molecules and is negligible in the LWIR. The second type of scattering, termed Mie scattering, is the result of the interaction between radiation and atmospheric aerosols (e.g., dust, soot, etc.) [24, 40, 41].

The prevalence of Rayleigh or Mie scattering can be understood in reference to a scattering size parameter x , defined as the ratio between the circumference of the scattering particle (assumed spherical) and the wavelength of radiation, i.e., $x = \frac{2\pi r}{\lambda}$. Fig. 6 summarizes where Rayleigh and Mie scattering phenomena occur as defined by the size parameter.

The first-principles derivation of scattering does not warrant a full discussion here. To understand the radiative transfer involved, it is sufficient to establish a

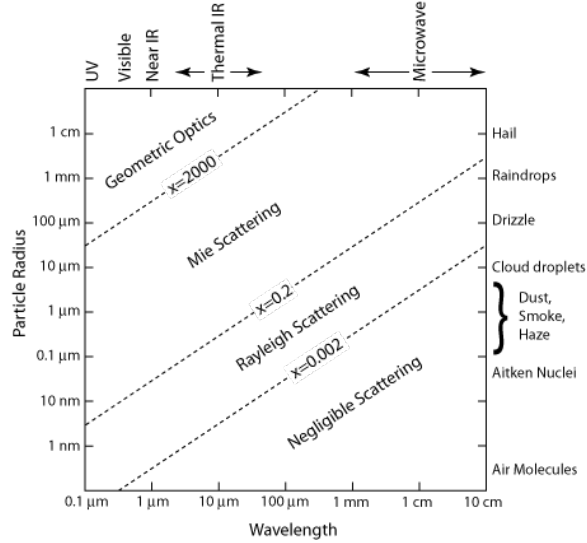


Figure 6. A depiction of dominant scattering processes as a function of particle radius and wavelength of interacting radiation [40].

scattering coefficient β_s which quantifies the matter-radiation interaction in an analogous fashion to the absorption coefficient. However, there is one distinguishing characteristic of scattering, in the spectral sense, that is relevant to atmospheric compensation. Scattering features in a spectrum are readily distinguished from absorption features because gaseous absorption manifests as distinct, typically narrow absorption lines, while scattering is much more spectrally smooth [44]. These distinguishing features can facilitate the development of an atmospheric compensation algorithm.

2.3.2 Beer-Lambert Law and Atmospheric Transmission.

In the most general case, neither β_a nor β_s are identically equal to zero and, thus, a total extinction coefficient (β_e) must be used to describe extinction. The extinction coefficient is defined as the sum of the absorption and scattering coefficients, $\beta_e = \beta_a + \beta_s$, and can be employed to solve for the attenuation of radiation between two points in a medium.

Taking two points s_1 and s_2 along a path, the monochromatic radiance (L) at position s_2 can be described as function of the radiance at s_1 using the Beer-Lambert Law (suppressing λ dependence for clarity):

$$L(s_2) = L(s_1)e^{-\int_{s_1}^{s_2} \beta_e(s) ds}. \quad (4)$$

A common simplifying assumption is to select a path length such that the extinction coefficient is invariant, such that Eq. 4 reduces to

$$L = L_0 e^{-\beta_e s} \quad (5)$$

where L_0 represents the radiance entering the medium. The ratio of L to L_0 is defined as the transmittance of the medium

$$\tau = \frac{L}{L_0} = e^{-\beta_e s} \quad (6)$$

where the unitless argument of the exponent $\beta_e s$ is often referred to as the optical thickness [40].

There are many narrow spectral regions in the VNIR/SWIR and LWIR for which the extinction coefficient is very nearly zero such that $\tau \rightarrow 1$. These atmospheric “windows” allow surface-based energy to propagate without significant attenuation, reducing the need for atmospheric compensation. At other wavelengths, significant attenuation occurs. These strong absorption regions often render the atmosphere completely opaque, especially over typical sensor-to-target path lengths. In these opaque regions, all surface-leaving radiance is completely attenuated before it reaches the sensor, thus no surface reflectance information is measured. In these regions, atmospheric compensation for surface studies is largely irrelevant. An

example of this “signal dropout” is shown in Fig. 7, which demonstrates the effect of two strong water vapor absorption bands in the VNIR/SWIR.

Atmospheric scientists and meteorologists can use “opaque” bands for sounding, but remote sensing research typically utilizes data in the regions of the spectrum where extinction is not total. Fortunately, this occurs in a significant portion of the spectrum in the VNIR/SWIR and the LWIR, where carbon dioxide, water vapor, molecular oxygen, carbon monoxide, ozone, and methane exhibit significant absorption features but do not render the atmosphere completely opaque [9, 40].

2.3.3 Schwarzschild Equation.

Using the concepts introduced in the previous sections, it is now possible to describe atmospheric radiative transfer more completely as an accounting of the credits and debits to a radiation budget, including all forms of scattering, absorption, and emission [24, 40, 41, 45]. The Schwarzschild Equation, a differential expression describing the change in monochromatic radiance along an infinitesimal path, is

$$dL = -\beta_e L ds + \beta_a B(T) ds + \frac{\beta_s}{4\pi} \int p(\Omega', \Omega) L d\omega' ds \quad (7)$$

where p is a scattering phase function, Ω is the angle of beam propagation, and Ω' represents all possible angles of incoming radiation. The debits and credits to the radiations are accounted for term by term on the right side of Eq. 7:

- the first term represents attenuation from the beam due to absorption and scattering, using the extinction coefficient;
- the second term is additive and defines the emission of radiation into the beam, taking the atmosphere to be in local thermodynamic equilibrium at temperature T with specific emission characteristics captured by β_a ; and

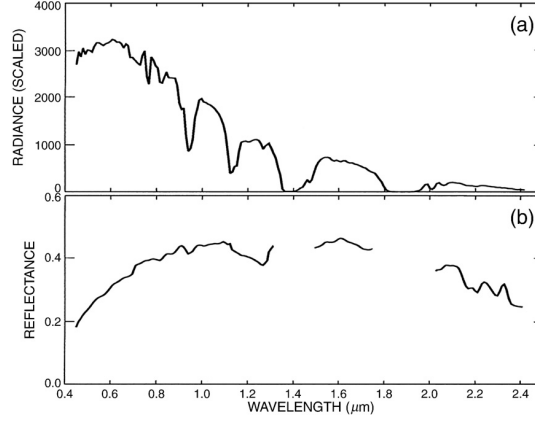


Figure 7. (a) A SWIR radiance spectrum obtained from an airborne instrument showing total signal attenuation at 1.4 μm and between 1.8 μm and 2.0 μm ; (b) the corresponding retrieved surface reflectance spectrum [9].

- the final term is an expression of radiation scattered into the beam, where in atmospheric applications, $\int p(\Omega', \Omega) L_\lambda d\omega'$ is typically integrated over 4π steradians. More detailed treatment of this type of scattering phenomena can be found in [40, 41].

2.4 Signal Propagation through the Atmosphere

Passive remote sensing instruments are typically designed to operate in either the VNIR/SWIR or LWIR bands. This research is designed to facilitate AC where data has been gathered in both bands simultaneously, i.e., “wide-band” hyperspectral remote sensing. Although the in-scene method presented in this research only utilizes LWIR data, a comparison of the phenomenology governing VNIR/SWIR signal propagation will also be included to highlight the differences in VNIR/SWIR and LWIR data. The discussion here refers to the radiative transfer, but the commonality is the atmospheric state. For temporally coincident data, the atmospheric state is invariant, and much can be learned about it through longwave AC analysis.

2.4.1 Propagation of Shortwave Radiation.

Coupling the radiative transfer through the atmosphere with the apparent spectral properties of a surface material permits an accounting practice for the energy arriving at the sensor. Considering only VNIR/SWIR radiation incident upon a flat, smooth, Lambertian material of reflectance $\rho(\lambda)$, the radiance arriving at a downward looking sensor along a nadir path is given by the following equation

$$L(\lambda) = \frac{\tau(\lambda)\rho(\lambda)}{\pi} \left(E_s(\lambda) + E_d(\lambda) \right) + L_a(\lambda). \quad (8)$$

where $\tau(\lambda)$ is the total atmospheric transmission function from target to sensor.

The other terms in Equation 8 are [24]:

1. direct solar irradiance $E_s(\lambda)$ reflected off of the object of interest and transmitted through the atmosphere,
2. integrated downwelling irradiance from all indirect sources $E_d(\lambda)$ reflected off of the object of interest and transmitted through the atmosphere, where the terms comprising $E_d(\lambda)$ are indirect solar irradiance from the atmosphere, irradiance scattered directly from adjacent objects, and irradiance scattered indirectly from adjacent objects, and
3. all solar radiance $L_a(\lambda)$ scattered directly into the beam path by the atmosphere.

It is not necessary to consider thermal emission phenomena in the shortwave band. As is shown in Figure 8, thermal emission at 300 K can be neglected at wavelengths less than $\sim 2 \mu\text{m}$.

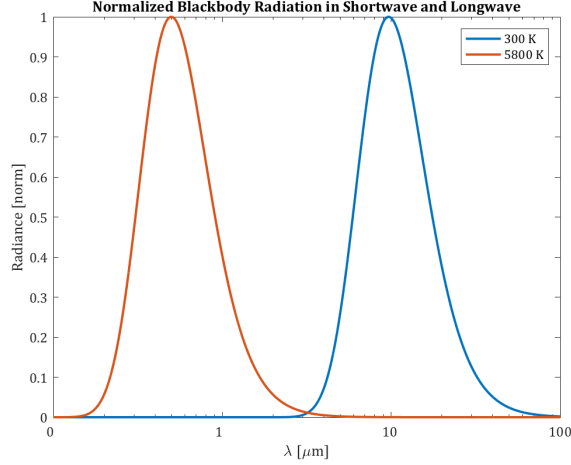


Figure 8. Normalized blackbody radiation curves for a 300 K and a 5800 K blackbody.

2.4.2 Propagation of Longwave Radiation.

In the LWIR, thermal emission must be included, but Fig. 8 shows that effects of all solar radiation can be neglected. Again, for a Lambertian surface and using the relationship between reflectivity and emissivity for an object in LTE, the radiance arriving at a LWIR sensor is

$$L(\lambda) = \tau(\lambda) \left(\epsilon(\lambda) B(\lambda, T) + (1 - \epsilon(\lambda)) L_d(\lambda) \right) + L_a(\lambda). \quad (9)$$

The terms on the right side of Eq. 9 represent the accounting of [24]:

1. direct thermal radiance $B(\lambda, T)$ from the object of interest at temperature T , modulated by its emissivity and transmitted through the atmosphere,
2. downwelling thermal radiance $L_d(\lambda)$ of the atmosphere and of adjacent objects, reflected $((1 - \epsilon(\lambda)))$ off of the object of interest and transmitted through the atmosphere, and
3. all upwelling thermal atmospheric radiance $L_a(\lambda)$ along the optical path of the sensor's FOV.

Equations 8 and 9 describe how the radiative transfer processes of the atmosphere provide the linkage between an HSI sensor and the Earth’s surface. $E_d(\lambda)$, $L_d(\lambda)$, and $L_a(\lambda)$ are additive terms, and $\tau(\lambda)$ encompasses the attenuation processes. A spectral representation of the LWIR atmospheric terms are depicted in Figure 9. If these spectra are properly removed from the at-sensor radiance, only spectral information about the surface remains.

2.5 Units and Conversions

To this point in this document, and consistent with the majority of the literature, the equations shown have been functions of the wavelength λ of the propagating energy. The equations and discussion with regard to the development of CHAERM will be presented with respect to wavenumbers $\tilde{\nu}$, whose conventional units are cm^{-1} . The conversion between these two quantities is relatively straightforward, but it requires careful unit analysis. Wavenumbers in cm^{-1} and microns μm are related by a scale factor of 10^4 such that

$$\frac{10^4}{\text{cm}^{-1}} \rightarrow \mu\text{m}.$$

Energy dependent quantities, such as spectral radiance, cannot be converted using a fixed scaling factor. In this research, spectral radiance will be expressed in either $\frac{\text{W}}{\text{cm}^2 \text{sr cm}^{-1}}$ or $\frac{\mu\text{W}}{\text{cm}^2 \text{sr cm}^{-1}}$. If radiance is to be plotted on a wavelength axis, the following conversion factor must be used

$$\frac{\text{W}}{\text{cm}^2 \text{sr cm}^{-1}} \cdot \frac{10^4}{(\lambda \mu\text{m})^2} \rightarrow \frac{\text{W}}{\text{cm}^2 \text{sr } \mu\text{m}},$$

where it should be noted that the conversion is a function of the variable λ expressed in μm . Often hyperspectral research uses the “microflick” $\frac{\mu\text{W}}{\text{cm}^2 \text{sr } \mu\text{m}}$, which

can be computed by multiplying the above conversion by an additional factor of 10^6 .

Although the spectra have different shapes and features, the underlying phenomena are the same. The wavenumber spectra associated with the previously discussed in the LWIR RT equation as a function of wavelength are presented in Fig. 9. Here, a transmission, upwelling, and downwelling spectrum are shown for a sensor flying more than 20 km above the Earth’s surface. Ozone absorption that occurs between $\sim 9 - 10 \mu\text{m}$ can be seen on a wavenumber axis between approximately $980 - 1080 \text{ cm}^{-1}$.

Because Planckian emission is a dominant contributor to at-sensor radiance, it is worth showing the characteristic shape and magnitude of Planckian emission on a wavenumber axis, $B(\tilde{\nu}, T)$. Figure 10 depicts Planckian radiation at several typical terrestrial temperatures. The most relevant part of these curves for LWIR HSI is the region between $700 - 1300 \text{ cm}^{-1}$. Outside of those regions, atmospheric absorption due to water vapor renders that atmosphere too opaque for surface sensing applications.

2.6 Approaches to Atmospheric Compensation

Equations 8 and 9 describe the phenomena which contribute to atmospheric effects in remotely sensed imagery. The dynamic nature of the atmospheric variables responsible for these effects, both temporally and spatially, means correlating at-sensor radiance to ground-leaving radiance is strongly dependent upon the atmospheric state and viewing geometry at the precise time of the measurement [15]. The distance between the target/surface and the sensor can be as small as $\sim 1 \text{ km}$ when done with an aircraft or as large as hundreds of kilometers when placed on a satellite.

Although it seems like AC would only be relevant when imaging the surface over

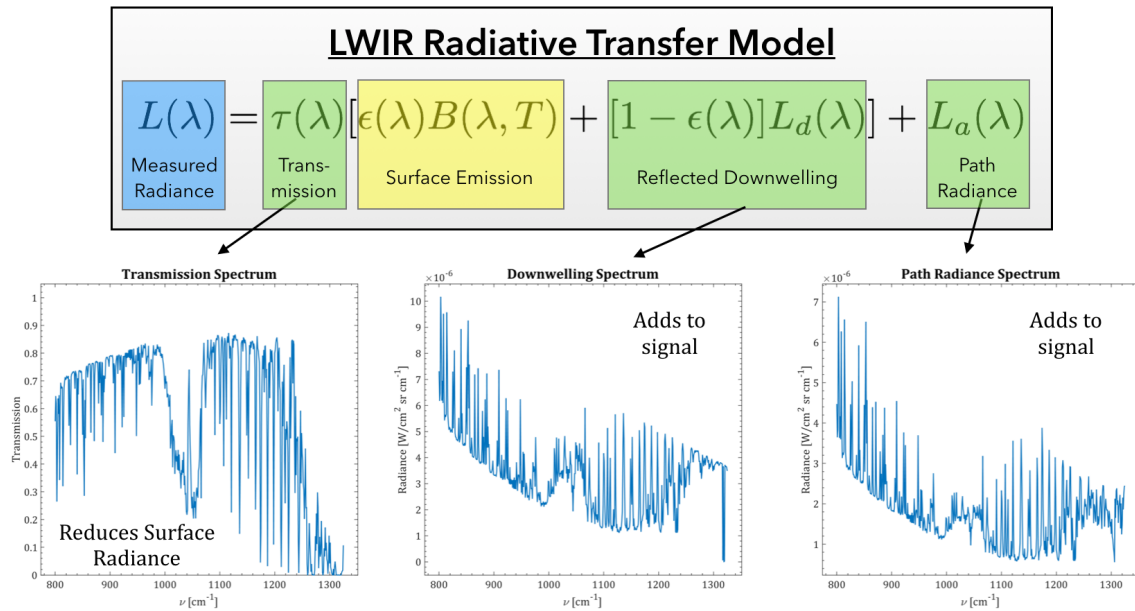


Figure 9. Example of LWIR spectra associated with transmission, upwelling, and downwelling radiance.

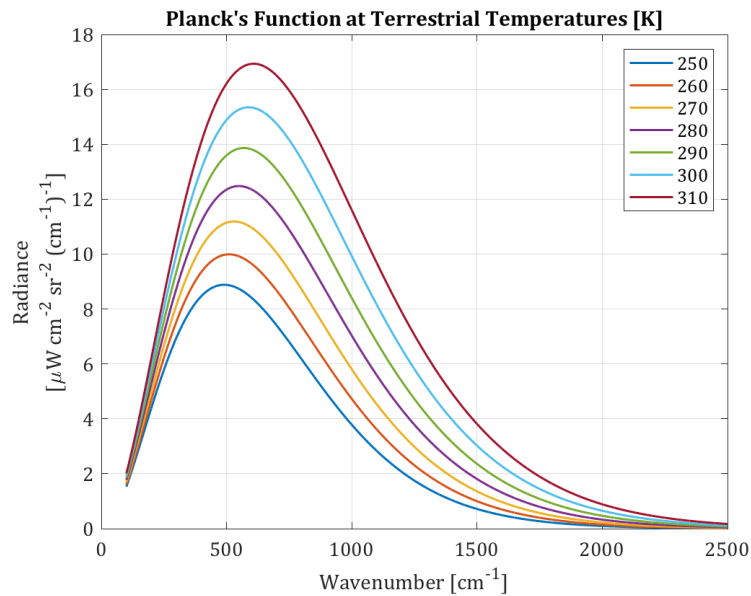


Figure 10. Example of LWIR Planckian emission at terrestrial temperatures.

long distances, studies have shown it must be taken into account in virtually all remote sensing scenarios. It is estimated that the vast majority of downwelling radiation, in some cases $\sim 90\%$ of the total, is created in the first 1 km of the atmosphere [46]. In a recent study, atmospheric effects were prevalent in hyperspectral imagery whose sensor-to-target distance was merely 100 m [33]. Generally speaking, if quantitatively accurate data about a remotely sensed target is of interest, then an AC method must be employed [47].

Solving Eq. 9 for the surface’s emissivity shows the extent of the decoupling that must be performed to compensate for atmospheric effects

$$\varepsilon(\lambda) = \frac{L(\lambda) - L_a(\lambda) - \tau(\lambda)L_d(\lambda)}{\tau(\lambda)(B(\lambda, T) - L_d(\lambda))}. \quad (10)$$

In this expression, only the measured radiance $L(\lambda)$ is known per pixel. Accurately determining the other quantities, to include transmission, upwelling, and downwelling spectra, so that $\varepsilon(\lambda)$ is accurately estimated is the fundamental pursuit of atmospheric compensation. Equation 10 also shows that emissivity cannot be derived unless the surface temperature is also determined. This step, often referred to as temperature-emissivity separation (TES), will not be incorporated into this research.

The past 30 years has seen two fundamental approaches to AC develop. As such, atmospheric compensation algorithms are usually described as either being an in-scene (also, “data-driven”) method or a model-based method. In-scene methods are generally computationally less expensive but have inherent limitations. Model-based methods, especially those at high-resolution, rely heavily on computational capabilities using well developed modeling algorithms [9]. Although CHAERM is best described as an in-scene method, an overview of both approaches to AC is included in what follows.

2.6.1 In-Scene AC.

If the goal of AC is to retrieve or derive information about the surface, then it can be argued that the best approach to AC should rely only upon at-aperture radiance data because, as is shown in Eq. 9, $L(\lambda)$ is a function of the exact atmospheric state at the time of the measurement [48]. By extension, then, a perfect AC method would decouple the exact atmospheric contribution to the measured signal from the surface-leaving signal by inferring the physical and radiative transfer properties of the atmosphere and predicting the amount of energy emitted from the surface [49]. If this could be done completely, then the atmospheric compensation would be no perfect. However, there are significant challenges associated with solving an inverse problem of this sort that resides in such a large and highly coupled dimensional space.

To facilitate solving them in AC, a common approach is to impose simplifying assumptions about the surface materials while treating the atmospheric state as invariant throughout the scene. For VNIR/SWIR imagery, this can be accomplished by assuming some population of pixels are in shadow or are composed of dense or dark vegetation. In the LWIR, it is often assumed that some materials in the scene exhibit large emission, closely approximating a perfect blackbody surface. CHAERM will also require the presence of some high-emission (i.e., blackbody-like) surface materials to run properly.

In-scene approaches offer the benefit of not requiring accurate *in situ* field measurements of the atmospheric state to initialize an RTM. However, they can become intractable if certain types of surface materials are not present or if *a priori* knowledge of the surface constituents is erroneous or absent. Furthermore, an in-scene method, if implemented as a purely mathematical tool, does not guarantee the solution will be physically realistic. The primary objective of an in-scene

method is to derive the best estimate for surface-leaving spectra by iteratively running a model and minimizing an error metric. The reduction of error metrics should be properly constrained if the solution is to remain meteorologically consistent. If it is not, the retrieved atmospheric state may not be the represent the actual atmospheric state at all. Some in-scene AC algorithms maintain large and comprehensive look-up-tables of previously computed spectra to limit computational expense and impose constraints. One of the tenets of this research and of CHAERM, itself, is to ensure the atmospheric compensation is performed while enforcing only realistic atmospheric state solutions be allowed.

2.6.2 Model-Based AC.

Model-based algorithms conduct atmospheric compensation in the forward sense. Here, a model typically ingests a number of atmospheric parameters and runs an RTM to compute downwelling radiance, transmittance, and path radiance spectra. These spectral quantities are then applied to the appropriate VNIR/SWIR or LWIR radiative transfer equation to compute at-aperture radiance. High-performance RTMs including MODTRAN [50], 6SV [51], and LEEDR [52] have the capability to simultaneously model millions of atmospheric absorption features, using narrow band, correlated- k , or line-by-line computations. The spectral outputs of these forward models can be calculated with resolutions of 1 cm^{-1} .

The atmospheric parameter inputs for an RTM can span a very large space, whose complete estimation is largely intractable. One of the most fundamental challenges besetting a model-based method involves obtaining accurate data of the atmospheric parameters necessary to run the RTM. Judicious choices can limit the parameter space to only the primary drivers without introducing significant modeling errors. The basic data required for most RTMs include a vertical

temperature, moisture, and pressure profile, an estimate of the aerosol composition at and near the surface, and a vertical distribution of the atmospheric gases [53].

As it contributes to effects in both the LWIR (e.g., absorption) and VNIR/SWIR (e.g., absorption and Mie scattering phenomena), it is particularly important to model the water vapor distribution well. Unfortunately, water vapor is not a well mixed gas, and it can vary vertically on short time scales as a function of time of day, time of year, and geography. The majority of the water content in the atmosphere is concentrated between the surface and 3 km, and approximately 90% of the total atmospheric water vapor is distributed between the surface and 6 km [31, 41, 54]. There are thousands, if not hundreds of thousands, line absorption features in the longwave and shortwave regions of the spectrum, which exhibit a wide variety of line depths and widths, owing to the complex spectroscopy of its bent molecular shape [55]. Water vapor also contributes to a significant manifestation of continuum absorption, a broadband, low-frequency spectral feature. Continuum, not entirely understood from a theoretical perspective, is likely thought to occur due to the accumulation of line wing effects [40] and water’s ability to form dimers and polymers [56].

The other atmospheric constituents are also important to accurate modeling but are more readily estimated using climatological model data. Although it is well-mixed and largely invariant, carbon dioxide renders the atmosphere completely opaque in portions of the VNIR/SWIR and the LWIR. It is likewise important to consider the presence of methane in the atmosphere, whose large absorption coefficient makes it an effective VNIR/SWIR and LWIR absorber despite its comparatively reduced concentration. Though better accuracy can be achieved if altitude variations are also included [24, 57], suitable accuracy is obtained by using a uniform concentration of these gases.

The final major consideration for model-based AC is the aerosol loading. Accurately modeling the scattering processes in the boundary layer requires knowledge of both the size distribution of the scatterers and their concentration, both of which are a function of water content, wind speed, and surface composition. Figure 11 shows the altitude regimes at which aerosols and molecules contribute to scattering. Mie scattering phenomena, primarily occur at and below 3 km, where tropospheric aerosols are prevalent. This can be one of the more difficult RT phenomena to accurately parameterize and forward model.

Even if the model is initialized perfectly, one downside of model-based AC is the computation time necessary to create the modeled downwelling, transmission, and upwelling spectra at sufficient spectral resolution. But, as computational technology has advanced, the more formidable limitation is obtaining reliable estimations of the key input parameters in data-sparse regions. Radiosonde data exists at many locations and can be used to inform an initial guess for interpolation to some later time. In many locations, however, real-time atmospheric data of any kind is never measured. In this case, climatological, reanalysis data, and numerical weather modeling may be used to initialize estimate the atmospheric state, but the associated errors may be significant [53].

2.7 Existing Atmospheric Compensation Algorithms

This section provides a review of five AC algorithms: Internal Average Reflectance (IAR)/Empirical Line Method (ELM), Atmospheric Removal (ATREM), Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH), In-scene Atmospheric Correction (ISAC), and Quick Atmospheric Correction (QUAC). This list is far from inclusive, but the summaries provide an overview of the various approaches that have been pursued in the field of AC.

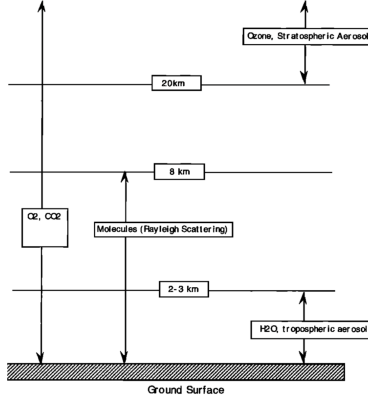


Figure 11. Illustrative distribution of atmospheric constituents as a function of altitude [31].

CHAERM has its foundation rooted in an ISAC-like approach, so the methods discussed in that section are particularly relevant to this research.

2.7.1 Internal Average Reflectance / Empirical Line Method.

A straightforward example of basic in-scene AC is the Internal Average Reflectance (IAR) method of Kruse [58]. The IAR method treats the atmospheric contribution to the at-aperture radiance as a bias to all pixels in the scene. To remove the bias, it divides each pixel spectra by the average spectral radiance of all of the pixels in the scene. The result is an apparent relative reflectance spectra. No advance knowledge of the surface is required, and no assumptions about materials in the scene are necessary. As is expected, this generic approach to AC lacks the fidelity to spectrally identify materials or detect targets.

Improving the accuracy of an IAR-type method can be achieved if *a priori* knowledge of the type and location of unique surface materials in the scene is available. Techniques known as empirical line methods (ELM) can be effective in this case [59]. To perform an ELM in the shortwave, the values of at least two pixel reflectances in the scene must be accurately known. These specific pixels are used to create a linear mapping function relating measured radiance $L(\lambda)$ to surface

reflectance $\rho(\lambda)$ using a gain term $a(\lambda)$ and an offset term $b(\lambda)$

$$\rho(\lambda) = \frac{L(\lambda) - b(\lambda)}{a(\lambda)}. \quad (11)$$

The known material reflectance spectra $\rho_1(\lambda)$ and $\rho_2(\lambda)$, associated with measurements $L_1(\lambda)$ and $L_2(\lambda)$, are used to determine the gain and offset parameters expressed by

$$a(\lambda) = \frac{L_2(\lambda) - L_1(\lambda)}{\rho_2(\lambda) - \rho_1(\lambda)} \quad (12)$$

and

$$b(\lambda) = \frac{L_1(\lambda)\rho_2(\lambda) - L_2(\lambda)\rho_1(\lambda)}{\rho_2(\lambda) - \rho_1(\lambda)}. \quad (13)$$

Equation (11) is unique to a particular atmospheric state but is otherwise applicable to all of the pixels in a scene. Thus once $a(\lambda)$ and $b(\lambda)$ are known the remaining reflectance spectra in the image can also be calculated using Eq. 11. ELMs are known for achieving an effective balance of accuracy and computational expense, but they are prone to errors. Primarily these errors originate because of signal impurities. Linear and non-linear pixel mixing, which can occur due to adjacency effects, are pixel impurities that cannot be accounted for by a typical ELM. Some studies have estimated that locations from which the spectral radiance associated with a known reflectivity is measured must comprise the equivalent surface area of a 3×3 pixel square to avoid adjacency contamination of the center pixel [60]. This requirement can pose a significant challenge in natural settings or for high-altitude sensors with large ground sample distances.

2.7.2 Atmospheric Removal (ATREM) Algorithm.

Early researchers quickly recognized the inherent limitations on the accuracy and operational functionality of ELM techniques. In the late-1980s, the Atmospheric Removal (ATREM) algorithm emerged as one of the first model-based AC algorithms [61, 62]. Built upon the radiative transfer principles established in Eq. 8 and the definition of reflectance, ATREM converts at-sensor radiance (L_s) to at-sensor reflectance (ρ_s) using the definition of reflectance

$$\rho_s = \pi \frac{L_s}{\cos(\theta_{solar}) E_{solarTOA}},$$

where $E_{solarTOA}$ is the irradiance at the top of the atmosphere and θ_{solar} is the solar zenith angle.

The at-sensor reflectance is then modeled in terms of surface reflectance (ρ) by the following expression (in which all terms are implicitly dependent upon wavelength)

$$\rho_s = T_g \left(\rho_{atm} + \frac{t_d t_u \rho}{1 - \rho S} \right) \quad (14)$$

where T_g is the total atmospheric gas transmittance, ρ_{atm} is the atmospheric reflectance into the sensor due to scattering, t_d accounts for scattering attenuation from top-of-atmosphere to the surface based upon solar zenith angle, t_u accounts for scattering attenuation from surface to sensor, and S represents the spherical albedo of the atmosphere. Solving Eq. 14 for surface reflectance yields the following expression

$$\rho = \left(\frac{\rho_s}{T_g} - \rho_{atm} \right) \left(t_d t_u + S \left(\frac{\rho_s}{T_g} - \rho_{atm} \right) \right)^{-1}. \quad (15)$$

A properly initialized RTM provides estimates of all of the atmospheric parameters

are estimated by an RT model. Originally, the Simulation of the Satellite Signal in the Solar Spectrum (5S) RT code [63] was used to compute the scattering parameters, based on user-defined inputs including aerosol optical depth, surface pressure, and water vapor content [24]. Later versions of ATREM were enhanced by the use of the Second Simulation of the Satellite Signal in the Solar Spectrum (6S) [64] and MODTRAN [22, 65] radiative transfer codes. Despite its pioneering success, ATREM’s simplified approach to adjacency has since been improved upon in other methods, and ATREM itself is no longer maintained.

2.7.3 Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) Algorithm and FLAASH-IR.

Another successful atmospheric correction algorithm, known as the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH), was originally developed in the 1990s by Spectral Sciences, Inc. and the Air Force Research Laboratory [30]. FLAASH is a forward model, rooted in basic first-principles methodology. In addition to using a band-ratio technique to estimate water content on a per-pixel basis, FLAASH advances ATREM by accounting for adjacency effects, multiple scattering phenomena, and clouds [66, 67]. Adjacency effects modify Eq. 14 in the following way

$$\rho_s = T_g \left(\rho_{atm} + \frac{t_d t_u \rho}{1 - \rho_{adj} S} + \frac{(\rho_{adj} - \rho) t_d t_u}{1 - \rho_{adj} S} \right) \quad (16)$$

where ρ_{adj} is the average reflectivity of surrounding pixels. Adjacency effects are prevalent during hazy conditions, where energy is more readily reflected from the surrounding surfaces and scattered by aerosols into the sensor’s FOV [30].

Accounting for adjacency has been found to make significant improvements to retrieved reflectivity spectra, especially when the surrounding area contains

materials with strong reflectivity signatures, like some vegetation and most man-made materials. As with ATREM, MODTRAN is used as the radiative transfer engine in FLAASH to calculate the atmospheric terms in Eq. 16.

FLAASH is one of the more popular methods of atmospheric compensation has been used worldwide throughout the 1990s, 2000s, and 2010s. Consistent with the theme of this research, FLAASH provided the AC in an advanced integrated hyperspectral data analysis study in 2015 [2]. Recently, its developers have also developed a longwave specific AC algorithm known as FLAASH-Infrared (IR) [28, 43]. FLAASH-IR, like its shortwave predecessor, is a first-principles, forward model that generates estimates for atmospheric transmission, upwelling (i.e., path radiance), and downwelling (TUD) using MODTRAN. It iteratively considers candidate atmospheres by applying the TUD to the longwave radiative transfer equation and assessing spectral smoothness to estimate the surface temperature of the emissive material(s) in the IFOV [43].

2.7.4 In-Scene Atmospheric Compensation (ISAC).

FLAASH demonstrates the reliance of model-based AC algorithms on both *a priori* knowledge of the atmospheric state and a RTM, like MODTRAN. In this way, model-based codes can be difficult to implement in an operational sense. To divest from this requirement, new ways to manipulate at-sensor radiance data to properly compensate for atmospheric effects were explored throughout the 2000s.

Arguably one of the more influential data-driven approaches to AC is the LWIR in-scene atmospheric compensation (ISAC) algorithm of Young et al. [14]. Owing to its relatively straightforward application, ISAC has remained widely utilized in LWIR compensation schemes, assuming its somewhat limiting assumptions about surface material content are satisfied. Portions of this research attempt to advance

ISAC, so a fair amount of discussion about the algorithm is warranted.

Fundamentally, ISAC represents an extension of an ELM into the LWIR. It starts by presuming some population of blackbody-like materials are present in a scene. The unique characteristics of blackbody-like materials, for which $\varepsilon(\lambda) \approx 1$, result in a powerful simplification of Equation 9 to

$$L(\lambda) = \tau(\lambda)B(\lambda, T) + L_a(\lambda). \quad (17)$$

ISAC's premise is that at every wavelength the at-aperture radiance can be expressed as a function of the surface material's Planckian radiance with the transmittance of that channel acting as a line-slope parameter and path radiance of that channel serving as the line-intercept parameter. Only using highly emissive materials, which is endemic to ISAC's operation, precludes its ability to directly derive downwelling radiation. ISAC will struggle in scene with little vegetation, water, or manmade materials with strong blackbody characteristics [14]. If the downwelling term is desired, most implementations of ISAC determine it term by querying a precomputed look up table (LUT) of downwelling spectra that have been forward modeled.

The essence of the ISAC method is a linear regression technique, done on a per channel basis, to obtain $\tau(\lambda)$ and $L_a(\lambda)$. The data for the regression is the measured radiance of a selection of predetermined pixels whose materials closely approximate blackbody emission plotted as a function of the their Planckian radiance $B(\lambda, T)$ with an estimate for their temperature. An example of this type of scatterplot is shown in Fig. 12, which depicts data obtained from the $8.5 \mu\text{m}$ channel of the Spatially Enhanced Broadband Array Spectrograph System (SEBASS) imaging system. More information about SEBASS will be included in Chapter 3. As the linear regression of this data shows, the estimate for the surface-leaving signal is

very nearly equal to the at-aperture radiance for all pixels (i.e., $L(\lambda) \approx B(\lambda, T)$). This condition implies that this channel is an atmospheric window, where few atmospheric effects are present. The slope of the regression line closely follows the theoretical maximum $\tau = 1$, requiring that $L_a(\lambda) \approx 0$ in accordance with Kirchhoff's Law. Selecting a more opaque channel would result in an increase value of $L_a(\lambda)$, and the regression line would have a smaller slope.

Having no dependence on external data of any sort, ISAC is required to estimate the surface temperature using from the at-sensor radiance measurements. To accomplish this, each pixel's radiance spectrum is converted to a brightness temperature spectrum by solving Eq. 3 for temperature. If the material is a perfect blackbody, its computed brightness temperature is also the object's kinetic temperature. For other high-emissivity materials, the true temperature is an upper limit, and the brightness temperature is modulated by the material's emissivity [24]. Each pixel is interrogated for the channel at which the largest brightness temperature occurs. The channel with the most tallies is defined as the reference channel. Assuming the atmospheric temperature distribution is cooler than the surface, this process is preferential to highly transmissive channels. The pixels for which the maximum brightness temperature was found in the reference channel are

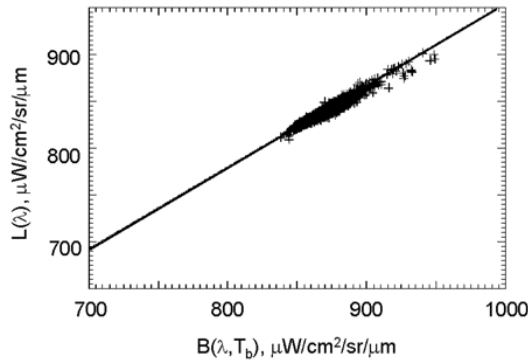


Figure 12. Scatterplot of $L(\lambda)$ vs. $B(\lambda, T)$ at $\lambda = 8.5 \mu\text{m}$ and the linear regression line used to estimate $\tau(\lambda)$ and $L_a(\lambda)$ [14].

deemed to be highly emissive and are plotted. None of the other pixel data is included. Of the population of pixels in the scatterplot, those near the top of the distribution most closely approximate blackbody characteristics and the regression to determine $\tau(\lambda)$ and $L_a(\lambda)$ is accomplished by fitting to the topmost points in the scatterplot [14].

Due to the estimation of the surface temperature, the transmittance and path radiance spectra computed by ISAC are spectrally consistent in shape but not magnitude. In order to use the calculated data in an absolute sense, a scaling operation is necessary. These are accomplished by making comparisons to external models (e.g., MODTRAN) or using a data driven, water-band ratio techniques used in other methods [14, 28]. The more complex task of performing temperature emissivity separation (TES) is left to subsequent processing. TES is a unique challenge to imaging in the LWIR, where thermal emission is a non-negligible component of the surface signal and of the atmosphere.

2.7.5 Quick Atmospheric Correction (QUAC).

A final AC method worth discussing, representing a significant departure from all of the methods employed by the previously described methods, is the Quick Atmospheric Correction (QUAC) code. Implemented in 2004, the QUAC code compensates VNIR/SWIR imagery using an in-scene approach that does not require any first-principles RT calculations. QUAC was devised to enhance the accuracy of a data-driven method while maintaining quick computational speed and an independence from external knowledge of the scene or of the atmosphere [18]. Its performance statistics are impressive. On a typical desktop computer, QUAC was able to atmospherically compensate a data cube consisting of 500×500 pixels with 220 spectral bands in approximately 3s [68].

The fundamental assumption on which QUAC relies is that for any diverse sampling of unique endmembers in a scene, there exists an average reflectance spectrum which is universal. This assumption has been empirically shown to hold for most scenes, although it is not attributed to a first-principles explanation. The universal spectrum is determined by averaging up to 50 endmember spectra obtained from an established library containing a wide selection of natural and manmade materials. An endmember is defined as a unique spectrum in a collection of spectra. Linear combinations of small numbers of endmembers can represent the large number of spectra contained in a scene or library [69]. The developers of QUAC employ the sequential maximum angle convex cone (SMACC) method of Gruninger et al. [70] to determine endmembers. The curves in Fig. 13 represent 50 endmember spectra obtained using SMACC from a database of 168 materials. The effectiveness of QUAC is partially attributed to the uniform and non-preferential spanning of reflectance space achieved by its endmember analysis.

The QUAC algorithm establishes a linear relationship similar to an ELM based on the following three-term representation of Eq. (8)

$$L_s = A + B\rho_{surf} + C\rho_{ave} \quad (18)$$

where A is path radiance, B is downwelling radiance incident on the material of interest, and C is radiance reflected off of adjacent sources ρ_{ave} . The first and third terms in Eq. (18) are considered to be scene invariant, such that surface reflectance can be expressed

$$\rho_{surf} = \frac{1}{B} \left(L - (A + C\rho_{ave}) \right) \quad (19)$$

where the quantity $\frac{1}{B}$ is an effective gain term and $A + C\rho_{ave}$ represents a common offset.

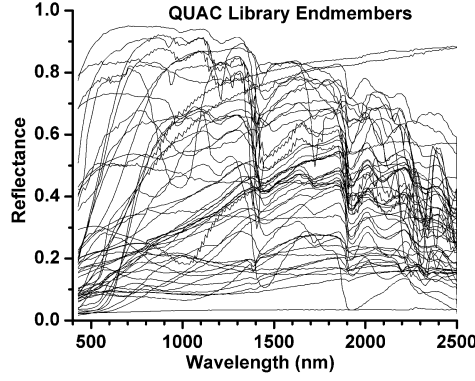


Figure 13. An example of the reflectance spectra of 50 endmembers obtained using SMACC analysis [18].

The offset term in Eq. (19) is simply calculated by finding the minimum at-sensor radiance of all pixels in the scene on a band-by-band basis. The gain term, which has units of inverse radiance, is found by employing the universal spectrum concept. The scene gain is given by

$$\frac{1}{B} = \frac{(\hat{\rho}_{library})_{endmembers}}{(\hat{L}_{scene})_{endmembers}} \quad (20)$$

in which the numerator is a 50-endmember average of library reflectance spectra and the denominator is a 50-endmember at-sensor radiance average. QUAC’s unique data-driven approach to AC achieves its goal by providing reasonably accurate surface spectra with a significant reduction in computational expense. The fact that QUAC is dependent upon the statistical assumption of diverse material spectra and not actual scene constituents [24] means its success occurs in spite of its distance from physics-based principles. But despite its lack of radiative transfer fundamentals, QUAC remains relevant because of its independence, flexibility, efficiency, and performance.

2.7.6 Summary of Atmospheric Compensation Algorithms.

The AC algorithms discussed in the previous section were chosen to highlight the different means of accomplishing AC and to emphasize the differences between model-based and in-scene methods. For the intrepid investigator, the following is a list of other well known algorithms which incorporate their own unique approaches and methods:

- Autonomous Atmospheric Compensation (AAC): Fielded in 2000, in-scene, LWIR [15]
- High-Accuracy Atmospheric Correction for Hyperspectral Data (HATCH): Fielded in 2003, model-based, VNIR/SWIR [71]
- Atmospheric Correction Now (ACORN): Fielded in 2004, model-based, VNIR/SWIR [72]
- Automatic Retrieval of Temperature and Emissivity using Spectral Smoothness (ARTEMIS) In-Scene Atmospheric Compensation: Fielded in 2008, in-scene, LWIR[38]
- Spectral Reflectance Image Extraction from Radiance with Relief and Atmospheric Correction (SIERRA): Fielded in 2009, model-based, VNIR/SWIR [73].

Some of the latest interests in AC are tending toward complex statistical analyses (e.g., Bayesian) and the coupled shortwave and longwave AC approaches in which this research seeks advances.

2.8 Spectral Similarity Metrics

Spectral radiance and emissivity are often represented as vectors of length N , where N is the number of spectral bands or channels. Comparing vectors is often necessary, as will be the case with CHAERM’s approach to AC. There are two commonly employed metrics that CHAERM uses to quantitatively determine how spectral similarity in a quantitative sense. The first is the spectral angle (SA), which calculates the angle between two vectors. It is calculated by

$$\theta = \cos^{-1} \left(\frac{\vec{x} \cdot \vec{y}}{\|\vec{x}\| \cdot \|\vec{y}\|} \right). \quad (21)$$

where the vectors represent two quantities, each having the same length (e.g., two at-aperture radiance spectra from hyperspectral scene). The spectral similarity of the vectors $\vec{x}$ and $\vec{y}$ increases as $\theta \rightarrow 0$, with the most spectrally dissimilar vectors having $\theta = \pi/2$. The spectral angle is a popular calculation in hyperspectral imaging science because it is relatively computationally inexpensive and easily tractable for comparisons. One of the downsides of the SA, however, is that it is invariant to differences in magnitude [74], which can be an important consideration in hyperspectral applications.

The Euclidean distance (ED) metric, therefore, serves as a nice complement to the SA, because it does compute a quantitative measurement of the aggregate difference in magnitude of two signals. ED, also known as the two-norm, is calculated using

$$d = \sqrt{\sum_{i=1}^N (x_i - y_i)^2}. \quad (22)$$

As a distance, $d \geq 0$, but it has no theoretical maximum. Many hyperspectral algorithms utilize SA and ED, and each can be valuable in different contexts.

CHAERM will primarily use the ED as its discriminator, though references will be made to spectral angle comparisons as well.

III. Forward Modeling Methodology

The fundamental purpose of this research is to develop a strategy for atmospheric compensation that is in tune with the needs of the intelligence, surveillance, and reconnaissance operations supporting national security priorities. As such, this research prioritizes robustness and functionality, especially in collection environments where accurate, real-time measurements of the atmospheric state from surface to sensor are not possible.

This research is anchored in exploiting the data contained in large atmospheric databases that have been compiled by external researchers. The two notable databases, the Thermodynamic Initial Guess Retrieval (TIGR) and the Global Atmospheric Profiles from Reanalysis Information (GAPRI), will be explained in subsequent sections. Additionally, this chapter contains information about how MODTRAN was utilized to generate transmission, upwelling, and downwelling spectra in the LWIR and SWIR.

3.1 Initializing MODTRAN's radiative transfer calculations

Atmospheric transmittance, path radiance, and downwelling radiance spectra have been computed on a $4000 - 25,000 \text{ cm}^{-1}$ wavenumber grid ($0.4 - 2.5 \mu\text{m}$) for the VNIR/SWIR band and a $700 - 1400 \text{ cm}^{-1}$ ($7.1 - 14.3 \mu\text{m}$) in the LWIR using MODTRAN 5.3.3 [22]. The initialization of the forward modeling is summarized in the list below:

1. 1 cm^{-1} band model for LWIR calculations and 15 cm^{-1} for SWIR calculations;
2. user-input atmospheric state variable profiles (e.g., temperature, pressure, and water content)

3. a nadir viewing geometry;
4. N-stream DISORT scattering model ($N = 2$ in LWIR and $N = 8$ or 16 in VNIR/SWIR);
5. 400 ppm uniformly mixed CO_2 ;
6. MODTRAN default O_3 profiles based on time of year;
7. Sun position corresponding to local noon for the time of year;
8. cloud-free line of sight;
9. variations in surface visibility based on geographic location;
10. variations in surface elevation based on geographic location; and
11. no spectral degradation (e.g., convolution with slit function) of the spectral axis.

In MODTRAN 5.3.3, users initialize the model run by incorporating this data into a specially formatted Tape 5 (tp5) input file. In order to input a user-defined atmosphere, instead of one of MODTRAN's 6 precomputed geographical-seasonal atmospheres designated as Models 1-6, MODTRAN must be set to run either Model 7, for which the user is required to input at least pressure, temperature, and water content as a function of altitude, or Model 8, in which MODTRAN computes geopotential height by solving the hydrostatic equation [75].

3.2 ASTER Surface Material Spectra

As is shown in both the LW and SW RT equations, measured radiance is a function of both atmospheric and surface variables. Surface modeling was accomplished by incorporating the spectral characteristics of 50 surface materials

obtained from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) database [23]. To ensure spectral diversity, a variety of naturally existing and man-made materials were selected. The laboratory data stored in the ASTER database was interpolated onto the same VNIR/SWIR and LWIR wavelength axes supplied to MODTRAN. The materials were assumed to be opaque and in LTE, such that reflectivity was given by $\rho(\lambda) = 1 - \epsilon(\lambda)$, as discussed in Chapter II. The emissivity and reflectivity spectra of the 50 materials used in this study are depicted in left and right panels of Fig. 14 respectively. Although there appears to be an emissivity bias in the LWIR material selection, many materials in the thermal region exhibit featureless emissivity spectra with a high mean emissivities [39]. The reflectivity spectra of materials in the VNIR/SWIR region, however, do exhibit much larger variance and high-frequency features.

3.3 World-wide Atmospheric Profile Data

It is common for an in-scene AC method to acquire a large set of atmospheric data. In many cases, this data is used to create a large look up table (LUT) that is referred to after some initial processing steps. The scheme employed by CHAERM requires reference be made to the transmission, path radiance, and downwelling spectra that are associated with a variety of physically realistic, meteorologically consistent, and diverse atmospheric profiles. It was determined that the GAPRI and TIGR datasets, whose researchers ensured both global coverage and atmospheric diversity, were appropriate for incorporation into CHAERM.

3.3.1 GAPRI Database.

The GAPRI database is a compilation of 8,324 vertical temperature, geopotential height, and relative humidity profiles, each of which is conveyed at 29

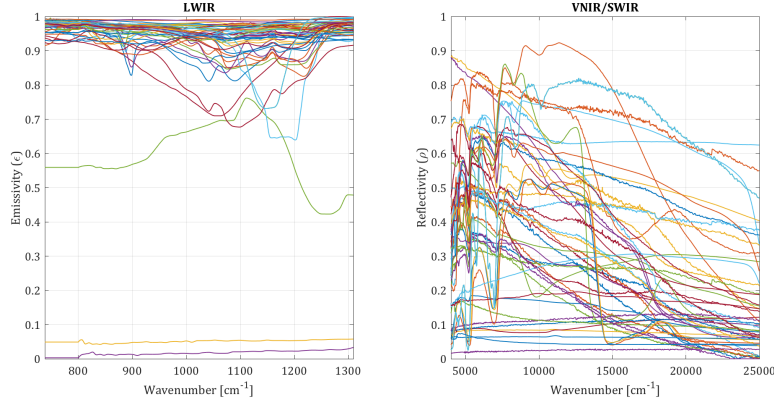


Figure 14. Examples of LWIR emissivity (left) and VNIR/SWIR reflectivity (right) spectra obtained from the ASTER database.

pressure levels from 1000 hPa to 20 hPa [76]. The GAPRI profiles are derived from the reanalysis products obtained from the European Center for Medium Range Weather Forecasts (ECMWF) in the year 2011. The goal with GAPRI is a dataset that spans most meteorological realizable states with a moderately sized ensemble, and each of its atmospheric profiles is included because it statistically contributes to complete atmospheric coverage between the surface and the top of the atmosphere (TOA) [76]. Salient to the clear-sky assumption in this research, it is worth noting that each GAPRI profile has also been screened to avoid incorporating any cloud layers.

The GAPRI profiles are described by latitude/longitude coordinates, a land/sea flag, a day/night flag, and an estimate of total precipitable water in the atmospheric column. This research incorporated 4,846 of GAPRI’s day only profiles over both land and sea, with no geographic filtering. The locations of the profiles are shown in Figure 15.

3.3.2 TIGR Database.

The TIGR database, first developed in 1985 and most recently modified in 2010, is a similar climatological library. Like GAPRI, its goal is a spanning database of

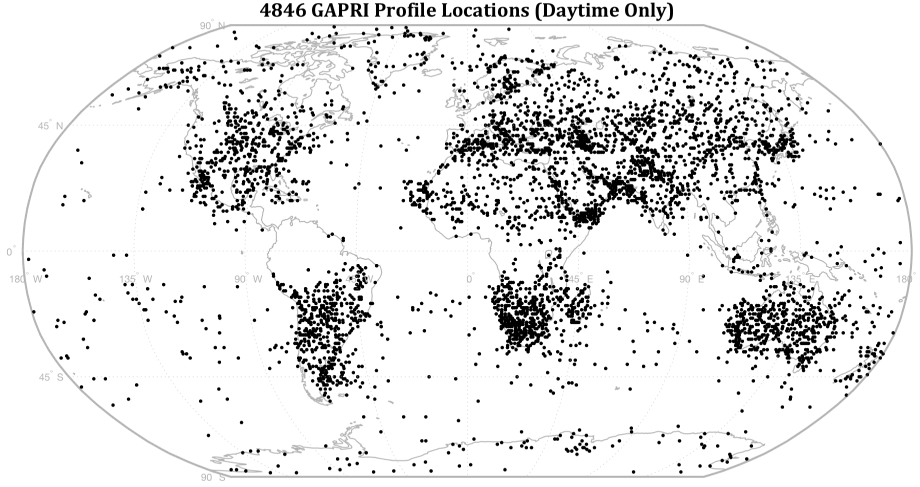


Figure 15. Geographic location of the 4,846 GAPRI atmospheric profiles.

worldwide meteorological profiles. The TIGR dataset comprises 2,311 atmospheres representing a statistical distillation of more than 80,000 diverse radiosonde data files, and its 2010 revision also incorporates climatological reanalysis data in the upper levels of the atmosphere [77]. The 2,311 database entries are binned into tropical, mid-latitude, and polar airmass categories and include temperature, water vapor, and ozone concentration at 43 pressure levels, starting at the surface (1013 hPa) and extending above 30 km (< 1 hPa). The geographic location of the TIGR atmospheric profiles is depicted in Figure 16. To maintain consistency with GAPRI and to facilitate comparisons, the TIGR profiles were truncated above 25 km. Unlike GAPRI, no guarantee of cloud-free conditions was asserted, and it was noted that in a few atmospheres ($< 1\%$) the water content in at least one atmospheric layer resulted in supersaturation (i.e., relative humidity greater than 100%). In each of these cases, the humidity values were capped at 100%.

2311 TIGR Atmospheric Profiles

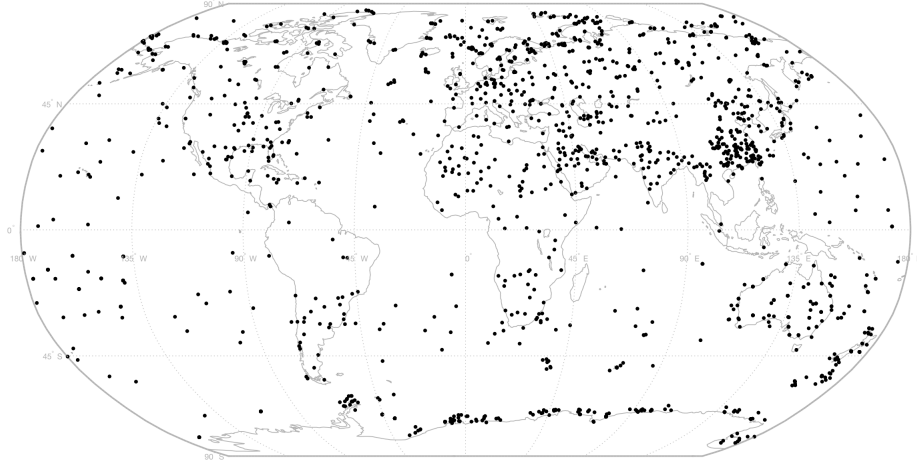


Figure 16. Geographic location of the 2,311 TIGR atmospheric profiles.

Although GAPRI and TIGR were developed with similar methodologies and intent, they are not identical datasets, which is why both are incorporated in this research. In Figure 17, the temperature profiles for each database are plotted as a function of atmospheric pressure. The mean profile is also overlaid, bracketed by the standard deviation. It is readily apparent that the GAPRI dataset contains a larger number of warmer profiles than does TIGR. The standard deviation in the TIGR dataset is also ~ 20 K larger than GAPRI's. There appears to be evidence of structure near the tropopause in many of the GAPRI files, evidenced by the sharp kink near 100 mb. This may be an artifact of the reanalysis data and is likely non-physical, however the contribution to the radiative transfer in this part of the atmosphere is negligible, these layers of the GAPRI profiles was not modified.

3.4 Use of LEEDR for visibility estimates

Like MODTRAN, the Laser Environmental Effects Definition and Reference (LEEDR), developed and maintained at the Air Force Institute of Technology, is a

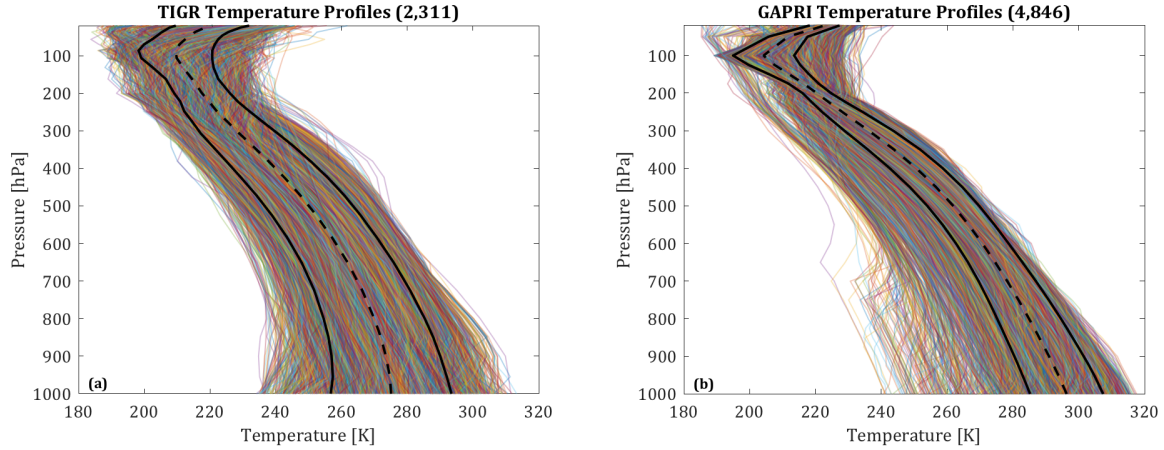


Figure 17. Temperature profiles of TIGR (left) and GAPRI (right) as a function of pressure. Mean temperature profile is indicated by black dashed line. Standard deviation is indicated by solid black line.

comprehensive atmospheric characterization tool capable of simulating radiative transfer processes at high spectral resolution. LEEDR farms its data from a variety of sources to achieve physically realistic vertical profiles of the atmosphere, placing emphasis on accurately describing the Earth's boundary layer at a specific location, given the time of day and time of year [78]. The boundary layer is defined using a probabilistic surface climatology database that stands at the forefront of generating realistic aerosol loading [52].

Aerosols are an important consideration in the calculation of surface visibility. This research, though beholden to MODTRAN for its radiative transfer calculations, incorporated LEEDR to facilitate the determination of realistic surface visibilities for the TIGR and GAPRI atmospheric profiles based upon the geographic location of each atmospheric profile. Surface visibility is a derived quantity obtained after calculating four extinction coefficients at 550 nm: aerosol scattering, aerosol absorption, molecular scattering, and molecular absorption. By providing LEEDR with a location and time of year for each of the TIGR and GAPRI profiles, the

extinction coefficients are determined through reference to the Global Aerosol Data Set (GADS), which provides aerosol constituent number densities as a function of geographic coordinates. LEEDR calculates and reports the four coefficients for each of the layers in the atmosphere. The sum of these coefficients in the lowest atmospheric layer determined the overall extinction coefficient β_{ext} , whose units are typically expressed in km^{-1} . MODTRAN’s definition of visibility (V) is given by

$$V = \frac{\log(50)}{\beta_{ext} + 1.159 \times 10^{-2}} \quad (23)$$

where the second term in the denominator accounts for Rayleigh scattering near sea level at 550 nm [22]. The β_{ext} obtained from LEEDR as used to calculate the visibility for MODTRAN’s runs using Eq. 23. MODTRAN’s V compares to LEEDR’s visibility value within ± 5 km.

Incorporating visibility into the database is valued added, as it can be shown that water content alone does not robustly estimate visibility at a particular location. Figure 18 demonstrates how data in the GADS database changes the visibility considerably for atmospheric states whose total water content and low-tropospheric water distribution are very nearly identical (water content data were obtained from MODTRAN’s tp6 files, see Section 4.1 for additional discussion). In spite of similar water profiles, the calculated visibility in the sub-Saharan African region, where dust and sand are prevalent on the surface is 14.7 km, compared to visibilities > 80 km in forested, un-industrial regions.

The extent that visibility is modeled accurately is particularly important for scattering calculations in the VNIR/SWIR. Figure 19 compares transmission spectra in the VNIR/SWIR and LWIR when two different visibilities are input into MODTRAN. The 23 km visibility corresponds to MODTRAN’s rural default visibility. The scattering calculations differ considerably in the VNIR portion of the

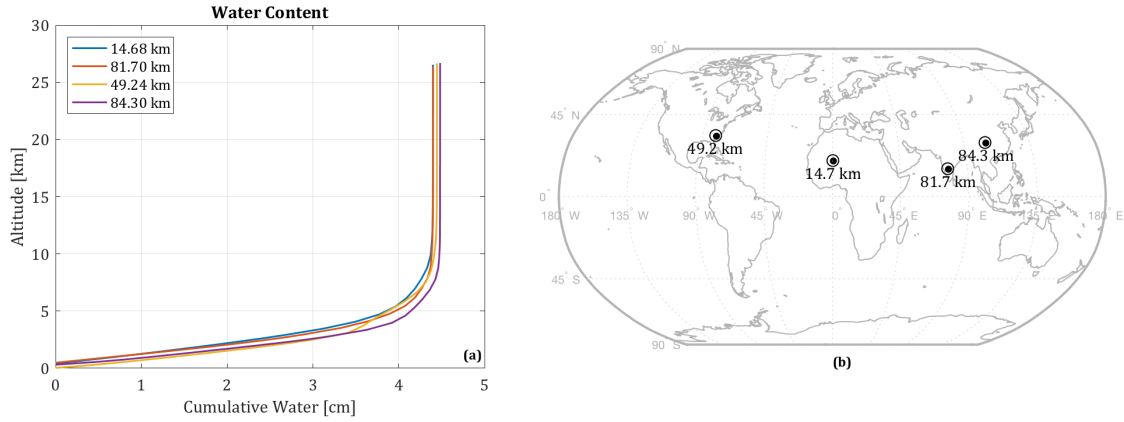


Figure 18. Demonstration of effect of geographic location on determining visibility at surface. (left) Cumulative water distribution functions of four GAPRI atmospheres, each having approximately 4.5 cm of water. (right) The locations of those profiles depicted with the associated visibility.

spectrum, and the overall trend of using the default rural visibility for all calculations is to underestimate the transmission function. In fact, based on the extinction coefficients retrieved by LEEDR, less than 3% of the GAPRI profiles have visibilities at or less than 23 km.

3.5 Incorporating surface elevation

This research added to the fidelity of the TIGR and GAPRI databases by using each profile's geographic coordinates to incorporate information about the surface elevation above mean sea level (MSL). The Google Maps Elevation Application Programming Interface (API) available at <https://developers.google.com/maps/documentation/elevation/> was utilized to query each profile for its respective surface elevation. Over most land surfaces, the API has geographic resolution less than 100 m, meaning the queried surface

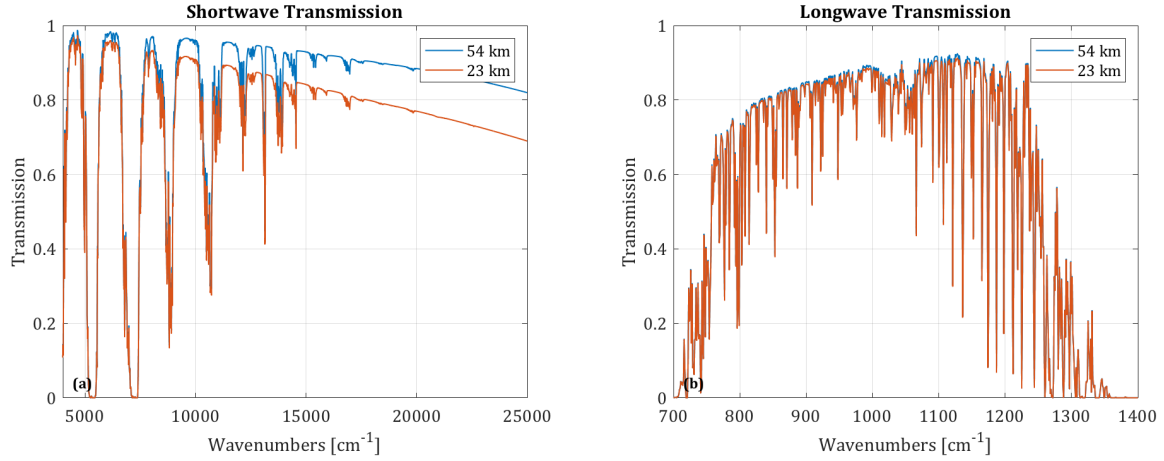


Figure 19. Transmission spectra comparison in the VNIR/SWIR (left) and LWIR (right) using 23 km and 54 km surface visibilities.

elevation is interpolated from data no more than 100 m away. Although no documentation could be found, it is assumed that the surface elevation reported by this API is accurate to within ± 10 m. For the purposes of this research, an uncertainty in either location or elevation was deemed to be suitably accurate.

The interest in including surface elevation into the radiative transfer modeling stems from the importance of accurately estimating the path length from surface to sensor. Suppling MODTRAN with a user-defined atmosphere that includes layer elevations initiates a Model 7 initialization, from which two undesirable outcomes occur if the surface elevation does not match the elevation of the lowest layer of the atmospheric profile:

1. If the surface elevation is below than the lowest atmospheric layer,
MODTRAN aborts the run entirely; or
2. If the surface elevation is higher that the lowest atmospheric layer,
MODTRAN reassigns the surface elevation to match the atmospheric data.

If Model 8 is used and only pressure and temperature are inputted, MODTRAN

will assign layer elevations using the hydrostatic equation. Since there is no implicit conflict, the Model 7 errors do not occur. However, MODTRAN was observed to always assign the inputted surface elevation to the first layer of the atmosphere, regardless of that layer’s pressure. This was problematic because both TIGR and GAPRI use invariant pressure profiles, resulting in a non-realistic atmospheric state at and near the surface.

A quick simulation was accomplished to determine the extent of the problem. MODTRAN was run with a 1.6 km surface elevation and GAPRI’s invariant surface pressure of 1000 hPa. This is, of course, an exceptionally unlikely combination of these two variables (i.e., surface pressures at this 1.6 km are typically between 810 – 850 hPa). As a result, the total water content in the layer was 4% higher than if the same atmospheric profile was run with a surface pressure equal to 843 hPa. Although this doesn’t seem overly significant, LWIR radiative transfer in the atmosphere is manifestly sensitive to water content deviations on this order.

Thus, it was deemed that developing an adaptation method was an important step to account for variable surface elevations with an atmospheric database, such as TIGR or GAPRI, whose data are reported on a fixed pressure grid. This research investigated two complementary methods, which will be summarized in what follows.

3.5.1 Method #1: Hypsometric Adaptation to Altitude Data.

Method #1 modifies TIGR’s pressure grid by assigning above ground level (AGL) altitudes to each pressure level. Because TIGR does not provide any elevation data, this method creates the elevation grid by taking a layer’s pressure and temperature and using the hypsometric equation to determine its vertical extent (i.e., thickness). The hypsometric equation, derived from the hydrostatic

equation and the ideal gas law, computes the layer thickness z as

$$z = \left(\frac{R_d T}{g} \right) \log \left(\frac{P_0(z_0)}{P(z)} \right), \quad (24)$$

where $g = 9.81 \text{ m/s}^2$, $R_d = 287 \text{ J/K}\cdot\text{kg}$, the specific gas constant for dry air, T is a representative temperature (K) in the layer, and P is the pressure at some elevation. Temperature is typically approximated in some meaningful way, and here it was found that there was no significant impact on accuracy if the layer temperature was used. Eq. 24 can easily be rearranged to estimate the pressure at some distance z from a known surface z_0 . In this form, the hypsometric equation is

$$P(z) = P_0(z_0) \exp \left(\frac{-gz}{R_d T} \right). \quad (25)$$

As z is calculated for each layer using the standard pressure grid and unique temperature profile, the AGL altitudes are added to the station elevation obtained from the Google API. Now using Eq. 25, it is possible to resample the pressure grid and map the temperature, water, and ozone profiles to the new grid. This method can also be applied to the GAPRI database. However, since GAPRI provides elevation data as part of the atmospheric profile, the first step of the method is simplified, not requiring Eq. 24.

The effect of this method on the elevation profile is a positive bias, since the surface elevation is technically being added to each layer. Unfortunately, this results in unphysical combinations of temperature, pressure, and elevation in the upper levels of the atmosphere. The most noticeable effect was a displacement of the tropopause in the mid-latitudes to altitudes above 20 km, which is not at all accurate. To combat this, a weighting factor was introduced, whose purpose was to “blend” the original altitude profile with the biased profile. Preference was given to

the adapted profile in the lower parts of the atmosphere and to the original profile approaching the typical tropopause altitudes. This results did achieve an effective compromise that was at least more physically viable albeit arbitrary. The subsequently investigate method attempted to maintain a closer connection to the actual physical processes governing the atmospheric state.

3.5.2 Method #2: Truncation & Resampling Modification to Altitude Data.

It is worth mentioning that the intention here is to convey the information content of each database atmospheric profile accurately with a geographic dependence. More simply, the point is to perform an adaptation to the database profiles that accounts for surface elevation and that results in an atmosphere that is likely to occur at the specified location. Simply truncating the profiles by removing all of the data in a profile “below” the actual geographic surface elevation was thought to likely eliminate near-to-surface features (e.g., a temperature inversion) that might be important to capture in radiative transfer. However, in the processing of the data, it became apparent that, in particular with the GAPRI database, if the information of the original profile was assigned in any way to the new surface elevation, the trend was a database whose temperatures near the surface were statistically too warm. To validate this, individual profiles were compared to radiosonde data obtained near the same location, and it was clear that the result of the initial modification was to create atmospheric profiles that were less likely to have occurred. Thus, it was determined that truncating the profiles was the most appropriate way to modify the profiles. Additionally, the data were then resampled to ensure the original sampling interval was maintained, such that the layer spacing nearer the surface is smaller than in the upper atmosphere.

With the TIGR data set, this method begins by again uses hypsometric equation to establish a surface pressure estimate P_{est_surf} , using the surface temperature and the surface elevation. Then, each layer is prescribed a scale factor $\alpha = \frac{P_0 - P_{layer}}{P_0}$, and new pressure data is calculated using $P_{new} = \alpha P_{est_surf}$. The original temperature, water, and ozone profiles are then truncated, removing the data below surface elevation. Finally, an adapted altitude grid is calculated using the new pressures and temperatures. This method was easily adapted to the GAPRI data by using GAPRI's original altitude grid to determine the sampling frequency. An example demonstrating how the the truncating and resampling method compares to truncating only for a GAPRI profile with a surface elevation of 1.6 km is shown in Figure 20. The dots indicate the discretized data points of the profile. In the far right plot, the vertical separation of the data is depicted on a vertical axis only to allow a comparison of the sampling step-size.

3.5.3 Validation of Adaptations with Real-world Data.

In Fig. 21, both modifications to GAPRI #1's temperature profile are shown. GAPRI #1's surface elevation is almost identical to Denver, Colorado, so here a comparison is warranted to Denver's climate. This is calculated by calculating the mean temperature profile of 211 radiosonde files measured over the course of 2015 by the the Denver station. As is shown in Fig. 21, Method 2, which uses both truncation and resampling, is the more appropriate way to modify the profiles for the 1.6 km surface elevation. Although the arbitrary blending technique used with Method 1 does model the conditions near the tropopause well, Method 2 has a more appropriate surface temperature and temperature lapse rate.

The next validation involved looking at more of the profiles whose assigned surface elevations were similar to the Denver example. Of the 4,846 individual

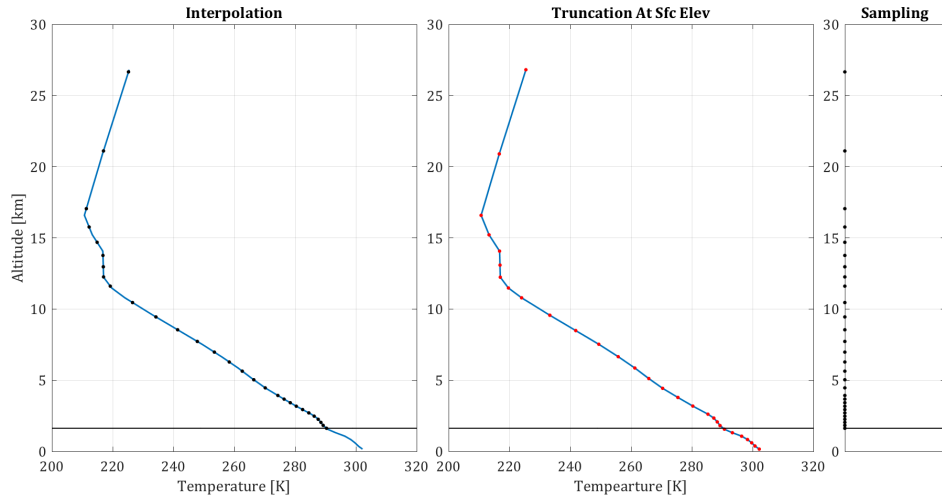


Figure 20. Example of truncating and resampling a temperature profile (left) versus truncating only (center). Sampling rates are shown in the rightmost plot, demonstrating the increased data sampling of the interpolation scheme below 5 km.

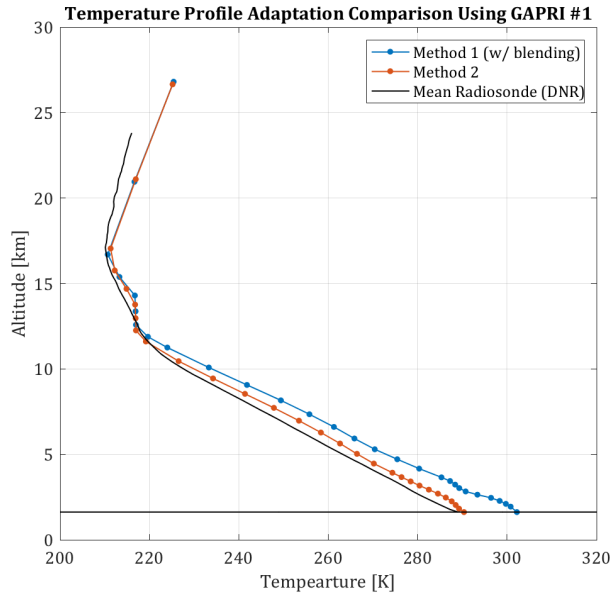


Figure 21. Comparison of temperature profile resampling results of Method 1 and Method 2, including the mean temperature profile from 2015 radiosonde data in Denver, CO.

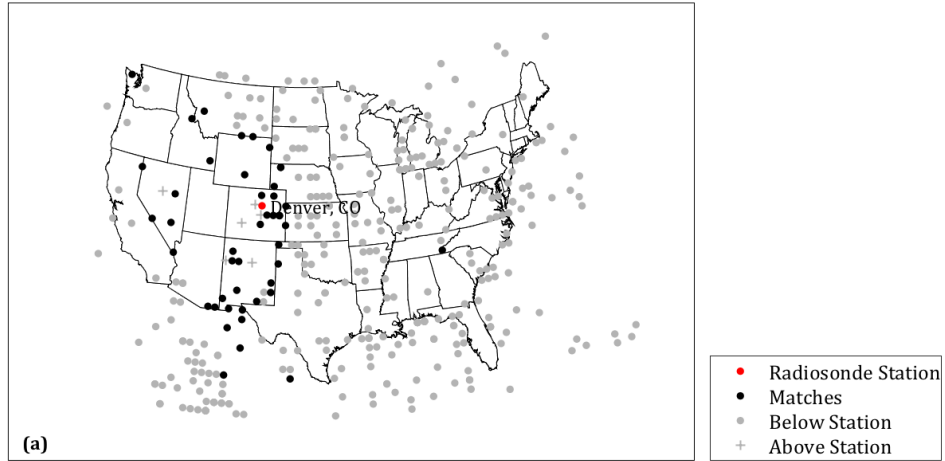
GAPRI profiles, 49 of them in the CONUS alone and 436 throughout the world had surface elevations within 500 m of Denver. These temperature profiles are compared with the mean radiosonde data discussed above in Fig. 22. The mean and standard deviation of the Denver’s radiosonde data is also shown. Qualitatively, at least, it would appear that the Denver climate is adequately represented by the data in the GAPRI database that takes into account surface elevation and appropriately modifies the atmospheric state profiles. A comparison to the TIGR database was also accomplished and is shown in Figure 23. TIGR is a smaller database and does not offer the same amount of geographic coverage, but its modified profiles were also shown to be consistent.

Because of the distribution of surface elevations on the Earth, locations at or near sea level match to a much larger number of entries in the GAPRI database. The next investigation was to determine the impact of paring the datasets using geographic filtering. Figure 24 depicts the CONUS and worldwide GAPRI matches to three different CONUS radiosonde station locations, Albuquerque, NM (elevation 1.6 km), Key West, FL (elevation 13 m), and Omaha, NE (elevation 350 m). Considering CONUS only profiles remains representative, but the most complete coverage requires a worldwide search. The motivations for modifying these databases were based upon their specific function in the CHAERM AC method that will be discussed in Chapter 5, but these databases would also be appropriate for any usage in which atmospheric characterization would be better served by consideration of surface elevations.

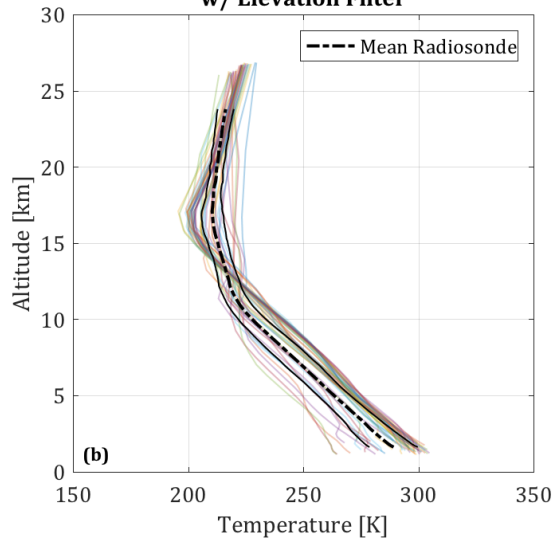
3.6 Building Simulated Hyperspectral Data Sets

The initial testing of the AC method developed in this research utilized simulated data exclusively. Simulated spectral radiance data was generated using

**GAPRI Profiles Matches to Denver, CO +/- 500 m
(Truncation Method)**



**CONUS GAPRI Matches (49)
w/ Elevation Filter**



**World GAPRI Matches (436)
w/ Elevation Filter**

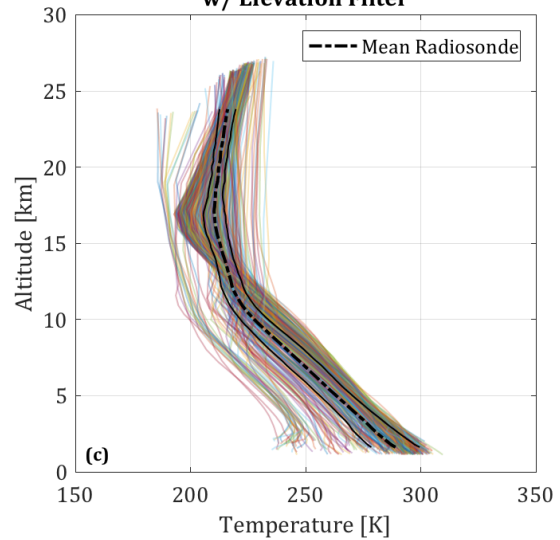
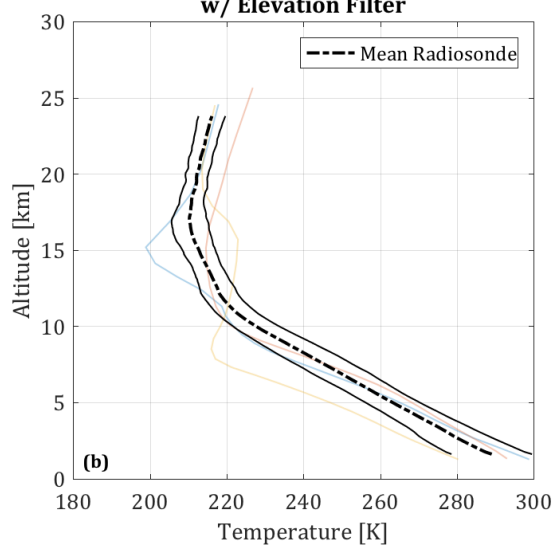


Figure 22. (a) Location of CONUS GAPRI profiles matching the Denver, Colorado radiosonde station elevation within 500 m; (b) CONUS GAPRI temperature profiles with mean DNR radiosonde profile overlaid; (c) Worldwide GAPRI temperature profiles with mean Denver radiosonde profile overlaid.

**TIGR Profiles Matches to Denver, CO +/- 500 m
(Truncation Method)**



**CONUS TIGR Matches (3)
w/ Elevation Filter**



**World TIGR Matches (37)
w/ Elevation Filter**

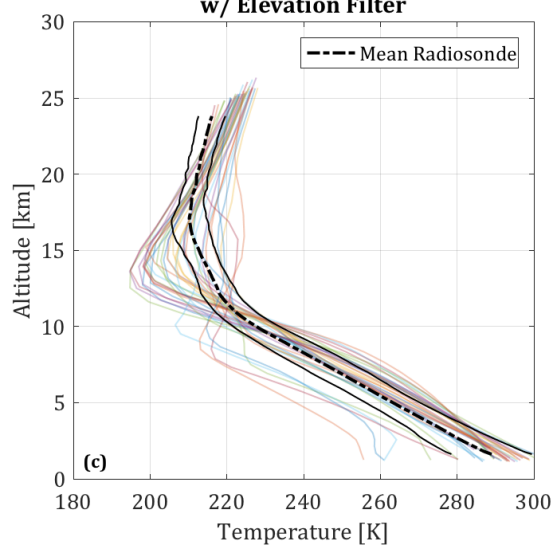


Figure 23. As with Figure 22 but using TIGR data.

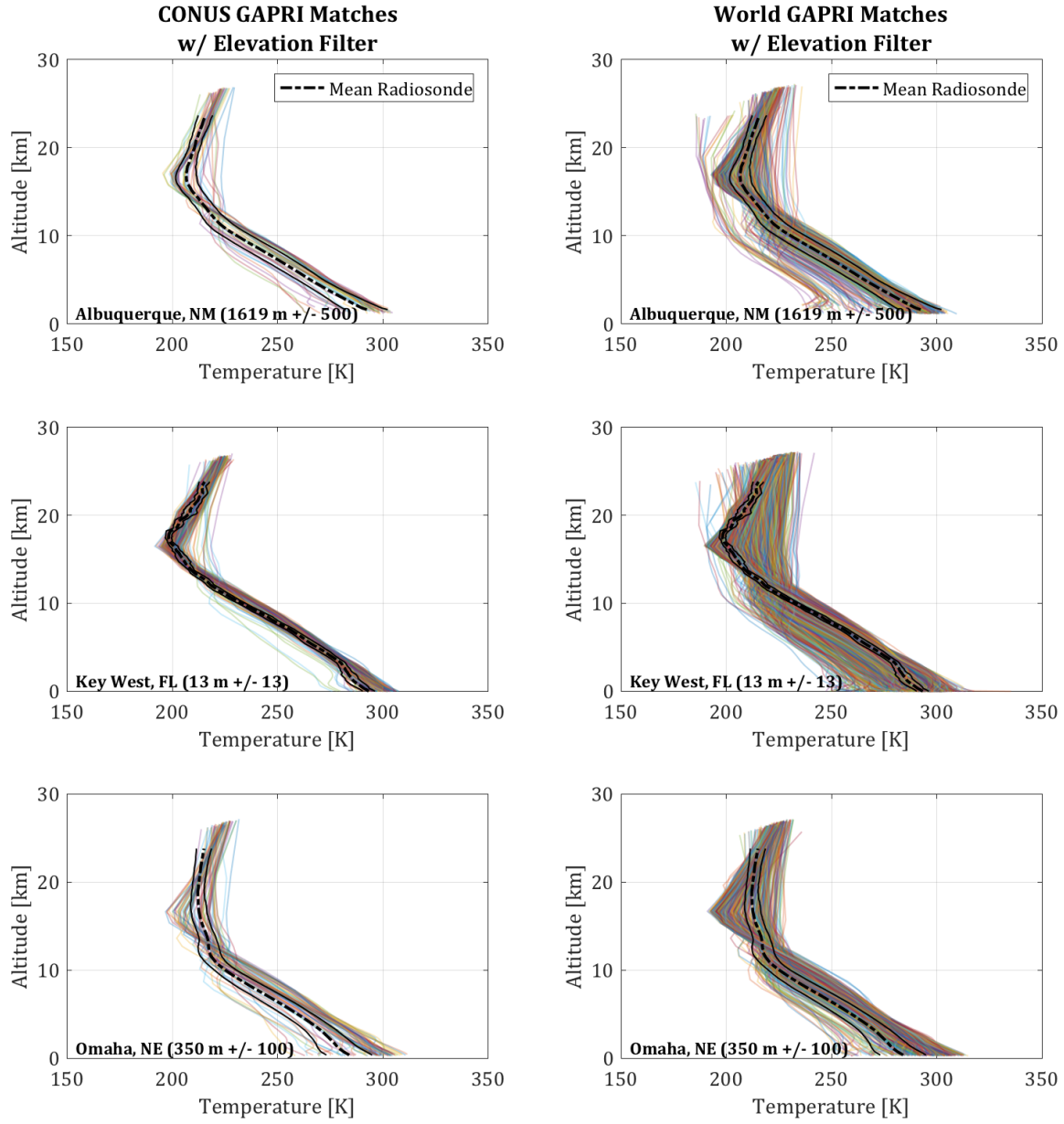


Figure 24. CONUS (left column) and worldwide (right column) GAPRI temperature profiles for three different CONUS locations. Location, surface elevation, and matching criteria are indicated at the bottom of each panel.

the longwave and radiative transfer equation. The TUD components of the RT equation were supplied by MODTRAN, using atmospheric profiles from TIGR, and the emissivity spectra of the surface was obtained from ASTER. Utilizing simulated data is commonplace, and the method by which it was created in this research was similar to several previous research efforts in this field [79, 80, 81].

The meteorological consistency of the TUD spectra were ensured by using the TIGR data as inputs to MODTRAN. A variety of atmospheric states, with different temperatures and water content, were pulled from the TIGR database to simulate a variety of atmospheric conditions. To help ensure cloud-free line of sight, the TIGR atmospheres were associated with actual radiosonde data that were confirmed to be cloud-free through reference to observation data maintained on the National Climactic Data Center’s website. Association was accomplished forward modeling the radiosonde data and comparing the concatenated transmittance and path radiance spectra to the forward modeled transmittance and path radiance spectra calculated with TIGR data. In all, a sample of 49 clear-sky sonde files yielded 49 unique TIGR atmospheres that were used to simulate viewing conditions. The similarity between the radiosonde and TIGR data was obtained using the spectral angle.

The TUD spectra chosen from the TIGR database was then used to model at-sensor radiance for an artificial scene of 3,200 pixels ($50 \text{ rows} \times 64 \text{ columns}$) by first assigning each pixel one of 50 ASTER spectra. Each pixel’s surface temperature was assigned from a normal distribution about the temperature of the lowest atmospheric layer with a standard deviation of 4 K. Suitable signal diversity was obtained using this approach, and five examples, at 1 cm^{-1} resolution, are depicted in Figure 25. Pixel #2’s signal is unique because its surface material was copper, whose LWIR emissivity is low across the entire band. As a result, this signal

is mostly composed of atmospheric energy. It will be shown these pixels are of little use to CHAERM’s algorithm, as is the case with most in-scene LWIR AC algorithms. A technique to avoid incorporating them into the algorithm will be discussed later.

The other signals shown are indicative of surface materials at terrestrial temperatures whose emissivity function is high. Because these materials do not reflect much downwelling radiation, these types of materials are very useful to AC methods, to include CHAERM. The lack of high frequency content in Pixel #3 and Pixel #4 indicates that the radiometric surface temperature and the effective temperature of the atmosphere are similar, whereas the more prominent line absorption features seen in Pixel #5 indicates the surface was radiometrically warmer than the atmosphere. The relative strength of these absorption lines will be crucially important to CHAERM’s calculations. This underscores the importance of temperature variation throughout the scene, which again, is necessary for the success of a most in-scene approaches to AC, to include Young et al’s ISAC and CHAERM. Most scenes naturally exhibit sufficient variability amongst the surface materials, even when the surface materials are very similar.

3.7 Real-world Sensor and Data Specifications

Portions of this research will be validated using real-world sensor response. The sensor incorporated into this research was the spatially enhanced broadband array spectrograph system (SEBASS), a dispersive infrared spectrometer developed by Aerospace Corporation [82]. The SEBASS disperses radiation into 128 contiguous spectral channels between $7.5 - 13.5 \mu\text{m}$ [83], whose band-center spacing is $30 - 70 \text{ nm}$. This corresponds to spectral resolution of $2 - 10 \text{ cm}^{-1}$. To assist with processing in MODTRAN, reference was made to a Environment for Visual Images

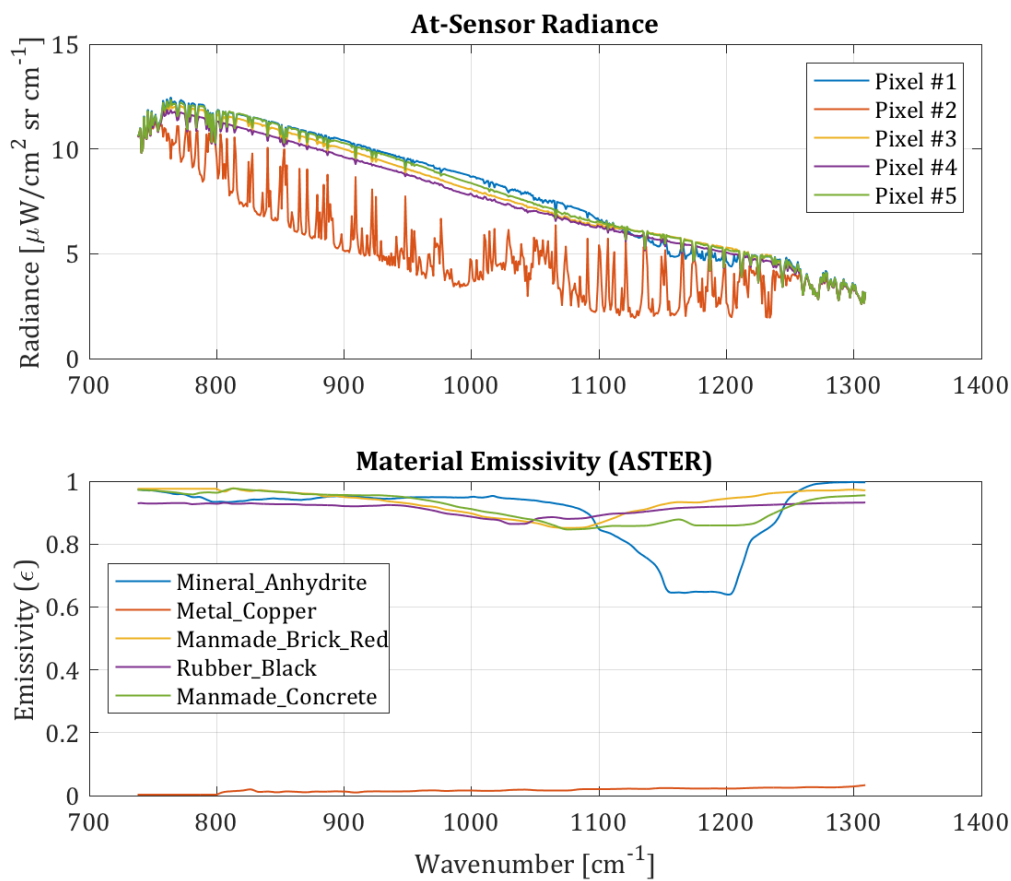


Figure 25. (top) Simulated at-sensor radiance spectra for five different materials. (bottom) ASTER emissivity spectra for the materials.

(ENVI) header file obtained from a real-world collection. However, the sensor response was not included in this file, which provided the band centers. To create realistic sensor effects using MODTRAN, a filter function was created with a triangle scanning function whose FWHM was set equal to the band center spacing. A previous studies by Kaiser et al. [84] validated this approach to sensor response modeling.

The final portion of this research incorporated six real-world HSI data sets collected by SEBASS. Each was obtained with a NADIR viewing geometry at or less than 5 km. The collections occurred in the summer months. In order to facilitate various aims, to include testing AC algorithms, the scene was populated various man-made materials, whose temperatures and emissivities were measured and recorded. *In situ* weather data, obtained from locally launched radiosondes were also made available.

IV. Parameterizing the Atmospheric State

The examination of the GAPRI and TIGR profiles in Chapter 3 only considered temperature profile comparisons. While temperature is an important variable to model, water content is often the more (perhaps most) influential variable in radiative transfer modeling. As was discussed in Chapter II, water is a difficult variable to estimate accurately because of its considerable variability in its distribution through the atmosphere as well as a dependence on other atmospheric variables such as temperature and pressure. It has been shown that the uncertainty in the water vapor profile is often the largest source of atmospheric error in radiative transfer modeling [85].

The purpose of this chapter is to explore more thoroughly the sensitivity of radiative transfer to the atmospheric state by quantifying the impacts of total water content, water distribution, and temperature on LWIR radiative transfer, specifically with regard to transmission and path radiance. Over the course of this investigation, focused relating atmospheric inputs to radiative transfer outputs, the underlying challenge associated with non-unique solutions manifested by the anti-correlation between transmission and path radiance will become readily apparent. This chapter will then go on to investigate whether or it is feasible to reduce the temperature and water concentration profiles comprising the atmospheric state into a parameterized function form using three or fewer tunable parameters. This will underscore the efficiencies that stand to be gained, at the expense of what turns out to be very manageable errors the radiative transfer outputs.

4.1 Inputs to Outputs Sensitivity Study

The GAPRI and TIGR databases each have a large span of meteorologically consistent atmospheric profiles. Here, the GAPRI atmospheric states were used to facilitate a comprehensive and quantitative relational study between atmospheric inputs and RT outputs. In addition using MODTRAN to generate the TUD spectra, the tp6 data of the atmospheric state variables was also gathered. Of particular interest was MODTRAN's calculation of the layer water density ρ_{H_2O} in each of the specified atmospheric layers. From the water density, the water content w in an atmospheric layer was estimated by

$$w = \rho_{H_2O} \Delta z, \quad (26)$$

for a layer thickness Δz . This value is equivalent to the columnar water content in cm. The cumulative water content Q is then

$$Q_j(\Delta z_j) = \sum_{i=1}^j w_i \Delta z_i \quad j = 1 \dots N, \quad (27)$$

where N is the last atmospheric layer at the top of the modeled atmosphere.

This discretized layer-by-layer approximation agreed with MODTRAN's water content calculation to within 10% for all atmospheres, and the small discrepancy was attributed to MODTRAN's internal discretization of the atmospheric state. For the methods employed here, consistency of the calculation with the water density profile was more important than absolute accuracy of the total water content.

Compiling the temperature, water density, and cumulative water profiles allowed the GAPRI atmospheres to be binned by parameter and explored computationally. An example of such an analysis is depicted in the panels of Figure 26, which

compares 2 atmospheres. The total water content of these atmospheres is approximately equal, but the water distribution and the temperature profiles are not. The atmosphere depicted in blue is warmer on average and has a small region near 2 km where it has less water than the atmosphere depicted in red. Two different types of transmission spectra are shown in the second row of this figure. On the left, total transmission is shown bounded by an estimate of the continuum absorption. On the right, the effects of line absorption only are shown. Total transmission is the product of the two phenomena, $\tau(\lambda) = \tau_l(\lambda)\tau_c(\lambda)$. The process by which line spectrum can be estimated from the at sensor radiance will be discussed in detail in Chapter 5.

What should be noted at this point is that the atmosphere depicted in blue in Figure 26, owing to less water content in the denser portions of the atmosphere, exhibits less continuum absorption. Because continuum absorption in the LWIR increases when the water is located lower in the atmosphere where the overall air density is higher [40, 41], this spread is consistent with RT theory. However, the estimate of its line absorption effects in the prominent water absorption line at 853 cm^{-1} is slightly greater. This points to a dependence of line absorption on both the number density of absorbers and their temperatures.

Because neither temperature and water content must exhibit any monotonicity as functions of altitude, there are a lot of different relationships that follow. For example, in Figure 27, the difference in the line transmittance values at 853 cm^{-1} is 0.05, despite the fact that the mean temperature profiles are and the total water content are very similar. The difference in water distribution profiles has the obvious effect on the continuum.

Exploring and understanding the coupled and individual effects of temperature, water density, and total water on both line and continuum RT phenomenology can

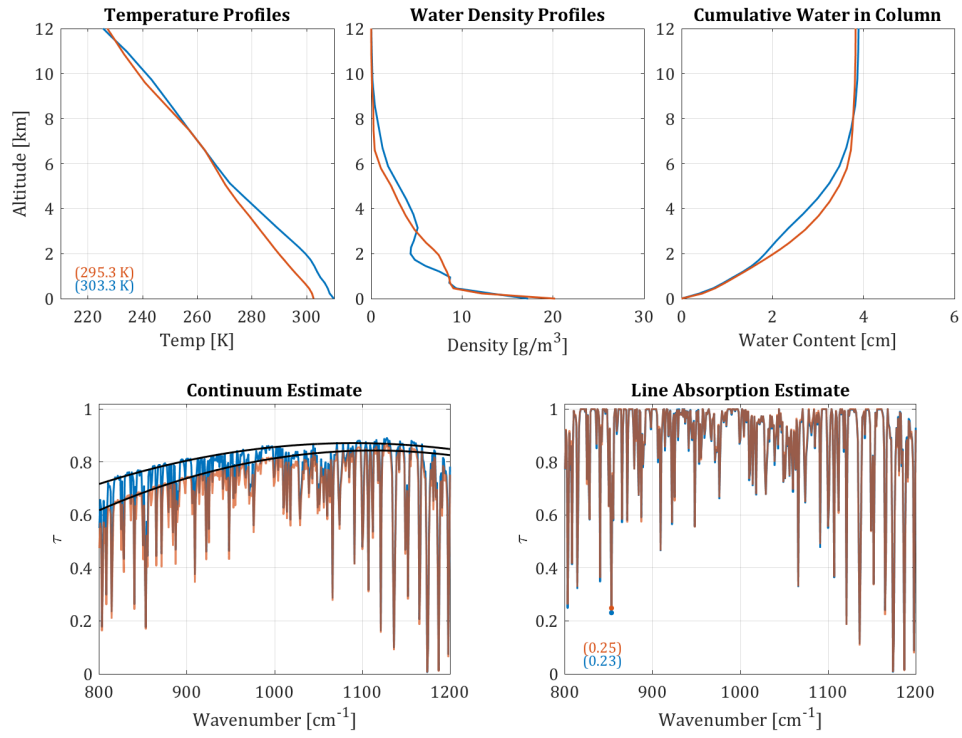


Figure 26. Comparison of atmospheric inputs and RT outputs for two atmospheres with similar water content but different water distributions and temperature profiles.

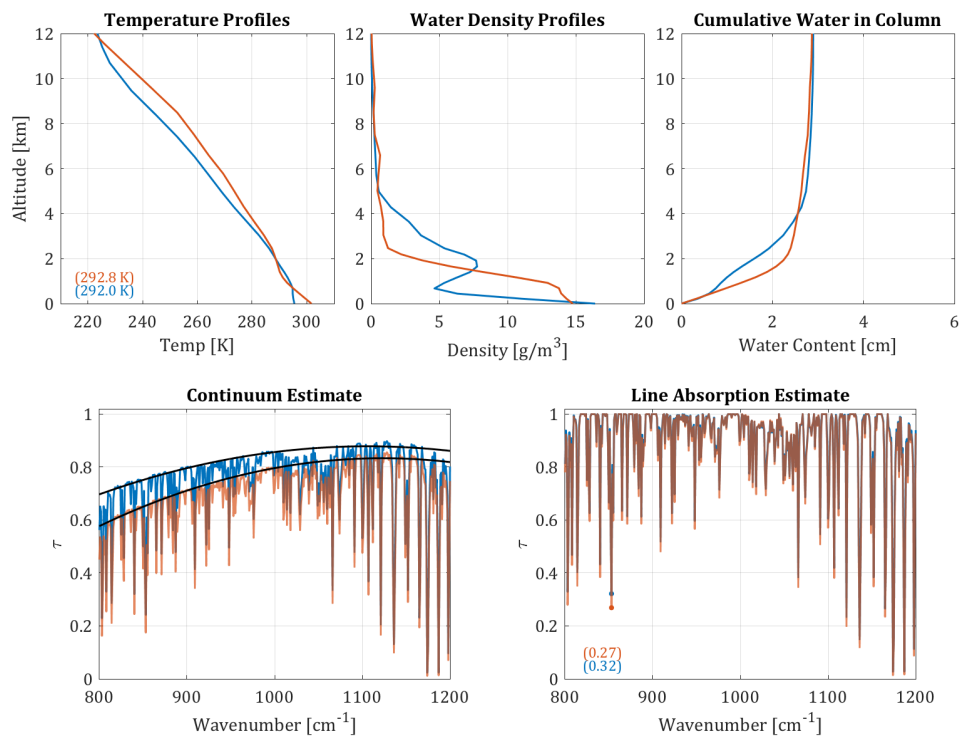


Figure 27. As with Fig. 26 but for two profiles with similar temperature profiles.

certainly help the development of an AC method but is also quite complex. As water content increases in an atmosphere, there is a more significant dependence on both how the water is distributed and the temperature profile.

In Figure 28, the temperature and water dependencies on the strong water absorption feature at 853 cm^{-1} are explored for all of the atmospheres in the GAPRI database. Looking at the entire dataset reveals some overall trends but also the subtle nuance in the interdependence. It is clear from these plots that for any appreciable water content in the atmosphere, the transmission effects are dependent upon the atmospheric temperature with warmer temperatures resulting in more line absorption and perhaps slightly less continuum absorption. To show the anti-correlated relationship between transmission and path radiance, the associated path radiance quantities for the GAPRI database are depicted in the plots in Figure 29.

In summary, Table 1 provides the statistics of the temperature and water dependencies of the 853 cm^{-1} water line. The first column shows that while warmer atmospheres do indeed contain more water, there is less variance in the mean of the temperature profiles. The transmittance also predictably decreases as water content increases, and the distribution tightens.

The interest in line transmittance is not simply anecdotal. Chapter 5 will show how CHAERM derives and utilizes the line transmittance spectra as a foundational

Table 1. Mean (standard deviation) of temperatures and line transmittance at 853 cm^{-1} as a function of total water content.

Total Water	Temp (T) μ (σ)	Line Trans (τ) μ (σ)
2 cm	289.5 (4.5)	0.40 (0.04)
3 cm	293.2 (3.8)	0.28 (0.03)
4 cm	296.5 (2.9)	0.20 (0.02)

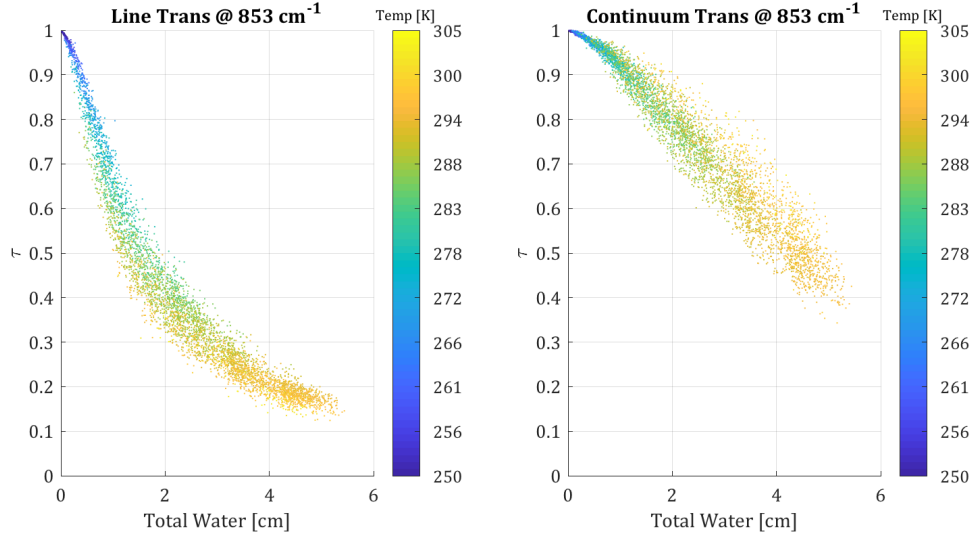


Figure 28. The dependence of line transmission (left) and continuum transmission (right) at 853 cm^{-1} on mean temperature in the lower troposphere and total atmospheric water.

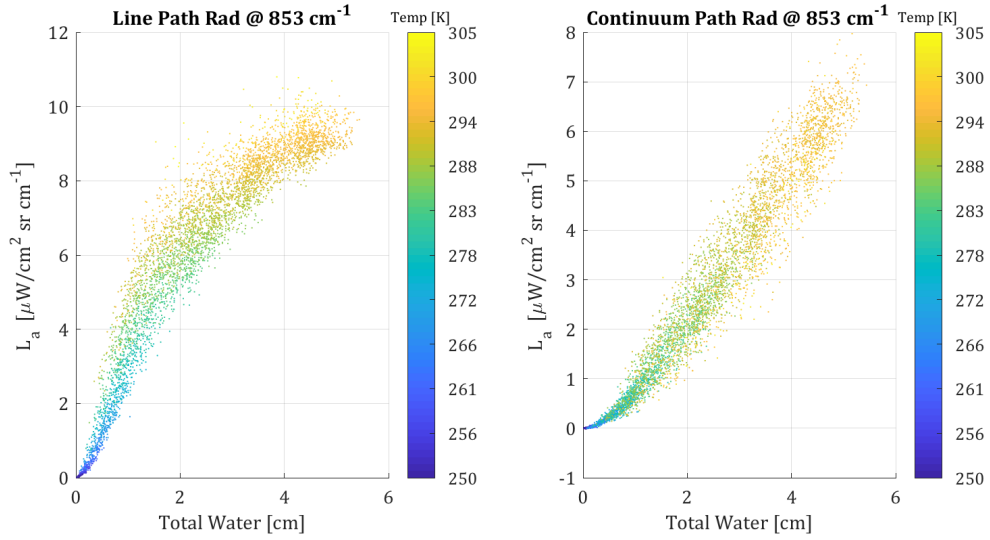


Figure 29. The dependence of line path radiance (left) and continuum path radiance (right) at 853 cm^{-1} on mean temperature in the lower troposphere and total atmospheric water.

part of its atmospheric estimation. Despite the uncertainty that temperature brings to the amount of line absorption and emission in a channel, the challenges associated with solving inverse problems and ensuring unique solutions can be, in part, mitigated by investigating the line and continuum absorption spectra separately. The next section will explore how the coupled effects of total transmittance and total path radiance in the LWIR RT equation can compensate for each other with a troubling effect on in-scene atmospheric compensation schemes. This occurs because the physical mechanisms governing both phenomena are linked, and thus, it can be shown that many atmospheric states manifest their effects on the surface-leaving signal in nearly identical ways. This can undermine the success of any inverse model, so it is worthy to cover in some detail.

4.2 Exploration of Uniqueness in Inverse RT Computations

Ensuring unique solutions is a typical problem with inverse methods and is a relevant concern for data-driven AC algorithms. Borel’s 2008 AC study [39], which used spectral smoothness as a metric of for its compensated spectra, found unique solutions were difficult to obtain, especially when columnar water was greater than 3 cm. His research clearly indicated that a variety of atmospheric states could give a smooth, yet physically incorrect, emissivity spectra.

Owing to the robustness of the atmospheric profiles in the climatological databases obtained for this research, it was deemed worthy to further examine this issue using at-sensor radiance prior to accomplishing any atmospheric compensation. This endeavor began by calculating a large number of at-sensor signals using the LW RT equation and the TUD spectra obtained from TIGR. The surface-leaving radiance term $\varepsilon(\lambda)B(\lambda, T)$ was determined by assigning a temperature to a high emissivity material from the ASTER database. The SEBASS

sensor response filter was used to simulate at-sensor radiance as MODTRAN performed the modeling. The signals, without simulating sensor noise, were compared based upon the RMS difference across the band. When similar signals were identified, the atmospheric states were compared.

This effort readily showed how propagating surface-leaving radiance through different atmospheric states could result in effectively indistinguishable at-sensor signals, and there were a variety of manifestations of the problem. In some cases, the radiative properties of the atmosphere (i.e., the TUD spectra) were the same, despite a different atmospheric state. In other cases, the at-sensor radiance was the same, but the radiative properties and the atmospheric states were both different.

This phenomenon occurs because transmittance and path radiance are coupled through Kirchhoff's Law. If the atmosphere is absorbing at a given wavelength, reducing transmission of surface-leaving energy, then Kirchhoff's Law (invoking LTE) necessitates that it also emit energy at that wavelength in the form of path radiance and downwelling. This can be shown in the panels in Figure 30. The at-sensor signals are generated by propagating the emission of water at 284 K through two different atmospheric states, one with 2.5 cm of total water content and the other with 3.5 cm. In this example, the transmittance and path radiance functions are clearly distinct, but the RMSE of the at-sensor signals is $0.02 \frac{\mu\text{W}}{\text{cm}^2 \text{ sr cm}^{-1}}$ across the entire band. The brightness temperature difference associated with the difference in the at-sensor signals yields an RMSE of 0.07 K. The grey lines in the upper right panel are drawn at 0.05 K, which is noise equivalent delta temperature ($\text{NE}\Delta\text{T}$) of the SEBASS sensor. In this simulated viewing scenario, it would be difficult to solve for surface-leaving radiance given the at-sensor signal.

This phenomenon can be replicated using a different surface emissivity. This is shown in Figure 31, using green grass at 286 K instead of water. Here, the RMSE of

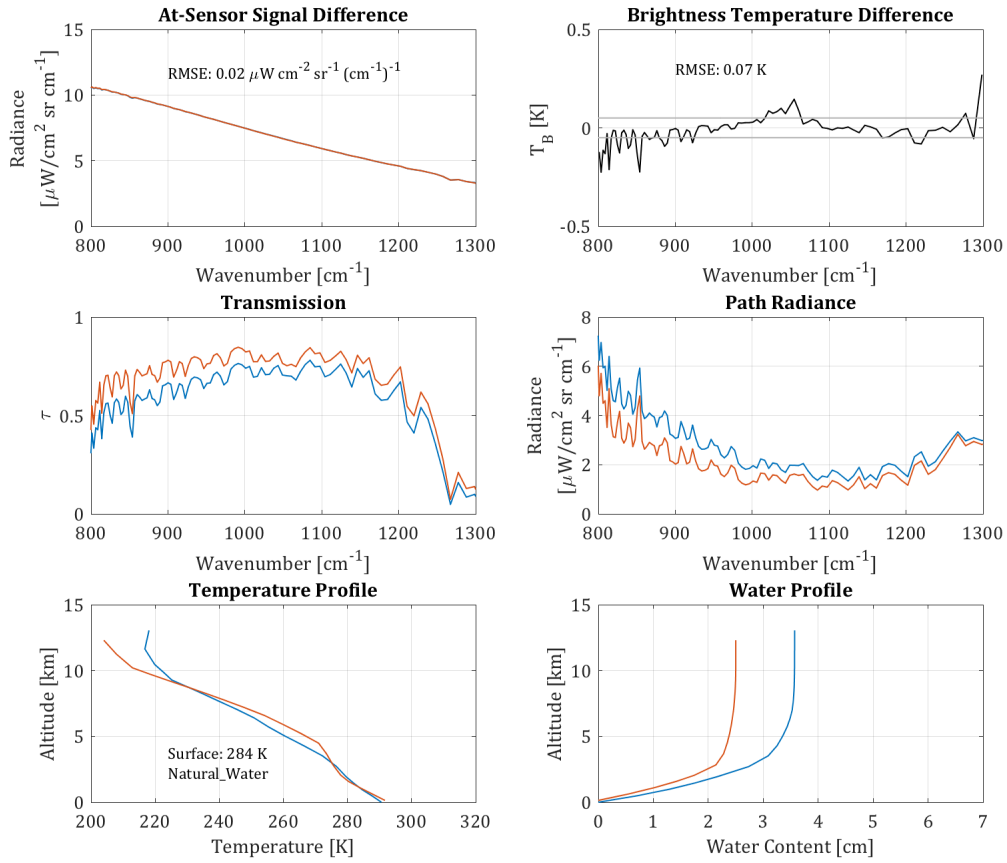


Figure 30. (top row) Difference between two simulated SEBASS measurements in radiance (left) and Kelvin (right). (middle row) Transmission and path radiance spectra of the two atmospheres through which the surface-leaving radiance was propagated. (bottom row) Temperature and water profiles of the two atmospheres. The surface in this simulation is 284K water.

the brightness temperature spectral differences equal to 0.06 K, showing that, again, two atmospheres are capable of producing indistinguishable signals when accounting for the basic noise statistics in the SEBASS.

The final circumstance giving rise to challenging inverse conditions is demonstrated in Figure 32, which depicts a situation where different atmospheric states produce virtually identical TUD spectra, necessarily resulting similar at-sensor signals. This condition can occur when the low altitude temperature profiles are very different.

There is nothing about the surface-to-sensor simulations that have been discussed in this section that is unreasonable in a physical sense, but it can certainly be argued that these are singular examples, each of which might be an unlikely scenario. Referring to Figure 33 gives credibility to the assertion that this issue is, at the very least, not singular.

For the data in the figure, the TIGR atmospheres were down-selected into two populations, 60 atmospheres having 2.5 ± 0.2 cm and 39 atmospheres having 3.5 ± 0.2 cm of total water. The best pairwise at-sensor signal match was captured, using the surface emission of water at six different temperatures. The differences between the at-sensor signals, in Kelvin, are shown in each panel. Also shown in each panel are the surface temperature, the reference number of the atmospheres creating the match, and horizontal lines showing the $NE\Delta T = 0.05$ K region. While TIGR #25 and TIGR #21 resulted in signal matches with 280, 284, and 288 K surface temperatures, three other atmospheric created indistinguishable signals at 282, 286, and 290 K.

To this point, the relationship between atmospheric state and RT variables has been discussed along with a demonstration of the effects of the anti-correlated transmission and path radiance terms in the LWIR RT equation. This chapter

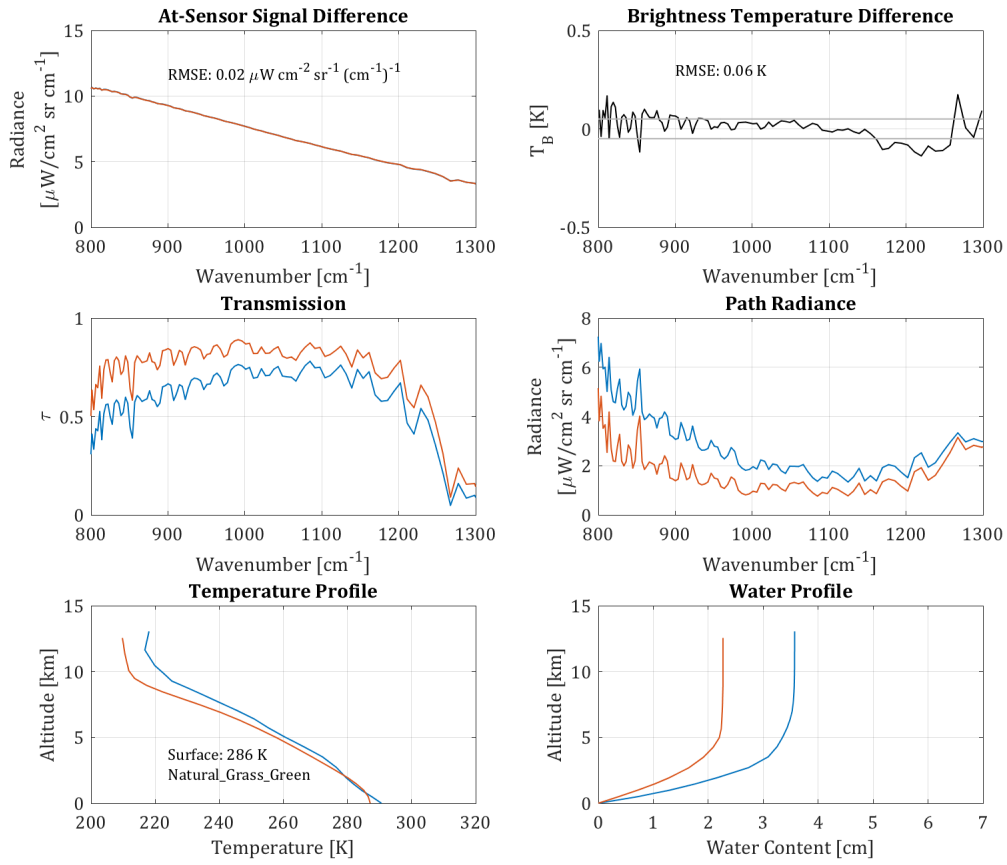


Figure 31. As with Fig. 30, but considering a grass surface at 286 K.

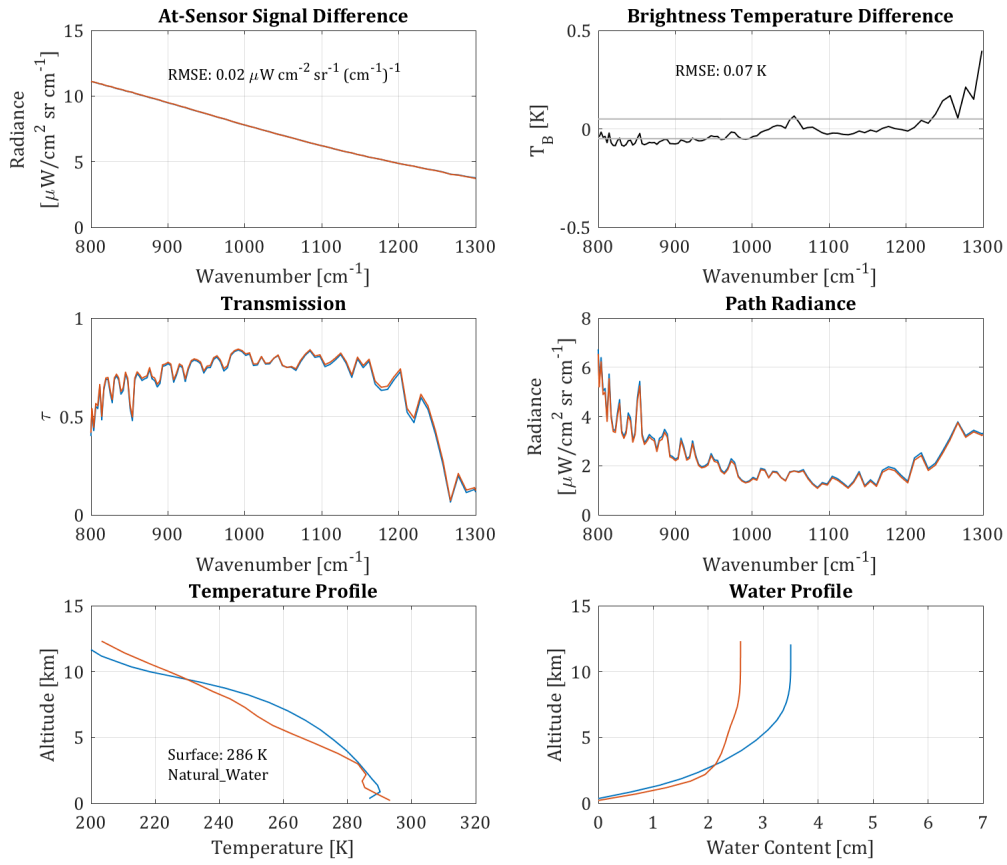


Figure 32. As with Fig. 30, but considering a grass surface at 286 K.

Brightness Temperature Differences

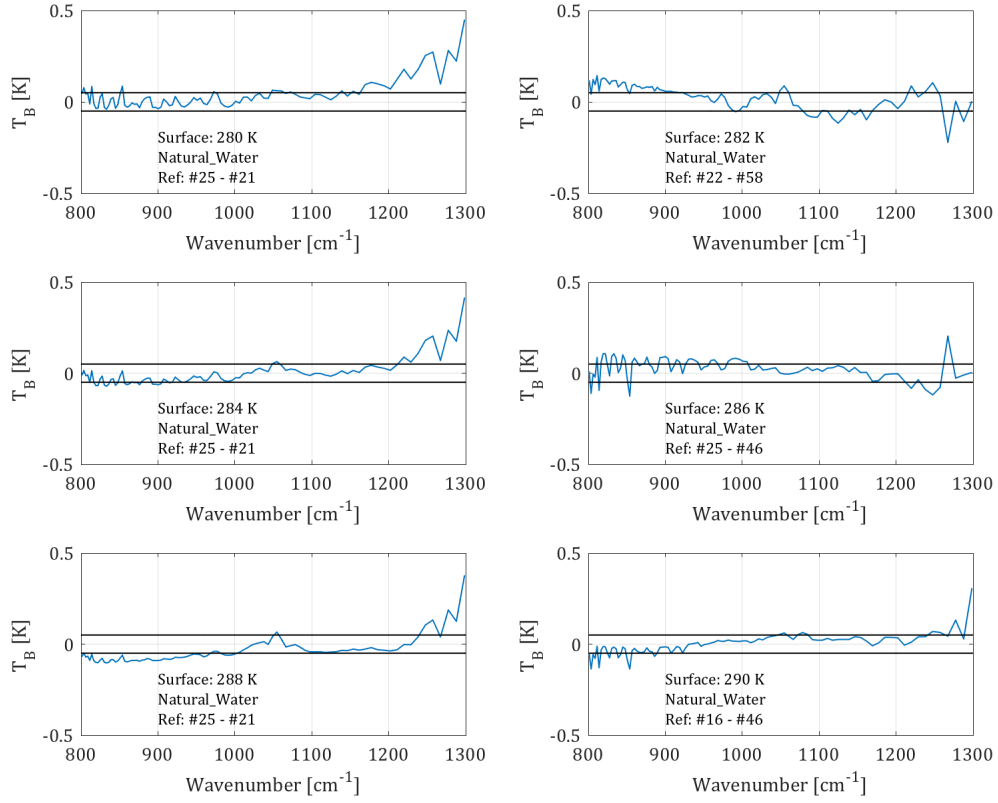


Figure 33. Pair-wise differences between SEBASS at-sensor signals, converted to brightness temperature, using surface water emission at temperatures between 280 – 290 K.

concludes with a discussion about the feasibility of representing the atmospheric state variables in functional forms that produce equivalent radiative outputs.

4.3 Functional Fitting of the Atmospheric State Variables

As was mentioned in Section 4.1, one of the benefits MODTRAN’s forward modeling is the amount of data it provides as it processes a tp5 input file. The post-processing Tape 6 (tp6) file is replete with information about how the atmospheric state was rendered by MODTRAN based on the tp5 inputs. Among the data in that tp6 is a table of the calculated water density in each atmospheric layer.

This data and the tp5 inputs were studied to determine to what extent a realistic atmospheric state could be modeled by analytic functions of altitude. Because of their importance to the physics of the radiative transfer, the temperature, water density, and cumulative water content profiles were selected for investigation. Trace gases, methane, ozone were kept at default settings, but the visibility and surface elevation inputs were consistent with the methods outlined in Chapter 3. Using the tp6 data from the model runs of the 4,846 GARPI atmospheres, functional representations were created for each of the variables. A weighting scheme was used to model the variables at and below 6 km more accurately than the upper atmosphere. It was determined suitable models could be developed using no more than three fit coefficients. The development of these functional forms follows.

4.3.1 Creating the Functional Forms.

The qualitative shape of any cumulative water profile shows it exhibits exponential growth to an maximum value as a function of altitude z . This shape is accurately modeled by a three-parameter logistic function,

$$f_{H_2O}(z) = a(1 - b e^{-cz}). \quad (28)$$

In order to prioritize the fit in the higher density regions of the atmosphere near the surface, the a weighting factor was applied to each layer, calculated as the ratio of the i^{th} layer's pressure to surface pressure $W_i = \frac{p(z_i)}{p(z_1)}$. Each of the GAPRI water content profiles was fit to Eq. 28, and the mean r^2 statistic for the ensemble of fits was greater than 0.99. The minimum r^2 statistic for all of the fits was $r^2 = 0.88$, which occurred in an atmosphere with less than 1 cm of total water. The shape of cumulative water in very dry atmospheres is not as well represented by Eq. 28.

Water density is the derivative of the cumulative water function. The equation describing a water density profile in terms of Eq. 28 is,

$$f_{dens}(z) = abce^{-cz}, \quad (29)$$

which is expressed in $\frac{g}{m^3}$ if multiplied by a factor of 10. Even though they are not independent, the density function can be expressed as in terms of two-parameters if a , b , and c are combined into one coefficient. It should be noted that water density measurements in the atmosphere do not necessarily increase as a function of z . As such, this has the potential to be a poorly modeled phenomenon with the two-parameter analytic expression given by Eq. 29. Thus, an alternate approach was also considered, in which an exponential expression of the same form as Eq. 29 was fit directly to the density data computed by MODTRAN. This resulted in different coefficients, but very nearly equivalent fit statistics. Thus, it was determined that the most self-consistent methodology was to only fit cumulative water content and use its coefficients in Eq. 29 to represent the density profile. The mean r^2 of the water density fits was 0.94.

The temperature profiles are also subject to dramatic changes with altitude, and they can also exhibit positive and negative rates of in the boundary layer. The fitting function chosen here focuses modeling as much of the variations near the surface as possible, while still capturing the general cooling trend seen in higher in the troposphere. The three-parameter function incorporated by this research models temperature deviations from the surface temperature $T(z_0)$, is given by

$$f_T(z) = a(z - z_0)^2 e^{\left(\frac{-(z-z_0)}{c}\right)} + b(z - z_0) \quad (30)$$

such that $T(z) = f_T(z) + T(z_0)$, where z_0 is the surface elevation associated with the GAPRI profile. The quadratic term multiplied by the exponential attempts to capture variations near the surface, while the last term captures the overall lapse rate.

In practice, any temperature inversion, where the atmosphere to warms with increasing altitude cannot be modeled accurately by Eq. 30. Thus, the calculated model coefficients were fit to the profiles at and below 10 km, before the lapse rate tapered off. For completeness, though, it can be shown that the RT impact of the atmospheric state above 10 km is negligible in the LWIR, temperatures from a MODTRAN standard atmosphere that most closely matched the termination of the fit were spliced to the profile. Because the air density at 10 km is $\sim 25\%$ of the density at the surface, the radiative transfer processes are adequately approximated using a default model, while introduces very little error in the overall radiative transfer calculations. To remain physical and consistent, however, the water density fitting data was also truncated at 10 km. Examples of the functional fits for a GAPRI atmosphere are provided in Figure 34. The surface elevation is approximately 1.6 km, which explains the vertical displacement.

A summary of the mean values of each parameter and its standard deviation for

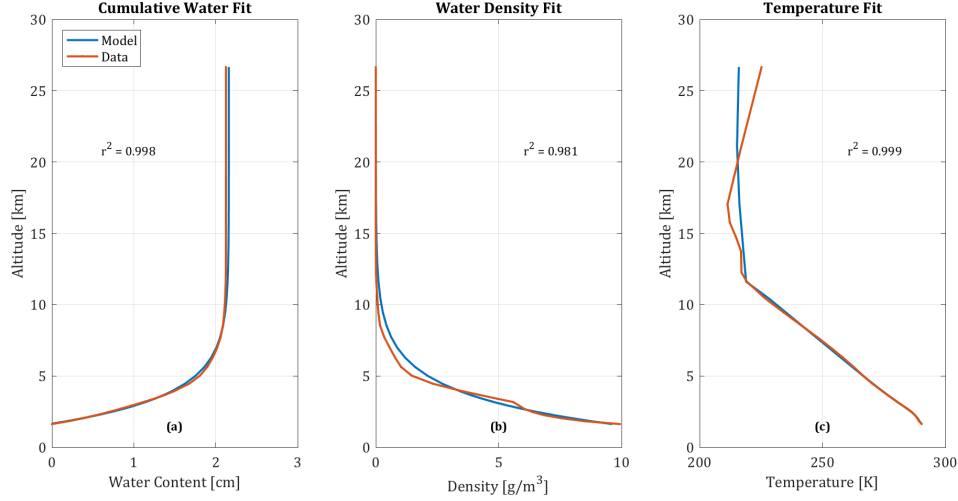


Figure 34. Functional fit examples of (a) water content, (b) density, and (c) temperature profiles, with goodness of fit statistics (r^2) depicted for fits to data ≤ 10 km.

all 4,846 GAPRI atmospheres is depicted in Table 2. The a coefficient for the temperature function has the largest standard deviation of values because this term attempts to capture the variations in temperature near the surface. The water density coefficients shown are the result of fitting individually to the data.

4.3.2 Validating the Functional Fit Method.

The TUD outputs using the functional fit representation were compared to the outputs using the GAPRI data. The results clearly indicated that carefully selected functions of few parameters can approximate temperature and water content profiles well enough to produce accurate TUD outputs. An example of a successful

Table 2. The mean and standard deviation (in parentheses) of the fitting coefficients for water, density (fit independently to data), and temperature profiles of 4,846 GAPRI atmospheres.

	Water Column	Water Density	Temperature
a	2.67 (1.5)	18.30 (6.7)	-5.85 (39.7)
b	1.02 (0.03)	0.54 (0.2)	-6.23 (0.84)
c	0.53 (0.17)	—	0.82 (0.69)

fit is shown in Figure 35. Eqs. 30 and 29 are used to represent the temperature and water density profiles of a relatively humid and warm atmosphere, with some structure in the water density profile. Failing to perfectly represent that structure does contribute to continuum errors across the band, but the overall accuracy is good with the RMS errors approximately $\sim 3\%$ of both the mean transmittance and mean path radiance.

In general, good results were seen using the functional forms with RMS errors typically well less than 10% of the mean spectral value. In atmospheres with very high amounts of water, the forward modeling errors were seen to increase. But, as is shown in Figure 36, good initial results were still obtained. In the next section, an approach to tuning the coefficients using nonlinear least squares will be explored.

4.3.3 Tuning the Coefficients with Nonlinear Least Squares Optimization.

To demonstrate a proof of concept, the feasibility of tuning the derived coefficients was explored. The purpose was to determine if using a mathematical tuning process would require significant departures from the original solution and possibly infringe upon the requirement to maintain a meteorologically consistent atmospheric state.

A nonlinear least squares algorithm was devised that sought to minimize the residuals between forward modeled spectra that used the functional inputs versus the high fidelity GAPRI inputs. The original coefficients were supplied as an initial guess and the coefficients were tuned iteratively. For each tuning step, new functional temperature and water content profiles were created, passed to MODTRAN, and forward modeled. The results of the tuning on minimizing retrieval errors were significant. An example is shown in Figure 37. The tuned

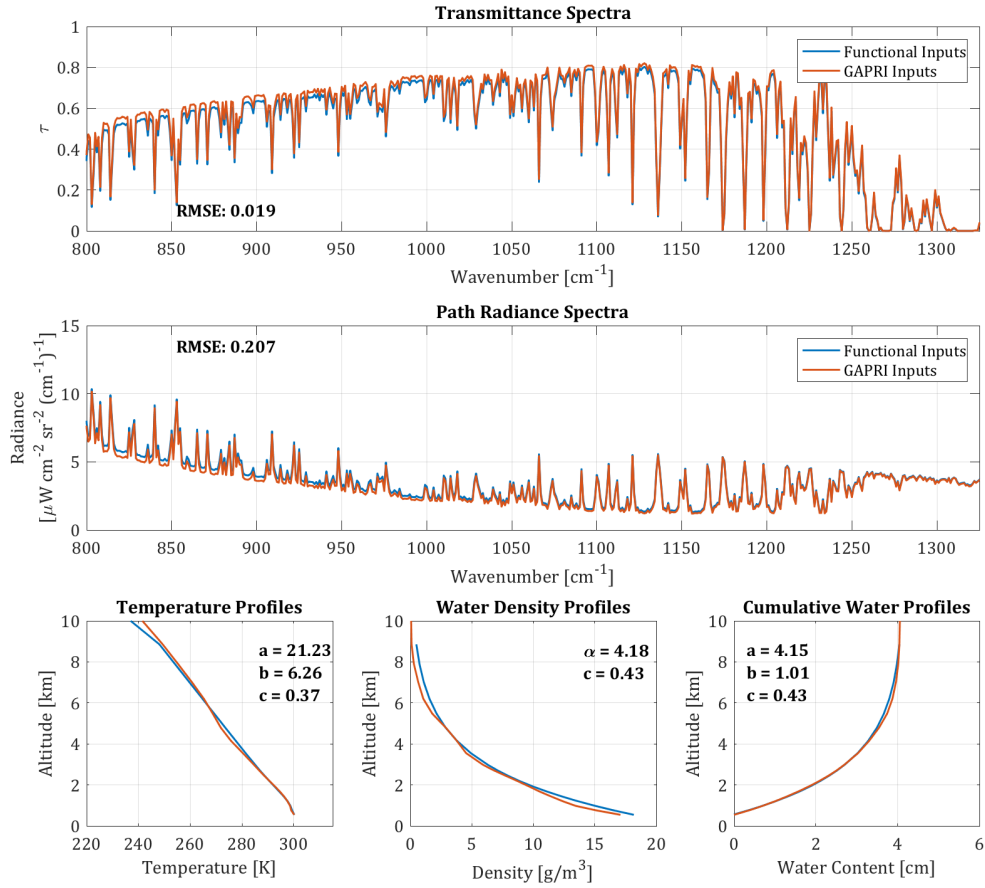


Figure 35. (top row) Forward modeled transmission spectra using functional fit inputs versus GAPRI inputs. (middle row) Path radiance spectra. (bottom row) Comparisons of functionally represented temperature, water density, and cumulative water profiles to GAPRI data.

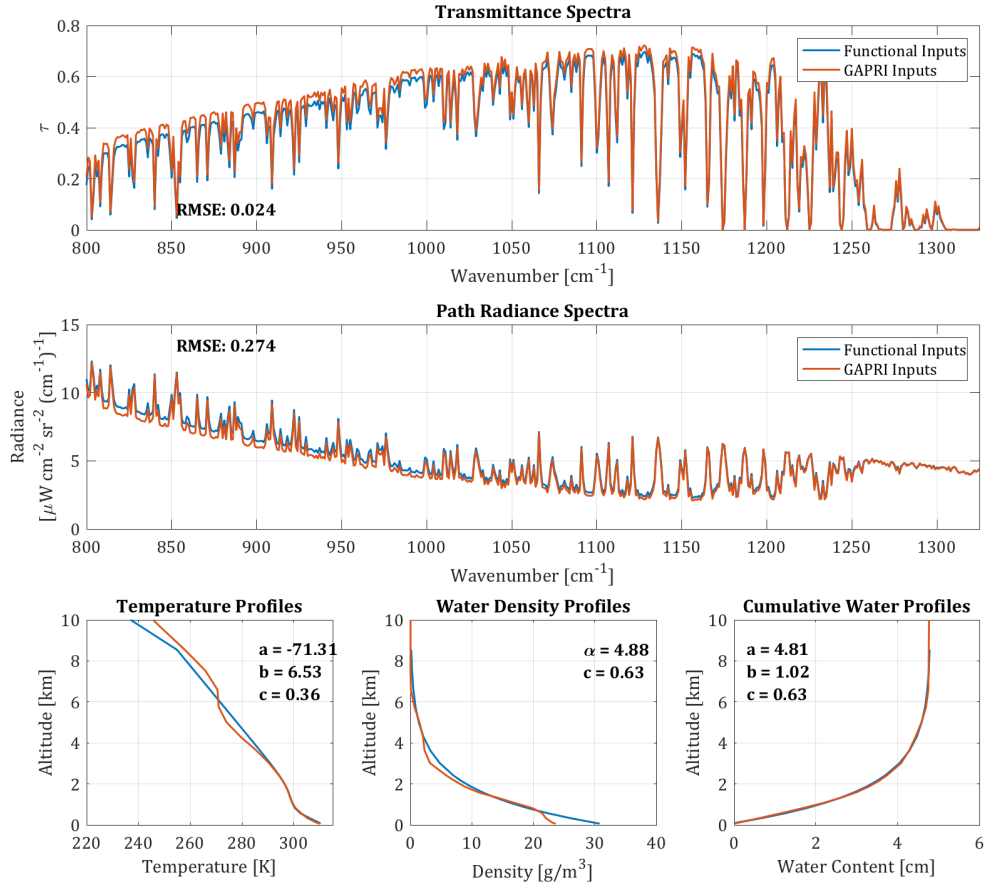


Figure 36. (top row) Forward modeled transmission spectra using functional fit inputs versus GAPRI inputs. (bottom row) Comparisons of functionally represented temperature, water density, and cumulative water profiles to GAPRI data.

spectra are represented with a dashed line because of the close overlay to the GAPRI spectrum. The final coefficient values are also displayed in the figure, and they show the deviations from the initial guesses remained relatively close to the original values. Although the validity of the resulting atmospheric state was not studied in great detail, the results of this tuning process are very auspicious. However, it should be noted that the error metric was easy to compute because a “ground-truth” solution was available. In an operational context, the error metric would have to be done on the measured data itself. This would add an additional layer of complication, but it does not appear that it would render this approach ineffective. It is intended for this to be an avenue of further study.

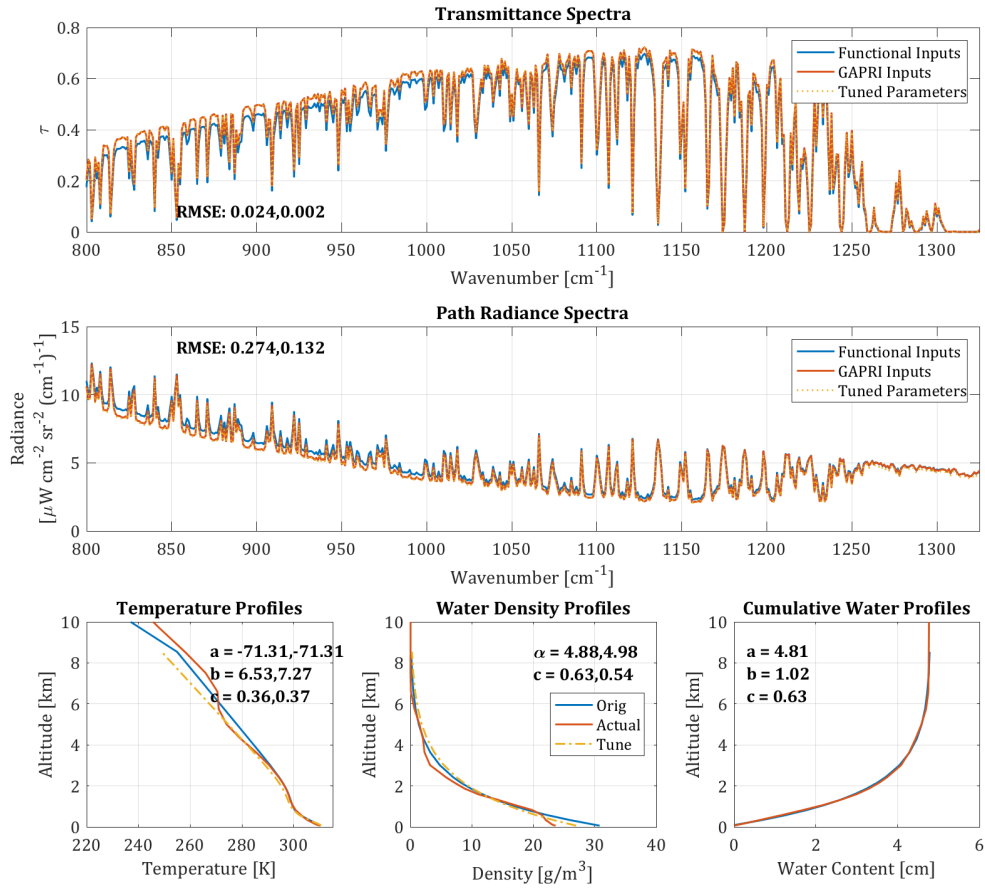


Figure 37. As with Figures 35 and 36, but showing the results after NLLS tuning.

V. Data-driven Atmospheric Compensation

In this chapter, a method of data-driven atmospheric compensation which incorporates the GAPRI atmospheric database and atmospheric fitting functions will be discussed. This research builds upon the foundation of the previous in-scene AC efforts, including researchers at the Rochester Institute of Technology in Rochester, NY [79, 80], Young et al.’s ISAC [14], and error function techniques used in Borel’s ARTEMIS [39].

A true end-to-end atmospheric compensation in the LWIR technique starts with observed radiance, performs a series of steps to compensate for atmospheric effects to derive surface-leaving radiance and then persist in the separation of the planckian emission at unknown temperature T from the material’s/materials’ emissivity, known as temperature-emissivity separation (TES). The model developed here only addresses atmospheric compensation, the purpose of which is to derive surface-leaving radiance with no atmospheric effects. To that end, any validation of the method’s accuracy will demand *a priori* knowledge of the surface temperature.

Referring to the LWIR RT equation, it becomes apparent that surface-leaving radiance for materials is also composed of the reflected downwelling radiance $(1 - \epsilon(\lambda))L_d(\lambda)$. This term is negligible for high-emissivity pixels, which compels the search for and identification of these materials in the scene. In the next section, a simple search algorithm will be discussed, which is technically outside the formal boundaries of the inverse AC method developed here. However, its inclusion here serves two purposes. First, it works quickly and is easy to implement. Secondly, it can be used to show how the retrieval of surface parameters can easily have non-unique solutions, in which the surface-leaving radiance and atmospheric parameters can combine to produce the same signal at the sensor. This was discussed at some length in the previous chapter by looking at forward modeling.

Here, it will be shown how the problem manifests from the inverse sense.

5.1 High-emissivity Pixel Identification

This simple, yet robust, technique uses catalog matching to identify high-emissivity (HE) pixels. To build the catalog, each profile in the GAPRI database is used to create a radiance spectrum for which the underlying surface material emissivity is unity. As a reasonable approximation, the surface temperature is set equal to the lowest temperature in the atmospheric profile. Identifying high emissivity pixels/target/regions in the scene then merely requires the calculation of the spectral similarity between its radiance and the catalog entries. The spectral angle (SA), discussed previously, is well suited, as is the

Although it isn't strictly necessary, this technique also enforces a geographic filter so that only profiles within a $\pm 10^\circ$ latitude band and a 1000 nm radius of the collection location are considered eligible to match. This was done as a way to investigate the introduction of a qualitative climatological constraint to the GAPRI catalog, but no positive impact in doing so was observed.

The SA and ED computed between high emissivity pixels and the catalog are smaller than pixels not exhibiting that quality. However, a caution is warranted because the similarity statistics are relative to the constituents in the scene. In practice, then, this approach can only identify BB-like materials if BB-like materials are present in the scene. If the scene is void of high-emissivity materials, SA and ED scores can still be calculated and sorted. The smallest values will indicate the pixels that most closely approximate BB-like pixels, but they may not be true HE pixels suitable for use in an AC method. In any event, scenes dominated by highly reflective materials are better suited for other AC methods that do not use a BB approximation (e.g., QUAC).

5.2 Manifestations of Non-Unique Solutions with Simple Catalog Matching

At this point, it is instructive to quickly expose how the uniqueness challenge manifests when employing an inverse method, even one as simple as the BB-selector of the previous section. To demonstrate this, the technique was applied to a simulated scene. The GAPRI atmosphere giving rise to the smallest SA and/or the smallest ED was recorded on a pixel-by-pixel basis. It might be tempting to assume that the atmosphere with the highest percentage of matches would closely represent the atmospheric state. Unfortunately, due to the anti-correlated relationship between transmittance and path radiance discussed at length in Section 4.2, this cannot be guaranteed and is often not true.

In this simulated scenario, the image data was composed of approximately 20% HE surface pixels. HE is defined as the condition $\epsilon(\lambda) \geq 0.95$ for all λ . The mean surface temperature was 292 K, and there was 4 cm of water in the atmosphere. The BB-catalog matching technique does successfully identify the highest emitters in the scene, and Figure 38 reports these results. The spectra of the 100 best catalog matches are shown using solid lines (note: many surface materials have identical emissivity spectra in this simulated scene). Importantly, no non-HE pixels were identified, and this could easily be used as a pixel filter to initialize a AC method.

But for the prevalence for non-unique solutions, this would be the end of the atmospheric compensation effort. However, in this case, the atmosphere with the highest percentage of matches was not representative of the actual atmospheric state. Instead, it had far less water, resulting in a transmittance function with a larger mean value and less path radiance per channel. The net reduction in energy from the atmosphere was recouped by the surface-leaving radiance. An example of a pixel-to-catalog comparison is depicted in the top panel of Figure 39. Below that is

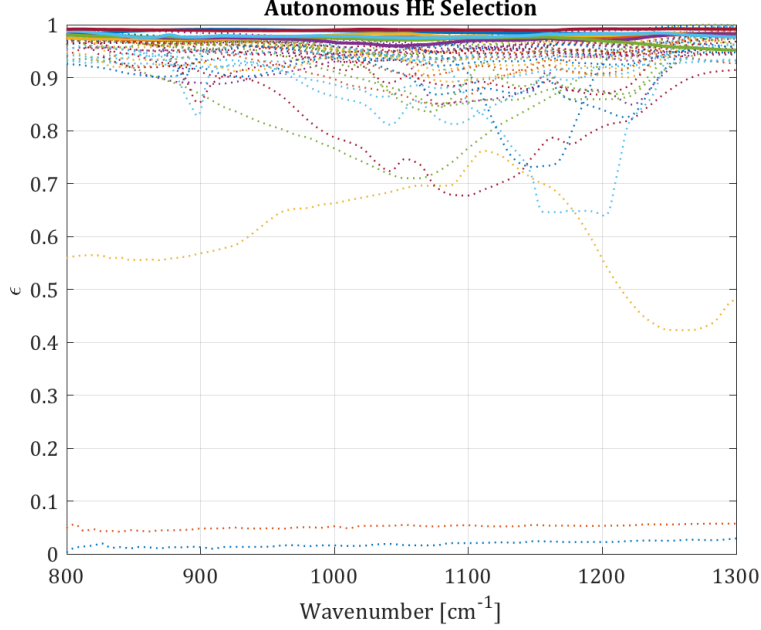


Figure 38. Results of using the BB-catalog method to identify HE pixels in a simulated scene. The thick solid lines represent the unique emissivity spectra of the top 100 matches to the BB catalog (many emissivity spectra are duplicated in the scene). The dotted lines represent the full ensemble of pixels in the scene.

a comparison of the transmission spectra, where the blue trace is the truth. There is no way reliable way prevent this from happening using a technique as simple as the BB-catalog match. It is for this reason that an additional layers of discrimination and analysis are employed by in-scene AC methods.

5.3 The Combined Hyperspectral Atmospheric Effects Removal Method (CHAERM)

For the AC method developed in this research, the additional analysis is achieved by shrewdly decoupling the line and continuum effects from the transmission and path radiance spectra. In the sections that follow, this development of the Combined Hyperspectral Atmospheric Effects Removal Method (CHAERM) will be studied. At its core, this method is employs many of the same fundamentals as is ISAC. However, by taking the results of a linear regression in a

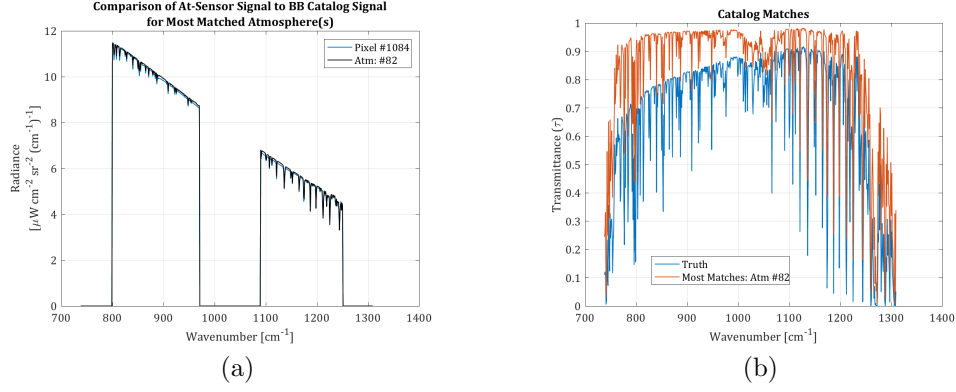


Figure 39. (a) Comparison of the at-sensor radiance of an HE pixel and the BB-catalog spectra most closely matching. (b) A comparison of the transmission spectra for the BB-catalog and the truth spectrum used to create the simulated dataset.

different direction, the necessity to scale the results is avoided. Additionally, CHAERM provides a meaningful realization of the atmospheric state, which can be immediately used to inform coincident compensation in the VNIR/SWIR.

5.3.1 Decoupling the Line and Continuum Components of Transmission and Path Radiance.

CHAERM is unique in that it specifically calculates line absorption effects using the at-sensor radiance data. Line absorption and emission effects are primarily a function of the number of absorbers present along the line of sight and for a spectrum with even moderate resolution exist as narrow and distinct features. The line transmittance is one of the two phenomenological components of total transmission, which is given by the following product

$$\tau(\tilde{\nu}) = \tau_c(\tilde{\nu})\tau_l(\tilde{\nu}), \quad (31)$$

where τ_c is the continuum absorption. The analogous expression for the path radiance is

$$L_a(\tilde{\nu}) = \tau_l(\tilde{\nu})L_a^c(\tilde{\nu}) + L_a^l(\tilde{\nu}), \quad (32)$$

where $L_a^c(\tilde{\nu})$ and $L_a^l(\tilde{\nu})$ are the path radiance contributions due to continuum and line emission respectively. This equation shows that the continuum emission is still attenuated by line absorption effects.

As was shown in the previous section, the coupled relationship between total transmittance and path radiance can frustrate the inverse approach to AC. The ability to derive the line components of the total transmission and path radiance provides an additional means of leveraging the radiative transfer to help hone the inverse method's solution.

CHAERM establishes a regression scheme to estimate the line transmittance and path radiance in a given channel. The decoupling of line and continuum effects follows ISAC's $11.7 \mu\text{m}$ (853 cm^{-1}) water band scaling [14]. As was shown in Section 2.7.4, for an underlying surface of unity emissivity, at-sensor radiance is given by

$$L(\tilde{\nu}) = B(\tilde{\nu}, T)\tau(\tilde{\nu}) + L_a(\tilde{\nu}). \quad (33)$$

Substituting Equations 31 and 32 into Equation 33 yields

$$L(\tilde{\nu}) = B(\tilde{\nu}, T)\tau_c(\tilde{\nu})\tau_l(\tilde{\nu}) + \tau_l(\tilde{\nu})L_a^c(\lambda) + L_a^l(\tilde{\nu}). \quad (34)$$

In a reasonably small region about λ , the radiance due to continuum effects only is

$$L_0(\tilde{\nu}) = B(\tilde{\nu}, T)\tau_c(\tilde{\nu}) + L_a^c(\tilde{\nu}). \quad (35)$$

Combining Equations 34 and 35 establishes a linear relationship between at-sensor

radiance $L(\tilde{\nu})$ and $L_0(\tilde{\nu})$ expressed as

$$L(\tilde{\nu}) = \tau_l(\tilde{\nu})L_0(\tilde{\nu}) + L_a^l(\tilde{\nu}). \quad (36)$$

This expression is valid for surfaces where $\varepsilon \approx 1$. Thus, with an accurate estimate of L_0 a population of HE pixels with sufficient temperature variations, a linear regression can be accomplished to determine the slope $\tau_l(\tilde{\nu})$ and intercept $L_a^l(\tilde{\nu})$. An equivalent setup can be derived instead in terms of the difference between the continuum only radiance and the measure radiance. Defining this depression $D(\tilde{\nu})$ as

$$D(\tilde{\nu}) = L_0(\tilde{\nu}) - L(\tilde{\nu}) \quad (37)$$

and substituting into Equation 36 establishes this linear expression

$$D(\tilde{\nu}) = (1 - \tau_l(\tilde{\nu}))L_0(\tilde{\nu}) - L_a^l(\tilde{\nu}). \quad (38)$$

Here the coefficients of the best fit line of D versus L_0 data can also be used to determine τ_l and L_a^l . As with ISAC, preferential fitting to the top of the scatterplot data incorporates those pixels whose surface emissivity near unity, fulfilling the underlying assumption and mitigating the effects of reflected downwelling as a source of error.

5.3.2 Obtaining L_0 .

The only quantity directly measured by a hyperspectral imager is $L(\tilde{\nu})$, so CHAERM utilizes a process to estimate L_0 . Because L_0 represents a modification to L by continuum effects only, it is devoid of high-frequency content. Ignoring the high-frequency content is equivalent to determining the spectral locations of line

absorption features. In some spectra, these line effects are quite prominent, but in other cases, they can be very subdued. Thus, CHAERM incorporates a specialized way to estimate line transmittance that broadens the technique's applicability.

CHAERM incorporates a self-contained way of analyzing the spectral data to ascertain spectral channels with low and high and low transmission. Its method is based on the following precept. In a typical scene, there is sufficient diversity in materials and their temperatures such that if the imaging were accomplished in vacuum there would be significant variance in each spectral channel. As long as it is invariant over the spatial extent of the image, the effect of the atmosphere absorbing energy along the line of sight is to reduce this variation. In fact, as the opacity of a channel increases toward saturation, the only signal that arrives is a particular layer of the atmosphere itself, which would have very little variation pixel to pixel.

CHAERM considers an ensemble of HE pixels in the scene and investigates their spectral standard deviation in a relative sense. Where the standard deviation is the largest, in a relative sense, provides a good estimate of the spectral locations where atmospheric absorption is active. These are regions to avoid in the determination of L_o .

However, radiance is a function of wavenumber, meaning the magnitude of the standard deviation spectrum also depends on wavenumber, so it is divided by the median spectrum to normalize its values. Then, using a small window, CHAERM estimates an envelope function using a small-window moving maximum and a smoothing algorithm is applied. This is depicted graphically in Figure 40. The ratio of the normalized standard deviation to the envelope function is calculated, and the channels with the highest values indicate transparent regions of the spectrum. This result is also shown in Figure 40.

As was mentioned, CHAERM attempts to be as self-contained as possible, so

this method demonstrates the proof of concept of a self-contained method. In practice, MODTRAN, after accounting for the appropriate sensor response, could be utilized to compute a transmission spectrum for a generic atmospheric state in order to determine highly transmissive channels. Either approach is valid in CHAERM.

CHAERM uses the at-sensor radiance in the most transmissive regions of the spectra to approximate L_0 . This is shown in Figure 41.

However, because one of the tenets of all of the CHAERM processes is to be faithful to physical processes to the greatest extent, CHAERM bolsters this approximation through the incorporation of a specifically designed catalog of L_0 radiance spectra modeled with realistic atmospheric states of the TIGR database. To build this catalog of continuum only signals, CHAERM utilized the “mt-ckd” continuum model developed by Aerospace and Environmental Research, Inc. for use in their Line By Line Radiative Transfer Model (LBLRTM). The forward modeling to create a catalog of continuum TUD was accomplished by supplying initialization parameters, including temperature, pressure, and water vapor profiles. The output was layer optical depths (OD), from which layer transmittances were found using $\tau = \exp(-OD)$. The total atmospheric transmittance along the line of sight was determined by multiplying the layer transmittances, and the continuum only path radiance of the i^{th} layer due was estimated using

$$L_{a_i}^c = \tau_i L_{a_{i-1}}^c + \epsilon_i(\tilde{\nu}) B(T_i), \quad (39)$$

where $\epsilon_i(\tilde{\nu}) = 1 - \tau_i(\tilde{\nu})$, using Kirchhoff’s Law and imposing LTE.

An example of an in-scene and catalog L_0 spectra are depicted in Figure 42. To estimate L_0 , the spectral angle is computed between an HE pixel’s L_0 and all of the L_0 catalog entries. The closest SA match is then pulled from the catalog. The SA metric is used because it will best match the shapes of the spectra, but it is not

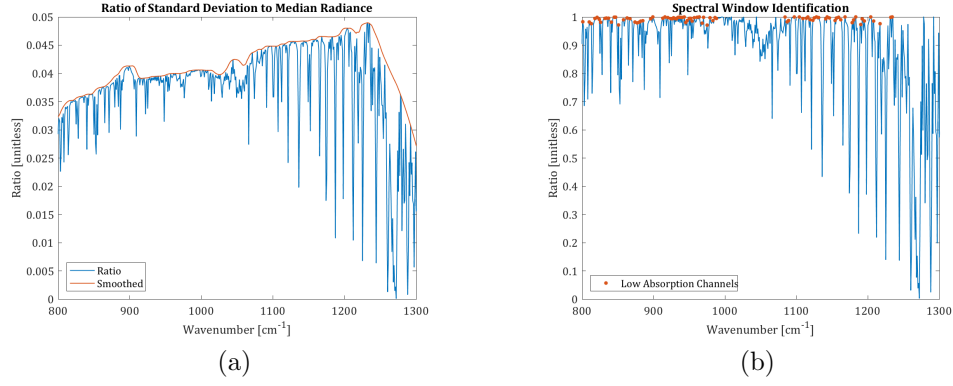


Figure 40. (a) Ratio of spectral standard deviation to median radiance of HE pixels in a scene and smoothly varying envelope function. (b) Ratio of normalized standard deviation to envelope function. The largest values of this distribution are most likely associated with high transmission.

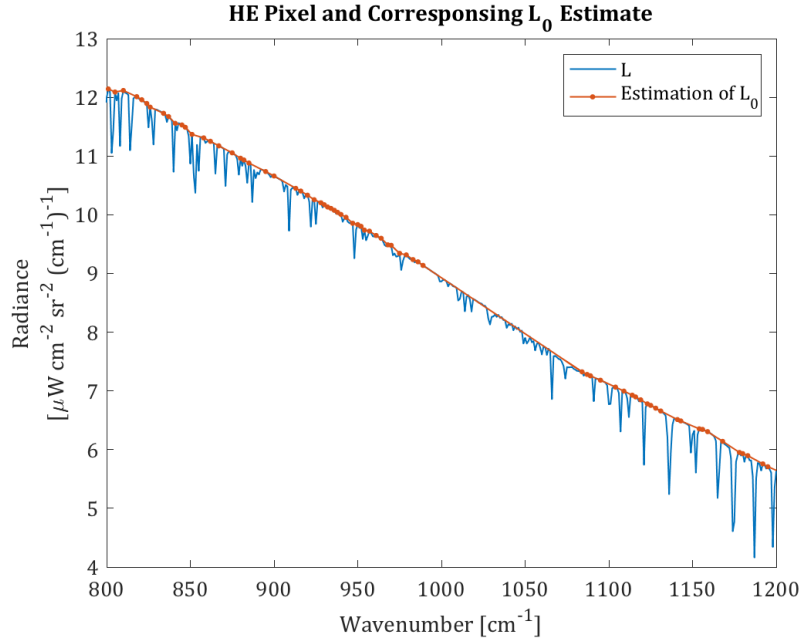


Figure 41. An HE pixel radiance and its corresponding L_0 estimate.

scaled appropriately. CHAERM scales the catalog entry to best fit the data using a quadratic function.

To this point, CHAERM has put in considerable effort to effectively estimate continuum only effects. The remaining task is to use this estimate to perform a linear regression analysis based on Equation 38 to determine $\tau_l(\tilde{\nu})$ and $L_a^l(\tilde{\nu})$. CHAERM performs the regression on channel-by-channel basis. Two examples of the results are shown in Figure 43 using simulated hyperspectral data. In this scenario, the atmosphere contained 4 cm of total water and had a 292 K surface temperature. The surface materials were distributed such that surface materials with emissivity spectra above 0.95 in all channels comprised $\sim 20\%$ of the scene. The left panel depicts regression at 850 cm^{-1} and the right panel at 853 cm^{-1} , at which water strongly absorbs. The small populations of data that are separated from the main population show the effects of materials with low emissivity. A weighting function is used in the linear regression to remove the participation of those pixels to the fit as they violate the high-emissivity assumption on which CHAERM's model is based.

Based on the formulation of Eq. 38, the regression line's slope represents $1 - \tau_l(\tilde{\nu})$ and its y -intercept represents $-L_a^l(\tilde{\nu})$. CHAERM's line-effects transmission and path radiance spectra are shown in Figure 44. It should be noted that due to the strong absorption characteristics in the region of the spectrum greater than 1250 cm^{-1} , the water content in the has made atmosphere nearly opaque. If little to no surface-leaving signal arrives at the sensor, resulting in no way to estimate of L_0 , CHAERM's regression computations are invalidated.

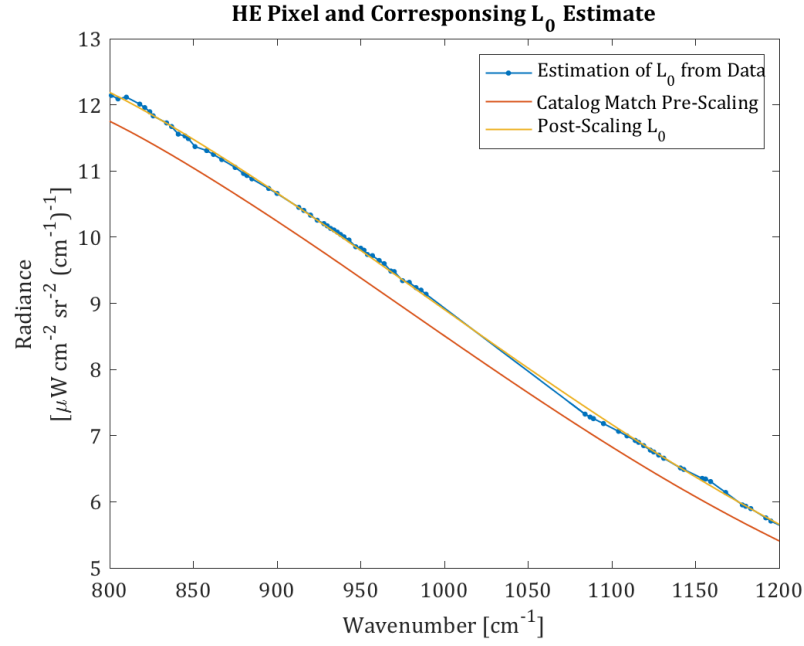


Figure 42. The process of matching the estimated L_0 from the data to a scaled L_0 obtained from a meteorologically consistent continuum-only catalog.

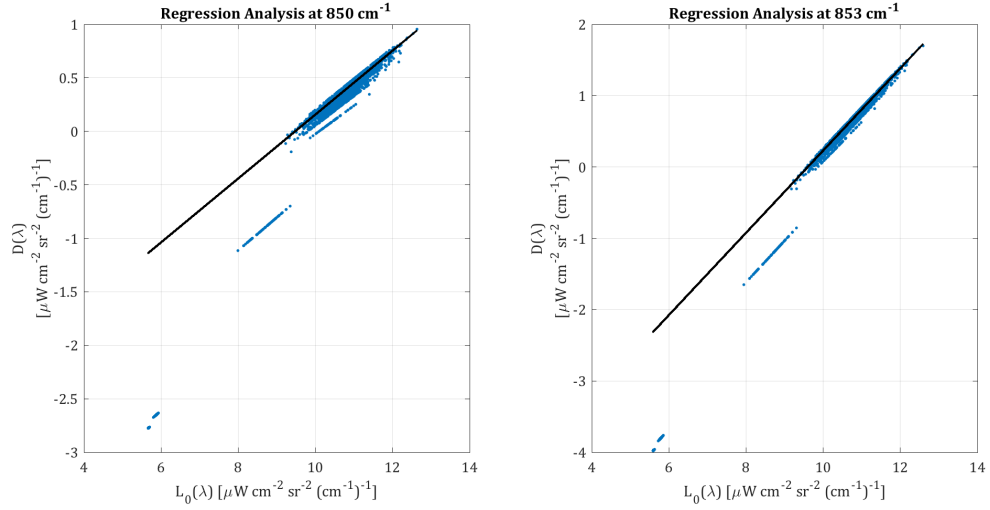


Figure 43. Scatter plots of D vs. L at (left) 850 cm^{-1} and (right) 853 cm^{-1} . The regression lines for each channel are indicated in black. The data is preferentially fit to the top of the distribution.

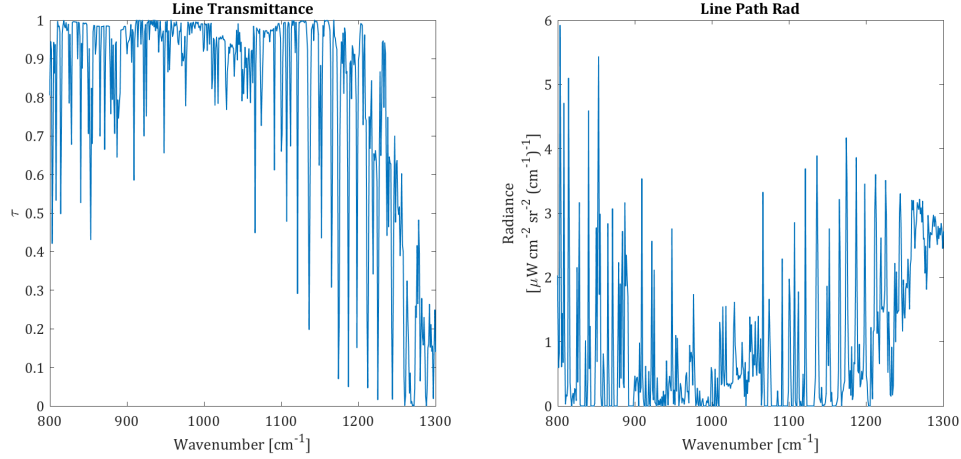


Figure 44. Estimates of the (left) line transmittance and (right) line path radiance spectra.

5.3.3 Compiling a Line Effects Catalog Using GAPRI.

CHAERM’s estimate for the line absorption transmission and path radiance spectra cannot be used independently to perform atmospheric compensation because no continuum effects are being modeled. To retrieve the continuum, CHARM’s next step is to compare the signals to a catalog of line-only spectra. This catalog must be precomputed and is unique to the viewing geometry (e.g., sensor altitude) of the sensing campaign.

CHAERM’s catalog of line-only transmission and path radiance spectra are compiled using the GAPRI database. This catalog is compiled by using MODTRAN’s total transmittance and path radiance spectra for each of the GAPRI atmospheres. There are a couple of ways to take a known transmission and path radiance spectrum and determine its line and continuum components, and CHAERM’s approach was chosen to remain as wholly independent as possible.

In effect, the exact same process that was utilized for the scene is replicated to determine the absorption line effects spectra. The difference is that instead of measured radiance from the sensor, the “at-sensor” signals are proxied by only

blackbody surface materials. A set of blackbody surfaces at various temperatures are propagated through a GAPRI atmosphere, creating a “dummy” hyperspectral image. Because the surface is made entirely of HE materials, this data is perfectly suited for incorporation into CHAERM’s existing infrastructure. The conversion of measured radiance to L_0 and the process to derive $\tau_l(\tilde{\nu})$ and $L_a(\tilde{\nu})$ are the same. This consistency approach is practical and robust. It is also quick because the “dummy” scene does not need to have very many pixels in order to enable an accurate regression because each pixel modeled as a theoretical blackbody.

5.3.4 Identifying the best atmospheric compensation spectra.

CHAERM’s final processing step uses ED to compute the similarity statistics between derived τ_l and L_a^l spectra from the scene and precomputed entries in the GAPRI line effects catalog. Because of the expansive nature of the GAPRI database and the specificity of the physical phenomena that manifest as the line effects spectra, this matching process is less likely to be fouled by the “one-to-many” problem discussed in Chapter 4. That being said, there will be a small population of atmospheres whose transmission and path radiance spectra may be appropriate for performing the atmospheric compensation. Typically good matches exist with the catalog entry that has the smallest ED value. CHAERM can also be easily be configured to report the best match atmosphere with regard to SA, or a user-specified spectral similarity statistic. The benefit of CHAERM’s novel use of line effects spectra is that it is less likely that the matched atmosphere will be associated with a significantly different atmospheric state. The flow chart in Figure 45 summarizes the steps that have been discussed that comprise CHAERM.

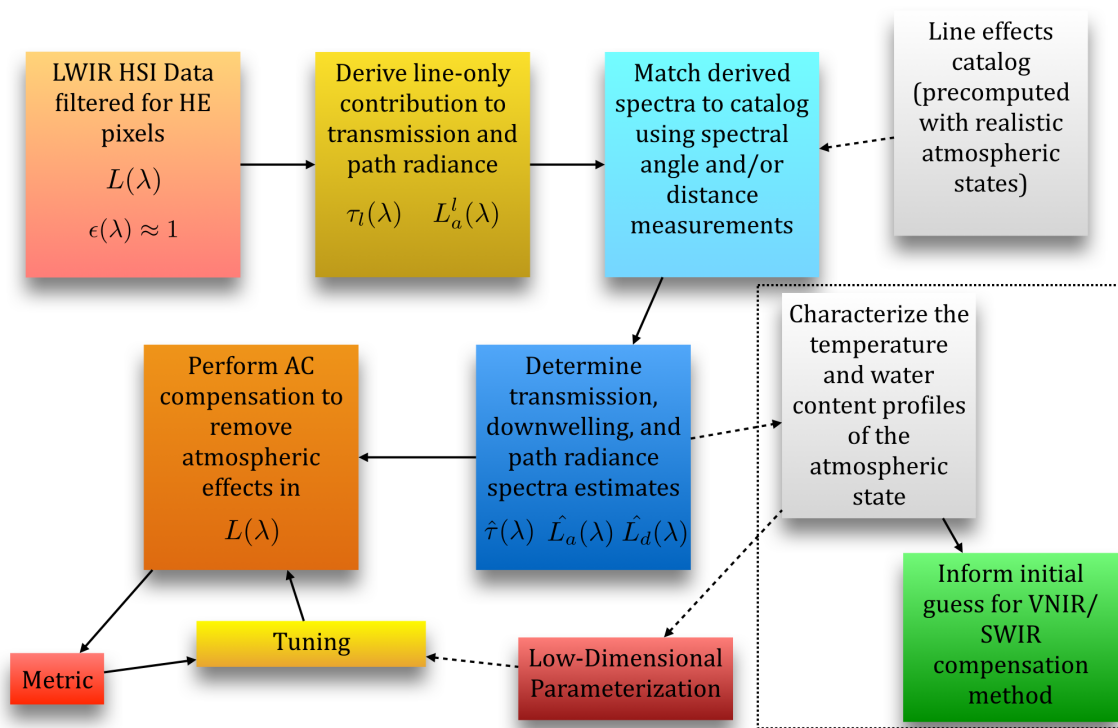


Figure 45. A graphical depiction of CHAERM's process.

VI. Results and Analysis

This chapter contains the analysis of CHAERM’s performance using simulated data and real-word data. With regard to the simulated scenes, the image data was created with the TIGR database while CHAERM’s catalogs were created with only GAPRI data. Both databases are well formed and meteorologically consistent, so utilizing both sets was a means to avoid any nepotism that might have occurred if GAPRI data were used to build the scenes as well as to compensate for their atmospheric effects.

6.1 Monochromatic AC with CHAERM

CHAERM was provided with 24 individual simulated scenes with different atmospheric states whose forward modeled TUD spectra used MODTRAN’s 1 cm^{-1} resolution. Of the 3,200 pixels in each scene, 22% were made to satisfy a high emissivity criterion $\epsilon(\tilde{\nu}) \geq 0.95$ and 4% were allowed to exhibit low emissivity characteristics (i.e., $\epsilon(\tilde{\nu}) \leq 0.60$). Because actual atmospheric state is known, CHAERM’s performance can be assessed by comparing its retrieved spectra to the actual TIGR spectra used to create the scene.

The results of these high-resolution experiments were very positive. CHAERM’s mean RMS transmission error was 0.031 with a standard deviation of 0.030, and the mean RMS path radiance error was $0.265\text{ }\mu\text{W}/\text{cm}^2\text{ sr cm}^{-1}$ with a standard deviation of 0.250. The maximum transmission retrieval error was 0.103 and occurred with an atmosphere having 2.6 cm of total water and a mean temperature of 280.0 K. CHAERM’s products for a specific scene are shown in Figs. 46-48. One of the unique aspects of CHAERM is associated atmospheric state that becomes readily available as soon as the spectral match is achieved. In this retrieval, the atmospheric

state, shown in Fig. 48, is a very close approximation of the actual conditions.

The emissivities of three pixels in the simulated scene were determined using Equation 10, which is often the final aim of the atmospheric compensation. To avoid the complicating factors of TES, the surface temperature of each was taken as *a priori* knowledge. The results are shown in Figure 49. Despite the very accurate retrieval, in spectral regions where the surface-leaving signal is more heavily influenced by the atmosphere, high frequency spectral artifacts are present. These artifacts are less relevant to the compensation's success than is the overall shape, and as is shown in figure, they are such narrow features at 1 cm^{-1} resolution that they are easily smoothed. In this regard, there is very good agreement as a result of the compensation technique.

The atmospheric state in Figure 48 is most in error with regard to the water profile near the surface. A certain benefit of CHAERM is its polling of a large physically realistic database, whose source terms are known. In addition, these atmospheric profiles have been functionally modeled. Based on the tuning discussion in Chapter 4, a reasonable question is whether or not the real atmospheric state could be reached through iterative tuning. In this case, the coefficients of the functional form of the actual water profile are $a = 3.07$, $b = 1.00$, and $c = 0.48$. The retrieved profile's coefficients are $a = 2.67$, $b = 1.01$, and $c = 0.51$, indicating that the NLLS tuning method of Chapter 4 would likely be able to further improve the results by slightly changing the water distribution.

6.2 CHAERM with SEBASS Sensor Resolution

The same 24 days were run through CHAERM using a signal that was representative of the SEBASS sensor resolution. The process by which CHAERM works is identical, but it requires a new set of catalogs be developed that match the

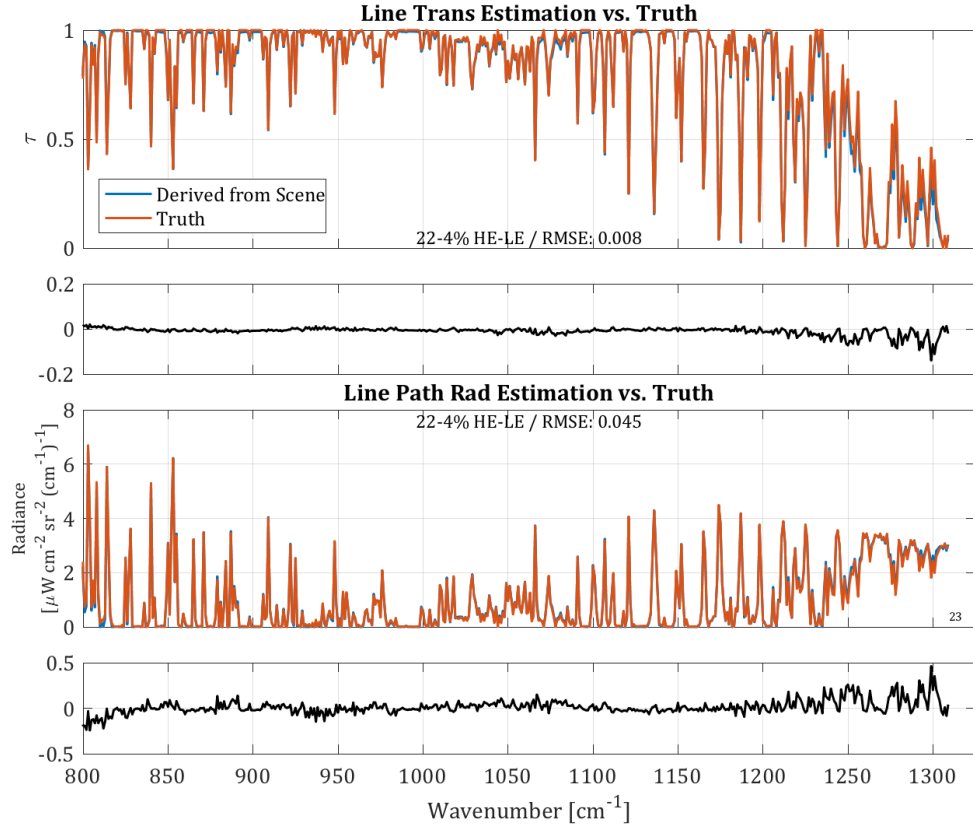


Figure 46. CHAERM's estimated line effects spectra and the residual errors compared to the truth spectra.

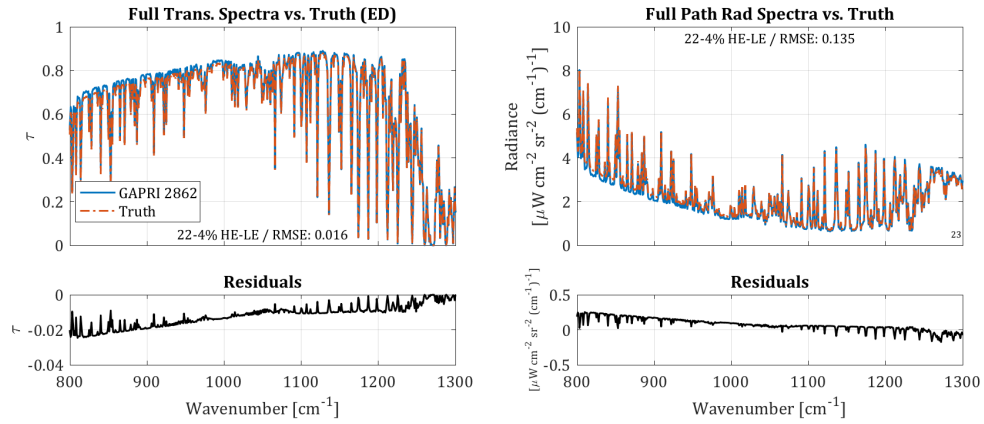


Figure 47. CHAERM's retrieved transmission and path radiance spectra.

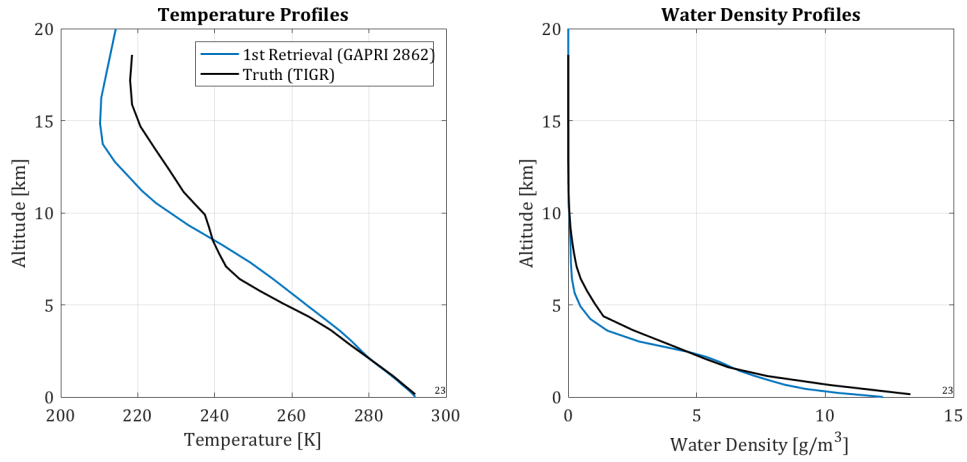


Figure 48. CHAERM's retrieved atmospheric state.

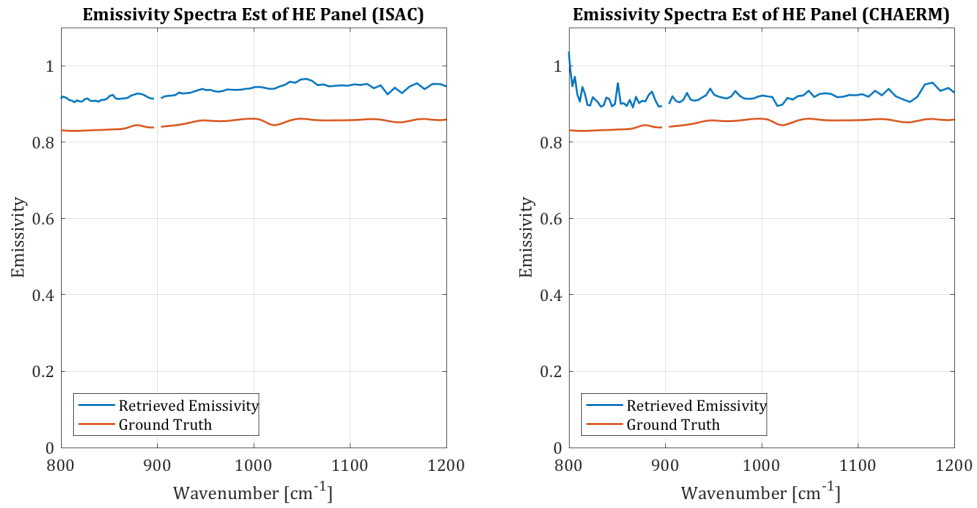


Figure 49. Comparing the truth and retrieved emissivity spectra for three different materials.

sensor resolution. The retrieval products and some compensated pixel spectra are shown in Figs. 50-53. This is an example of another good output by CHAERM, although in aggregate, the overall errors were worse. The average retrieval error in the transmission profiles increased to 0.063 with a standard deviation of 0.051, and the path radiance RMS mean error was $0.752 \mu\text{W}/\text{cm}^2 \text{sr cm}^{-1}$ with standard deviation of 0.575.

These results are still good, but the performance loss is not unexpected. CHAERM's leverage over other methods is that it calculates the line emission effects across the entire LWIR band. Because the absorption coefficients at every wavenumber are slightly different, these calculations across the band inform more of the specificity of the atmospheric state. In the case of the monochromatic spectra versus those of the SEBASS sensor, the total number of channels is reduced from 572 to 128. There just isn't as much information about the atmospheric state that can be obtained when a sensor's starts aggregating the energy individual absorption lines. The manifestation of the retrieval errors, therefore, typically has to do with retrieving the correct water content, resulting in a significant error in the continuum absorption effects. It is in this way that CHAERM is poised for success as future sensors, with increasing resolution, are developed.

6.3 Aggregate Results

CHAERM was additionally tested under a variety of different surface material distributions. For each of the 24 different atmospheric conditions, the percentage of underlying HE pixels in the scene was varied between 20% and 30%. The results of the 96 CHAERM runs showed an overall invariance to the percentage of HE pixels in the scene. Using ED to select the matching spectra, the same atmosphere was selected for all four surface material configurations in 6 of 24 opportunities, and the

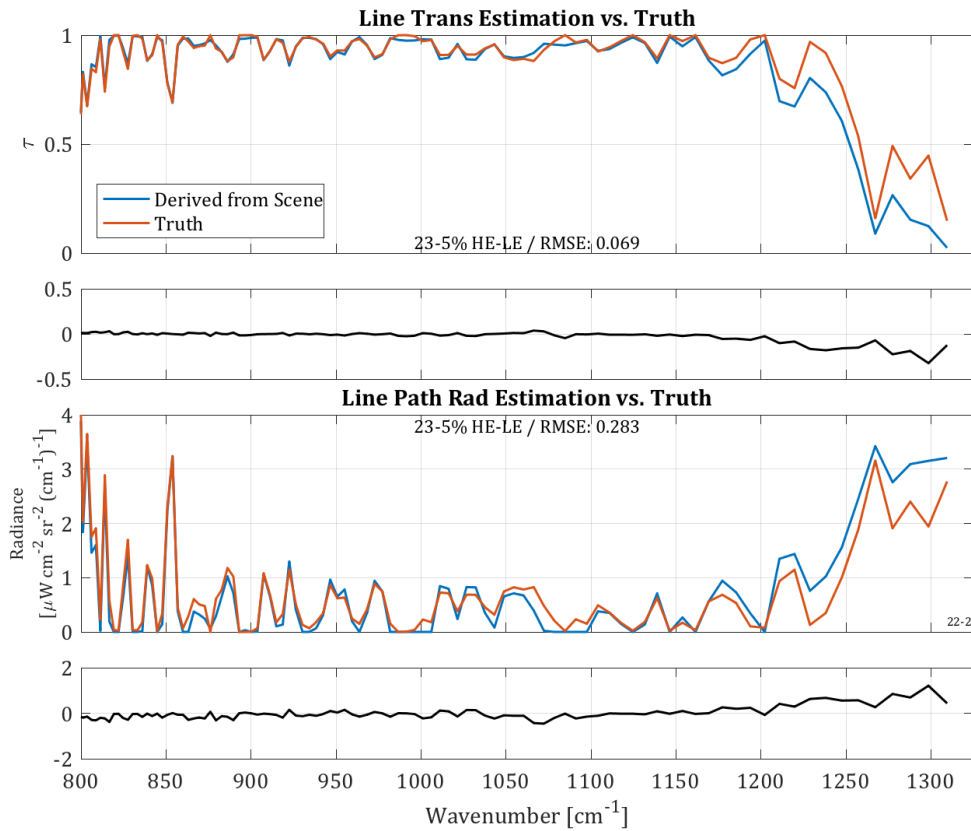


Figure 50. CHAERM's estimated line effects spectra and the residual errors compared to the truth spectra.

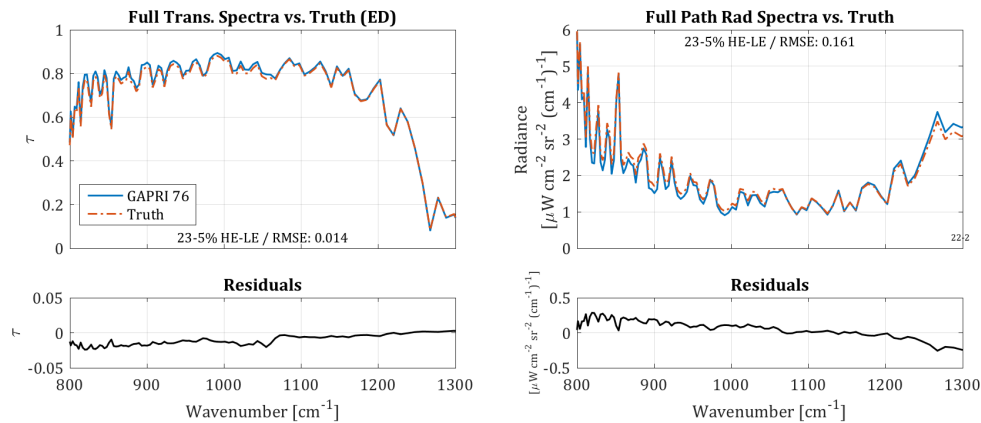


Figure 51. CHAERM's retrieved transmission and path radiance spectra using SEBASS resolution.

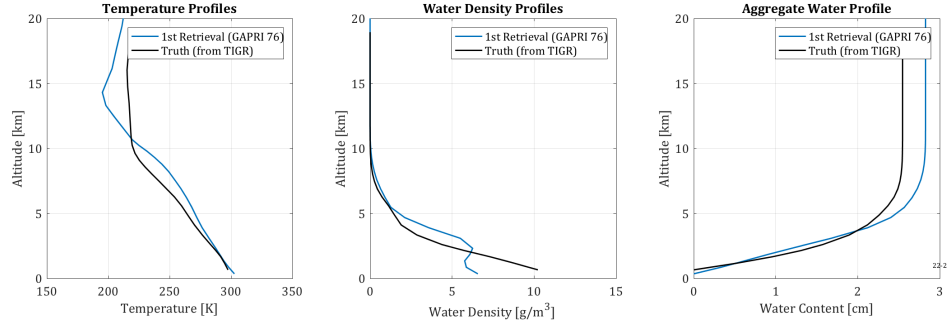


Figure 52. CHAERM's retrieved atmospheric state using SEBASS resolution.

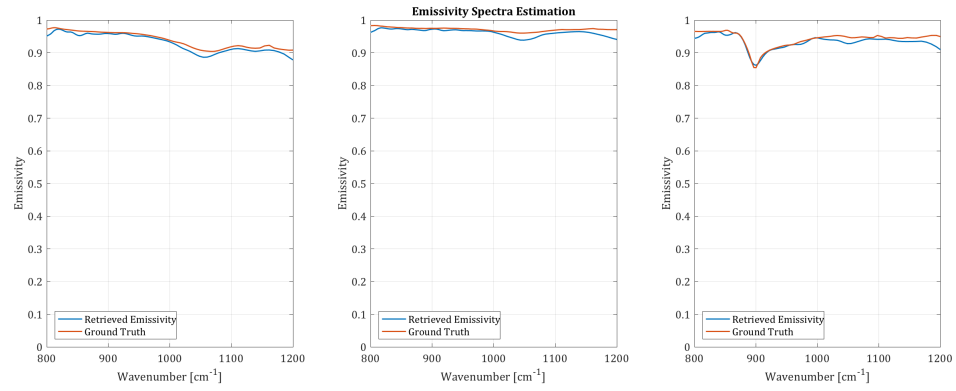


Figure 53. Comparing the truth and retrieved emissivity spectra for three different materials using SEBASS resolution.

same model was selected in 3 of the 4 configurations in 12 of 24 opportunities.

That being said, additional refinements could certainly be explored to configure the database more appropriately for viewing condition, but it is worth noting that in none of the 24 cases, with water content amounts varying between 1 – 3 cm, did CHAERM select four different atmospheres to match to the same viewing conditions. Additionally, it was noted that the match consistency was not a function of total water content meaning that CHAERM performed as well with more moist atmospheres, where compensation tends to be more challenging. Furthermore, there was a strong correlation between the total water content in CHAERM’s selection and the actual water content of the atmosphere. In 88 of the 96 CHAERM runs (24×4), the water content of the matching atmosphere agreed with the actual water content within ± 0.5 cm.

The final statistic, RMS error between the retrieved spectra and the truth spectra demonstrates CHAERM’s capability to manage accuracy with expediency. This is shown in Figure 54, which reports RMS error for each of the 96 trials as a function of total water content. There does exist a correlation to water content, but it is not egregious. In total, the results in this section advocate CHAERM’s approach to atmospheric compensation.

Table 3. Number out of 24 atmospheric states for which CHAERM matched the same atmosphere when presented with four different underlying surface materials distributions.

Match Consistency	Euclidean Distance
4	6/24
3	12/24
2-2 [†]	3/24
2	3/24
1	0

([†] denotes when there were a total of 2 unique atmospheres retrieved, which is deemed to be distinct from the case with 3 unique atmospheres and only 1 matching set)

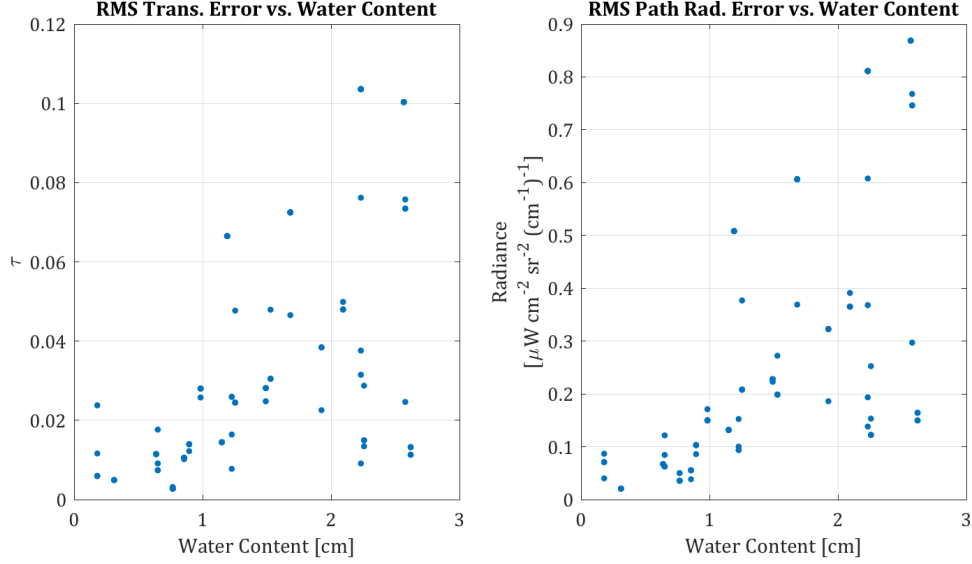


Figure 54. RMS error as a function of total water content in total transmittance retrievals (left) and total path radiance retrievals (right) using ED to determine the best matches.

6.4 Noise Resilience

Sensor noise in the simulated data was computed by multiplying the mean radiance of the scene across all channels and pixels by an $n \times p$ matrix of normally distributed random numbers, where n was the number of pixels in the scene and p was the number of spectral channels, and then dividing this matrix by a scalar value as a proxy for the SNR. This matrix was added back to the original hyperspectral data matrix.

Modeled this way, CHAERM exhibits good resilience to SNR. The panels in Figures 55 and 56 show the results of RMS retrieval errors for 24 simulated scenes with variable water content. The reported errors in this simple noise analysis represent the RMS error of CHAERM's retrieval compared to the actual transmittance and path radiance spectra used to create the simulated scene. These preliminary results indicate that CHAERM is somewhat robust to signal noise, though its performance does degrade as the signal degrades. The robustness is the

result of CHAERM's regression based approach to estimating the line effects and inclusion of many pixels in those computations.

6.5 Real-World Data and the SEBASS Sensor

Finally, CHAERM was tested with real-world measurements using the HSI data discussed in Chapter 3. For operational data, the truth TUD spectra are not known. Thus, to determine an appropriate truth state to measure the success of CHAERM, *a priori* data in the scene was leveraged. Three pixels were selected from the scene for which temperature and emissivity were known. The temperature was monitored with thermocouples and the emissivity spectra were previously measured. The corresponding three pixels were then obtained from the HSI data set.

A nonlinear least squares search algorithm was developed to minimize the residual error between the model's computed radiance and the at-sensor measurements in each channel. Because the pixels selected had diverse emissivity spectra, transmission, path radiance, and downwelling could be estimated. Mathematically, this can be represented as solving for the parameter vector $\vec{p}$ which minimizes the squared errors

$$S_i = \sum_{i=1}^N r_i^2$$

where r_i represents the residuals between the observed radiances y_i and the

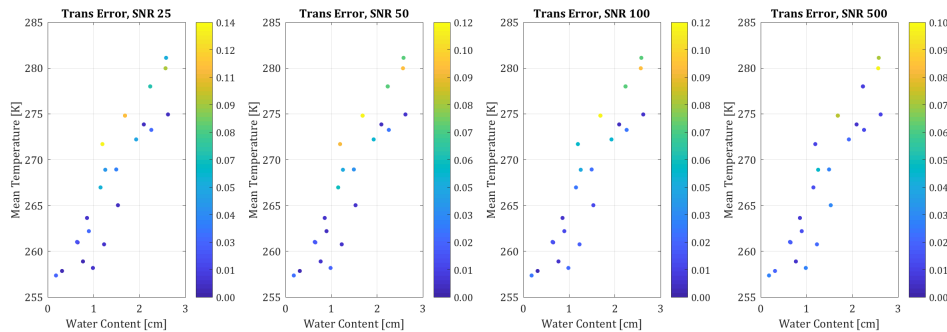


Figure 55. Transmission spectrum retrieval errors as a function of SNR.

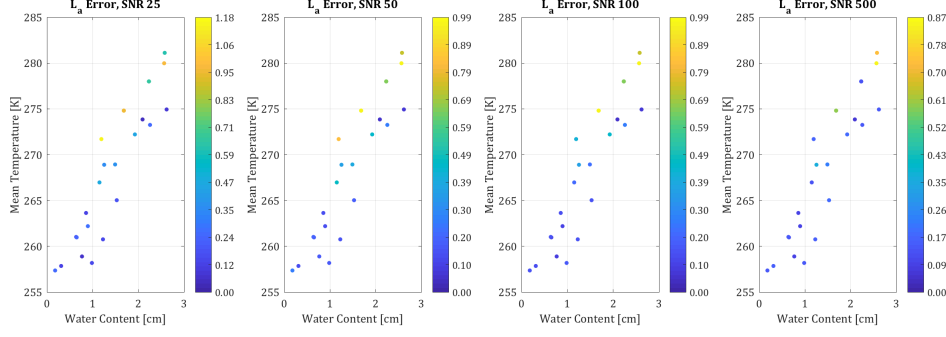


Figure 56. Path radiance spectrum retrieval errors as a function of SNR.

parameterized model f

$$r_i = y_i - f(\vec{x}_i, \vec{p}) \quad (40)$$

and $\vec{x}_i$ are the known inputs to the model. The parameters determined by this fitting comprise the TUD spectra in a particular channel, i.e., $\vec{p} = \{\tau, L_a, L_d\}$. This process is repeated for each spectral channel to determine the entire TUD spectra. An example of the results of the optimization are shown in Figure 57. In this case, the real-world data was collected by a SEBASS sensor flying 1 km above the ground, thus there is no ozone absorption apparent in the path radiance. However, the incorporation of a low emissivity target into the observations allows the downwelling spectrum to be obtained, which shows the downwelling component of ozone.

In the far right panel of Fig. 57, the results of an emissivity retrieval are shown. This was done with another HE pixels whose temperature and emissivity spectrum were known. To solve for the pixels emissivity, the TUD parameters were used with Equation 10. The calculated emissivity spectra closely agrees to the ground truth. The close agreement indicates that the TUD that has been derived for this real-world collection is a good representation of the true RT state of the atmosphere. This process was repeated on two additional days, during which the sensor flew at 2 km and 3 km.

CHAERM was contested against ISAC for these real-world data sets. The ISAC

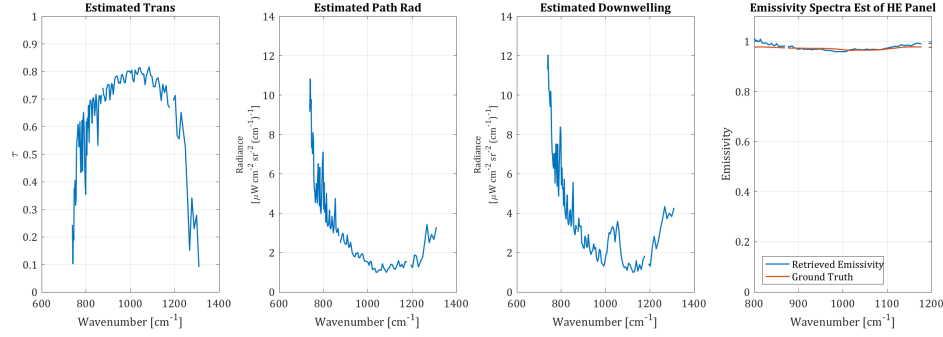


Figure 57. The estimated TUD spectra obtained using ground truth temperature and emissivity and a NLLS model.

approach to AC, discussed at length in Chapter 2, was chosen because CHAERM also takes an ISAC-like approach to in-scene AC. In particular, CHAERM’s use of line absorption spectra is an extension of ISAC’s 853 cm^{-1} absorption band scaling applied to all spectral channels. The ISAC implementation was developed using the methodology outlined in [14].

6.5.1 Collection Day #1.

On this day, the sensor flew 3 km over the scene. Because of the IFOV of the SEBASS sensor, this resulted in a considerable amount of pixel blending of the small targets in the scene. A grey scale image of the scene is shown in 58. The FOV of the sensor includes some naturally occurring water and the extent of the data cube includes a large amount of natural grassland vegetation.

CHAERM ingested all of the pixels in the scene. Because its fundamental assumptions are built on the HE approximation to the LWIR RT model, a weighting scheme was assigned to each pixel based on spectral similarity to the surface leaving radiance L_0 catalog entries. The results of this weighting scheme are shown in Figure 59. That large weights of the naturally occurring water feature located at the top of the image near column 700 is consistent with the known emissivity characteristics of water. The purpose of this weighting factor is to reduce

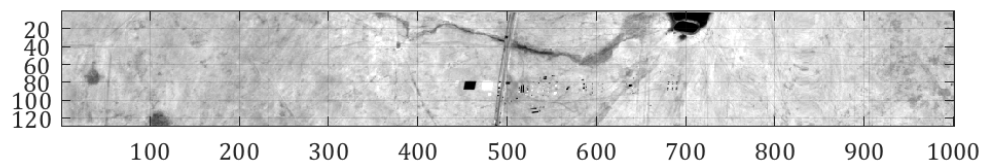


Figure 58. A grey scale image of the scene as viewed by SEBASS with sensor altitude of 3 km.

the influence of pixels with low wide-band emissivity or significant spectral structure when it comes to performing the linear regression to determine the line absorption and line path radiance.

An example of CHAERM’s regression on a large data set of real-world measurements is shown in Figure 60. The excluded pixels comprised the lowest 5th percentile of the weighting factors, and the iterative scheme discussed in Chapter 5 was used to determine the least squares line to the “top” of the data distribution. CHAERM’s computed line effects in this absorption channel are $\tau_l = 0.722$ and $L_a^l = 2.91 \mu W / \text{cm}^2 \text{ sr cm}^{-1}$.

An elevation filter requiring the catalog surface elevation be within 200 m of the 700 m surface was employed to down-select. The derived line transmittance and absorption spectra resulting from the CHAERM analysis, shown in Figure 61, demonstrate good agreement. The retrieved atmospheric state profiles, shown in Figure 62, also show agreement with the conditions measured by a radiosonde.

The purpose of both ISAC and CHAERM is to retrieve the TUD which can be used to transform the entire scene into emissivity space. In Figs. 63-64, each method’s TUD spectra are compared to the spectra derived using NLLS fitting. In both cases, the continuum absorption is not modeled well. As a result, the compensated spectra exhibit some small artifacts of high-frequency content, and they have an overall bias. These derived emissivity spectra are shown in Figure 65. These spectra are not perfectly compensated, but there are indications that both AC algorithms are functioning properly because the smooth varying content of the spectra is maintained.

This is a common feature for in-scene AC. However, CHAERM distinguishes itself from ISAC because of its capability for fine tuning, as was discussed in Chapter 4. In that chapter, it was shown that a low parameter representation of the

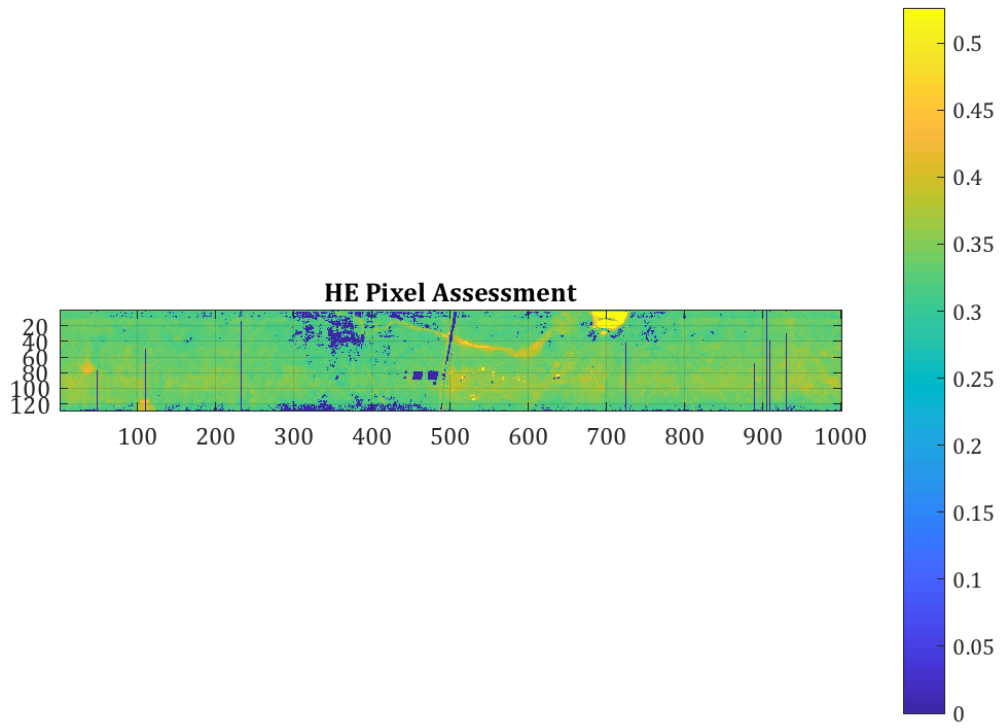


Figure 59. The results of a HE assessment per pixel for the HSI data. The color scale indicates the weights, with higher weights indicating the best HE pixels candidates.

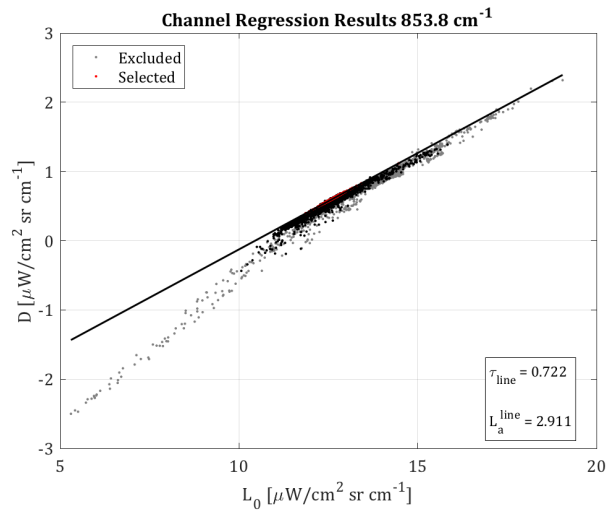


Figure 60. Scatter plot of the selected and excluded pixels for the linear regression at 853 cm^{-1} .

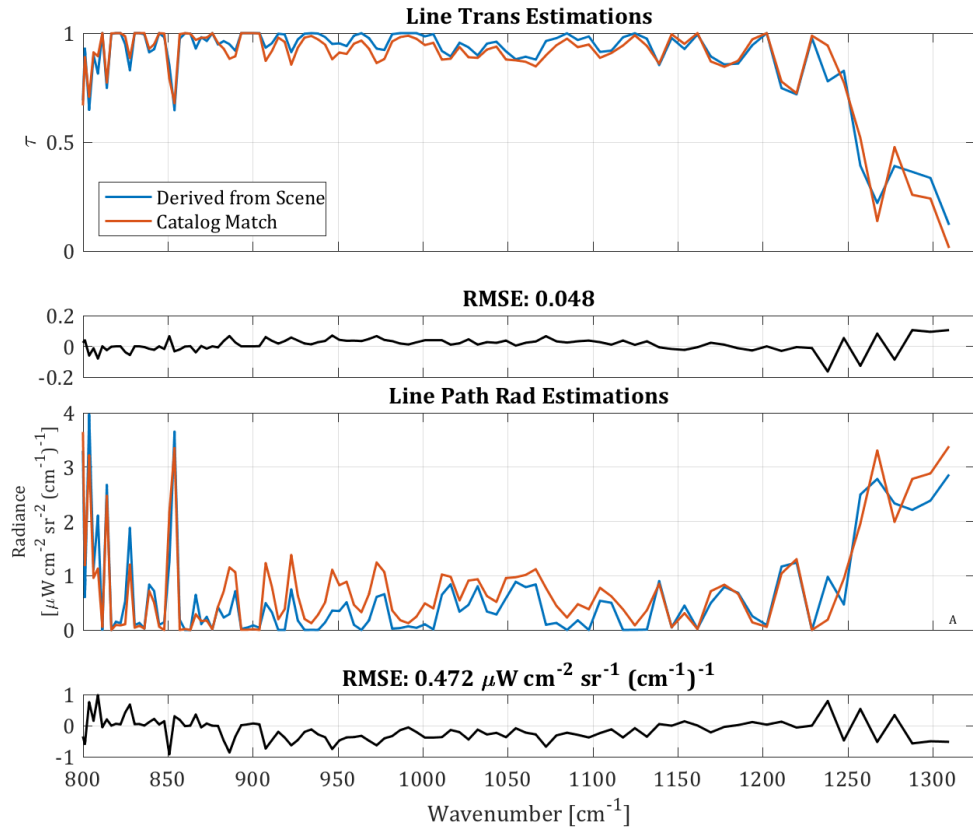


Figure 61. The line transmission spectra (top) and the line path radiance spectra (bottom) derived from a real-world CHAERM analysis.

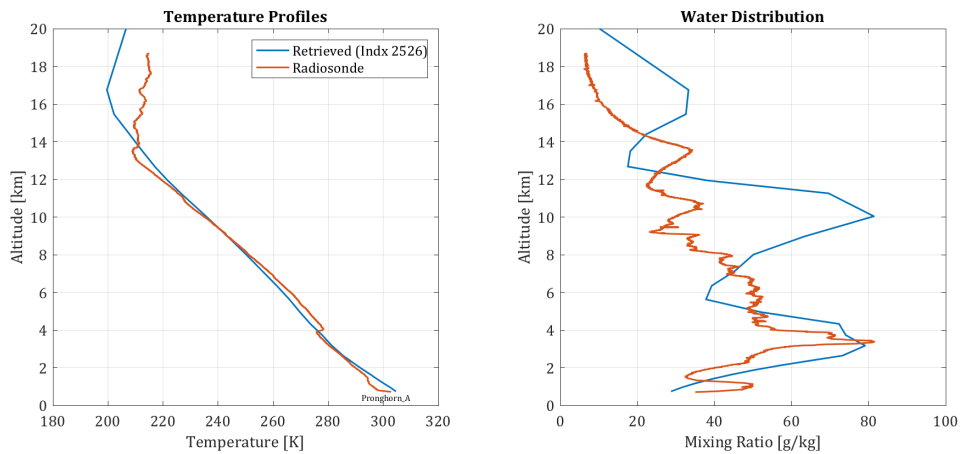


Figure 62. The temperature profile (left) and water content (right, in mixing ratio) of the radiosonde data and the associated atmospheric state for CHAERM's in-scene atmospheric compensation algorithm.

atmospheric state can not only adequately represent the RT to accurately model the TUD, but that the parameters can be functionally tuned. This is perhaps the most exciting horizon of this research, and it will be pursued in greater detail in subsequent studies.

6.5.2 Real-World Collection #2 and #3.

Two additional collections were analyzed using CHAERM and ISAC. The datasets were acquired on different days, and the sensor altitudes were 1 km and 2 km. The results of the atmospheric compensation are shown in Figures 66 and 67 with many of the same issues as before. The compensation is not perfect, but it is functional, and in CHAERM's case, tuning to a more refined answer will likely be an option.

The errors in these collections can be attributed to a couple of possibilities. First is the sensor resolution. This impacts CHAERM considerably because this method seeks to discriminate atmospheric features based upon the absorption features of the RT. As such, CHAERM is clearly better suited for sensors whose spectral resolution is as high as possible. There are also strong indications that the ubiquitous anti-correlation problems are manifest with transmission losses and path radiance

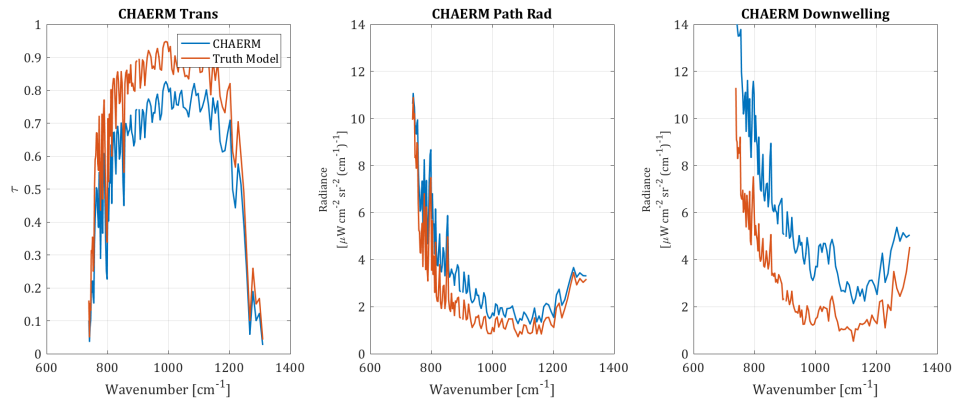


Figure 63. CHAERM's derived TUD spectra compared with the modeled TUD.

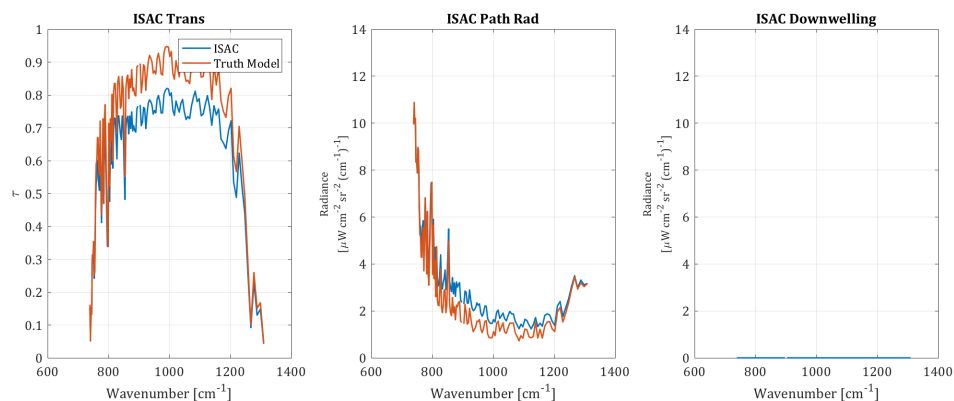


Figure 64. ISAC's derived TUD spectra compared with the modeled TUD. Note that ISAC does inherently compute a downwelling spectrum, although most applications of ISAC would look up in the same manner as CHAERM does.

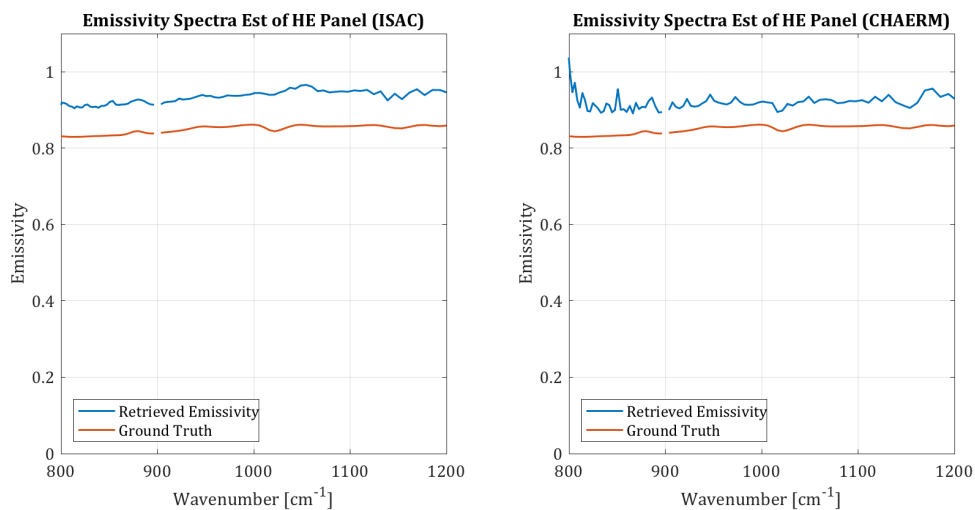


Figure 65. ISAC's (left) and CHAERM's (right) computed emissivity spectra.

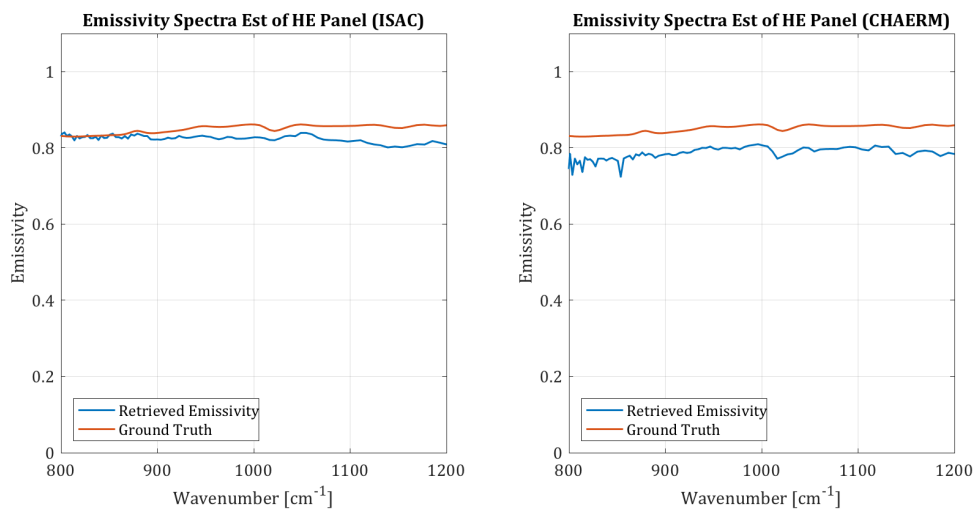


Figure 66. ISAC's (left) and CHAERM's (right) computed emissivity spectra.

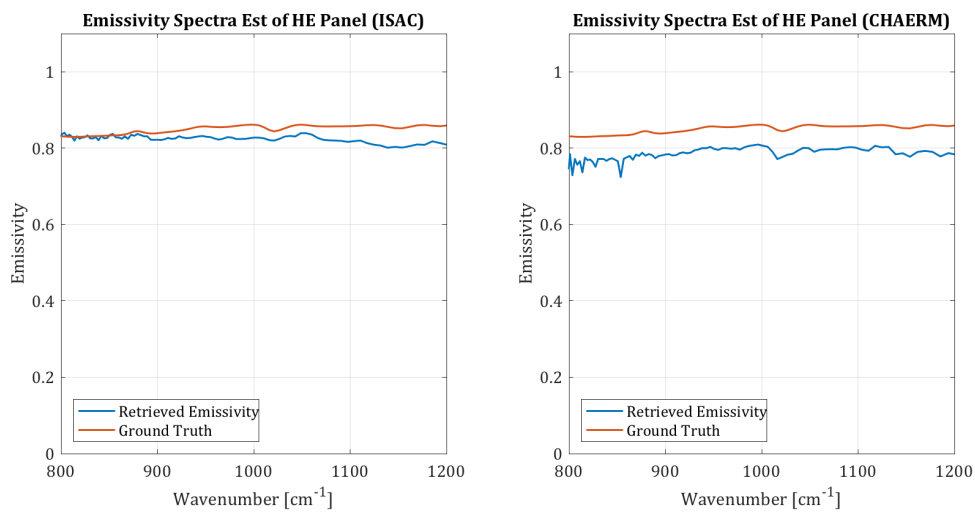


Figure 67. ISAC's (left) and CHAERM's (right) computed emissivity spectra.

gains. This, unfortunately, will plague most in-scene AC methods, especially those whose sensors are aggregating a lot of energy from different line features. That being said, CHAERM is a valid approach to AC, and its future is filled with even more capabilities. These will be discussed in the final chapter of this document.

VII. Conclusion and Extensions

The research discussed in this document has presented meaningful contributions in two main avenues of atmospheric compensation approaches for LWIR hyperspectral imagery. In the first avenue, enhancements to existing climatological databases have been accomplished and validated. This will serve the atmospheric compensation community well in a variety of situations for which radiative transfer modeling is needed. Secondly, this research has developed CHAERM, an operationally relevant, robust, and accurate way to accomplish atmospheric compensation, whose products include an accurate characterization of the atmospheric state and an accurate estimation of the radiative transfer properties of the Earth's atmosphere. Throughout, the methods incorporated by this research have maintained a connection to meteorologically and physically consistent processes.

7.1 Summary of Substantive Contributions

7.1.1 Enhancement of the climatological databases.

The TIGR and GAPRI atmospheric databases provide robust initialization data of an atmospheric state. In this research, the fidelity of that data was enhanced by incorporating surface elevation data, realistic atmospheric surface pressures, and more realistic aerosol loading and visibility estimates. In so doing, these existing datasets have been made more relevant to location specific, operational remote sensing applications. The enhancements to the database were accomplished smartly, such that the relative sampling frequency of the original databases were maintained in order to facilitate accurate radiative transfer in lowest layers of the atmosphere. The resulting modification show excellent agreement with location specific

radiosonde data, for which surface elevation is obviously incorporated, and maintain realistic temperature and water vapor profiles that maintain unique information content of the original atmospheric state.

7.1.2 Demonstration of the anti-correlation of transmission and path radiance.

The development of the atmospheric compensation method in this research exposed the inherent difficulties decoupling the effects of transmission and path radiance in a way that has not been overtly discussed in the AC research community. This research clearly demonstrated how the anti-correlated nature of extinction and emission processes along a target-to-sensor line of sight can offset each other in such a way that efforts to determine the atmospheric state by using the measured data alone can be severely compromised. It, furthermore, quantitatively demonstrated specific viewing conditions under which two disparate atmospheric states from the GAPRI database create nearly identical at-sensor-signals. Although this issue was somewhat uniquely related to the particular methods employed by the AC method here, this research exposed this heretofore unmentioned consideration that may be useful to the development of other in-scene methods.

7.1.3 Low-order parameterization of the atmospheric state.

This research developed a means of representing the temperature and water vapor profiles as functions of altitude and validated the efficacy of the approach. Here, it was shown that by using two nonlinear functions of only three parameters, the specific information content of both temperature profile and water vapor profiles could be accurately conveyed to a radiative transfer model with negligible impact to the radiative transfer calculations. Using few parameters promotes reduces the

dimensionality of the state space and shows great application to operationally minded remote sensing and atmospheric compensation by simplifying radiative transfer inputs while maintaining meteorologically consistent bounds.

7.1.4 Data-driven atmospheric compensation.

Finally, the development of this in-scene atmospheric compensation technique shows great promise in simultaneously achieving a two-fold goal, determining the radiative transfer properties of the atmosphere and describing the atmospheric state. This approach selectively and effectively exploits the vast and comprehensive data in the GAPRI dataset by developing a unique process that mitigates the ubiquitous issues with non-unique solutions. In particular, this approach demonstrates a new process by which the information content in the line absorption transmission and path radiance spectra can be uniquely and accurately estimated. The high-frequency information content in the line absorption effects spectra serve to accurately identify and inform an atmospheric state from the GAPRI database. Thus, not only is the associated transmission, path radiance, and downwelling spectra available for compensation, but the atmospheric state is also described. Using the newly developed three-parameter functions paves the way for the development of an efficient tuning method that can be used to remove residual atmospheric and fine tune the atmospheric state. Although, a certain degree of material and temperature diversity are required as are a reasonable population of high emissivity materials in the scene, this method can be used to quickly determine the TUD spectra without the need for scaling, as is necessary in ISAC. The following provides a summary of CHAERM’s capabilities.

- It is fast. As an operationally minded approach to AC, the majority of the time consuming initialization of CHAERM can be done in advance and once

done can be maintained for all future uses. The methods which it employs are currently accomplished in under 60 seconds on a laptop computer using 3200 pixel scenes. Adaptation to an infrastructure designed for large data processing would like reduce this already manageable processing time considerably.

- It is meteorologically consistent. Successful in-scene approaches that use mathematical methods to perform constrained optimization in a multivariate parameter space or to perform multivariate regression may or may not place a priority on remaining physically realistic. Because CHAERM's methodology never incorporates anything other than valid atmospheric data, its outputs remain physical.
- It is customizable. All of the analysis of CHAERM has been done with GAPRI atmospheres. By definition, this is a global dataset. For users whose HSI interests are more regional, a customized database could easily be plugged into CHAERM. For example, if an extended hyperspectral imaging campaign were to be conducted in Ohio, radiosonde data could be readily compiled and shaped into a regional atmospheric database. Exclusions to the database could even be made to account for time of year. Fundamentally, there are no restrictions to what kind of atmospheric database is used by CHAERM since all of its internal methodology is self-consistent.

7.2 Application to Simultaneous VNIR/SWIR Remote Sensing

Because this LWIR AC technique derives an atmospheric state, it offers a great initialization step for performing in-scene AC on VNIR/SWIR spectra. The meaningful addition of a location-dependent visibility parameter is not an overly

important consideration for compensation efforts in the LWIR, but it can be very important to VNIR/SWIR AC. The benefits to having a good estimate for the atmospheric state from the LWIR can be used to estimate, and ultimately bound, compensation made in the shortwave.

7.3 Extensions of this Research

This research endeavor has laid a solid foundation for future work. One gainful extension would be further enhancements to the TIGR and GAPRI databases to ensure an even broader applicability and expanse of real-world data. These modifications could come in the form of additional data, to include carefully conditioned and screened radiosonde data, or could come in the form of realistic modifications to the existing atmospheric profiles. For example, MODTRAN allows the total water profile to be scaled up or down, and assuming small scale factors were used, this could add some additional, yet importantly realistic, variation to the existing profiles. The only real limitation on such an endeavor is the time it takes to forward model. To this end, the burgeoning forecasting capability of Numerical Weather Prediction will likely serve this type of in-scene atmospheric compensation well in the future as it represents a dynamic collection of physically realistic atmospheric states.

One of the limitations of this approach to in-scene AC is that the various catalogs must be initialized to closely approximate the sensor’s viewing geometry. This requires a considerable dataset, including the BB-catalog, the continuum effects catalog, and the line effects catalog, to be run for specific sensor-to-target path lengths. A potential, and intriguing adaptation, might involve the recent work of O’Keefe [86], who explored the effects of range in oblique viewing geometries, but whose techniques may well be applicable to variable ranges in nadir viewing

geometries.

A vision for CHAERM-v2 incorporates a refined fine-tuning capability that uses the functional representations of the atmospheric state, which will certainly be value added to the final product, as long as small perturbations to the coefficients maintain meteorological consistency. To this end, advances in computing power will continue to enhance operationally minded atmospheric compensation as more and more data is able to be processed more and more quickly. CHAERM represents a method which can grow and improve as modern computing capabilities continue to advance.

Bibliography

1. J. Schott, *Remote Sensing: The Image Chain Approach*, 2nd ed. New York: Oxford University Press, 2007.
2. S. R. Cone, F. A. Kruse, and M. L. McDowell, "Exploration of integrated visible to near-, shortwave-, and longwave- infrared (full range) hyperspectral data analysis," in *Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XXI*, M. Velez-Reyes and F. A. Kruse, Eds., vol. 9472, 2015, pp. 1–12.
3. J. A. Richards and X. Jia, *Remote Sensing Digital Image Analysis: An Introduction*. New York: Springer, 2006.
4. F. D. van der Meer and S. M. de Jong, *Imaging Spectroscopy: Basic Principles and Prospective Applications*. Dordrecht, Netherlands: Springer, 2011.
5. J. M. Bioucas-Dias, A. Plaza, G. Camps-Valls, P. Scheunders, N. Nasrabadi, and J. Chanussot, "Hyperspectral Remote Sensing Data Analysis and Future Challenges," *IEEE Geoscience and Remote Sensing Magazine*, vol. 1, pp. 6–36, 2013.
6. G. Shaw and H.-h. K. Burke, "Remote Sensing," *Lincoln Laboratory Journal*, vol. 14, no. 1, pp. 3–28, 2003.
7. J. Ahlberg, "Estimation of atmosphere and object properties in hyperspectral longwave infrared data," 2006.
8. J. B. Campbell and R. H. Wynn, *Introduction to Remote Sensing*, 5th ed. New York: Guilford Press, 2011.
9. B. C. Gao, M. J. Montes, C. O. Davis, and A. F. H. Goetz, "Atmospheric correction algorithms for hyperspectral remote sensing data of land and ocean," *Remote Sensing of Environment*, vol. 113, pp. 17–24, 2009.
10. A. Plaza, J. Plaza, A. Paz, and S. Sanchez, "Parallel hyperspectral image and signal processing," *IEEE Signal Processing Mag.*, vol. 28, no. 3, pp. 119–126, 2011.
11. P. A. Rochford, P. K. Acharya, S. M. Adler-Golden, A. Berk, L. S. Bernstein, M. W. Matthew, S. C. Richtsmeier, S. Gulick, and J. Slusser, "Validation and refinement of hyperspectral/multispectral atmospheric compensation using shadowband radiometers," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 43, no. 12, pp. 2898–2906, 2005.

12. M. K. Griffin and H.-h. K. Burke, "Compensation of Hyperspectral Data for Atmospheric Effects," *Lincoln Laboratory Journal*, vol. 14, no. 1, pp. 29–54, 2003.
13. P. W. T. Yuen and G. Bishop, "Enhancements of target detection using atmospheric correction preprocessing techniques in hyperspectral remote sensing," in *Proceedings of SPIE 5613*, 2004, pp. 111–118.
14. S. J. Young, B. R. Johnson, and J. A. Hackwell, "An in-scene method for atmospheric compensation of thermal hyperspectral data," *Journal of Geophysical Research*, vol. 107, no. 24, pp. 1–20, 2002.
15. D. Gu, A. R. Gillespie, A. B. Kahle, and F. D. Palluconi, "Autonomous atmospheric compensation (AAC) of high resolution hyperspectral thermal infrared remote-sensing imagery," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 38, no. 6, pp. 2557–2570, 2000.
16. E. F. Vermote and S. Kotchenova, "Atmospheric correction for the monitoring of land surfaces," *Journal of Geophysical Research*, vol. 113, no. 23, pp. 1–12, 2008.
17. X. Liu, W. L. Smith, D. K. Zhou, and A. Larar, "A principal component-based radiative transfer forward model (PCRTM) for hyper spectral sensors," *Applied Optics*, vol. 45, no. 1, pp. 201–209, 2006.
18. L. S. Bernstein, X. Jin, B. Gregor, and S. M. Alder-Golden, "Quick atmospheric correction code: algorithm description and recent upgrades," *Optical Engineering*, vol. 51, no. 11, pp. 1–11, 2012.
19. D. A. Roberts, D. A. Quattrochi, G. C. Hulley, S. J. Hook, and R. O. Green, "Synergies between VSWIR and TIR data for the urban environment: an evaluation of the potential for the Hyperspectral Infrared Imager (HypIRI) Decadal Survey mission," *Remote Sensing of Environment*, vol. 117, pp. 83–101, 2012.
20. S. P. Grigsby, G. C. Hulley, D. A. Roberts, C. Scheele, S. L. Ustin, and M. M. Alsina, "Improved surface temperature estimates with MASTER/AVIRIS sensor fusion," *Remote Sensing of Environment*, vol. 167, pp. 53–63, 2015. [Online]. Available: <http://dx.doi.org/10.1016/j.rse.2015.05.019>
21. F. A. Kruse, "Integrated visible and near-infrared, shortwave infrared, and longwave infrared full-range hyperspectral data analysis for geologic mapping," *Journal of Applied Remote Sensing*, vol. 9, pp. 1–17, 2015.
22. A. Berk, G. P. Anderson, P. K. Acharya, L. S. Bernstein, L. Muratov, J. Lee, M. Fox, S. M. Adler-Golden, J. H. Chetwynd, Jr., M. L. Hoke, R. B. Lockwood, J. A. Gardner, T. W. Cooley, C. C. Borel, P. E. Lewis, and E. P. Shettle,

- “MODTRAN5: 2006 update,” in *Proceedings of SPIE*, vol. 6233, 2006, pp. 62 331F–62 331F–8.
23. A. M. Baldridge, S. J. Hook, C. I. Grove, and G. Rivera, “The ASTER spectral library version 2.0,” *Remote Sensing of Environment*, vol. 113, no. 4, pp. 711–715, 2009.
 24. M. T. Eismann, *Hyperspectral Remote Sensing*. SPIE Press, 2012.
 25. T. He, S. Liang, D. Wang, Q. Shi, and M. L. Goulden, “Estimation of high-resolution land surface net shortwave radiation from AVIRIS data: Algorithm development and preliminary results,” *Remote Sensing of Environment*, vol. 167, pp. 20–30, 2015.
 26. J. Gruninger, M. Fox, J. Lee, A. J. Ratkowski, and M. L. Hoke, “Use of the Vis-SWIR to aid atmospheric correction of multispectral and hyperspectral thermal infrared (TIR) imagery: The TIR model,” in *SPIE Proceeding: Imaging Spectroscopy VIII*, 2002.
 27. A. Goetz, G. Vane, J. E. Solomon, and B. N. Rock, “Imaging spectrometry for earth remote sensing,” *Science*, vol. 228, no. 4704, pp. 1147–1153, 1985.
 28. S. M. Adler-Golden, P. Conforti, M. Gagnon, P. Tremblay, and M. Chamberland, “Long-wave infrared surface reflectance spectra retrieved from Telops Hyper-Cam imagery,” in *SPIE: Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XX*, vol. 9088, 2014, p. 90880U1:8.
 29. F. Dell’Endice, J. Nieke, B. Koetz, M. E. Schaepman, and K. Itten, “Improving radiometry of imaging spectrometers by using programmable spectral regions of interest,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 64, no. 6, pp. 632–639, 2009.
 30. M. Matthew, S. M. Adler-Golden, A. Berk, and G. Felde, “Atmospheric correction of spectral imagery: evaluation of the FLAASH algorithm with AVIRIS data,” in *Proc. 31st Annual Applied Imagery Pattern Recognition Workshop*, 2002, pp. 1–6.
 31. E. F. Vermote, N. El Saleous, C. O. Justice, Y. J. Kaufman, J. L. Privette, L. Remer, J. C. Roger, and D. Tanré, “Atmospheric correction of visible to middle-infrared EOS-MODIS data over land surfaces: Background, operational algorithm and validation,” *Journal of Geophysical Research*, vol. 102, no. D14, pp. 17 131–17 141, 1997.
 32. P. Shippert, “Introduction to hyperspectral image analysis,” *Online Journal of Space Communication*, 2003.

33. M. R. Smith, A. R. Gillespie, H. Mizzon, L. K. Balick, J. C. Jiménez-Muñoz, and J. a. Sobrino, "In-scene atmospheric correction of hyperspectral thermal infrared images with nadir, horizontal, and oblique view angles," *International Journal of Remote Sensing*, vol. 34, no. 9-10, pp. 3164–3176, 2013.
34. C. Borel, "Surface emissivity and temperature retrieval for a hyperspectral sensor," *IGARSS '98. Sensing and Managing the Environment. 1998 IEEE International Geoscience and Remote Sensing. Symposium Proceedings. (Cat. No.98CH36174)*, vol. 1, no. AUGUST 1998, 1998.
35. P. S. J. Chavez, "Image-based atmospheric corrections—revisited and improved," *Photogrammetric Engineering and Remote Sensing*, vol. 62, no. 9, pp. 1025–1035, 1996.
36. J. A. Sobrino, J. Cuenca, H. E. Kharraz, and L. Dempere, "Experimental investigation of the angular variation of emissivity in the thermal infrared band," in *Proceedings of SPIE 3499: Remote Sensing for Agriculture, Ecosystems, and Hydrology*, E. T. Engman, Ed., 1998, pp. 427–436.
37. Z.-L. Li, H. Wu, N. Wang, S. Qiu, J. A. Sobrino, Z. Wan, B.-H. Tang, and G. Yan, "Land surface emissivity retrieval from satellite data," *International Journal of Remote Sensing*, vol. 34, no. 9-10, pp. 3084–3127, 2013.
38. C. C. Borel, "ARTEMIS - An algorithm to retrieve temperature and emissivity from hyperspectral thermal image data," *GOMAC Tech Conference: Hyperspectral Imaging Session*, 2003.
39. C. Borel, "Error analysis for a temperature and emissivity retrieval algorithm for hyperspectral imaging data," *International Journal of Remote Sensing*, vol. 29, no. 17-18, pp. 5029–5045, 2008.
40. G. W. Petty, *A First Course in Atmospheric Radiation*. Madison, WI: Sundog Publishing, 2006.
41. K. N. Liou, *Introduction to Atmospheric Radiation*, 2nd ed. San Diego, CA: Academic Press, 2002.
42. J. M. Wallace and P. V. Hobbs, *Atmospheric Science: An Introductory Survey*, 2nd ed. Amsterdam: Elsevier Academic Press, 2006.
43. S. M. Adler-golden and P. Conforti, "Emissivity Retrieval in LWIR Hyperspectral Desert Scenes," in *Hyperspectral Imaging and Sounding of the Environment*, vol. 204, no. June 2014. Optical Society of America, 2015, pp. HT3B–2.
44. B. Cairns, B. E. Carlson, R. Yinga, and J. Laveignec, "Accuracy vs speed: evaluation of tradeoffs in atmospheric correction methods," in *SPIE Proceeding:*

Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery VIII, vol. 4725, 2002, pp. 427–437.

45. Q. Fu and K. N. Liou, “On the Correlated k -Distribution Method for Radiative Transfer in Nonhomogeneous Atmospheres,” *Journal of the Atmospheric Sciences*, vol. 49, no. 22, pp. 2139–2156, 1992.
46. A. Ohmura, “Physical basis for the temperature-based melt-index method,” *Journal of Applied Meteorology*, vol. 40, no. 4, pp. 753–761, 2001.
47. P. V. Villeneuve and A. D. Stocker, “Oblique projection retrieval of the atmosphere,” in *SPIE Proceeding: Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery VII*, S. S. Shen and P. E. Lewis, Eds., 2002, pp. 95–103.
48. R. J. DiStasio and R. G. Resmini, “Atmospheric Compensation of Thermal Infrared Hyperspectral Imagery with the Emissive Empirical Line Method and the In-Scene Atmospheric Compensation Algorithms: A Comparison,” in *Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XVI*, S. S. Shen and P. E. Lewis, Eds., 2010.
49. E. Hernandez-Baquero and J. Schott, “Atmospheric and surface parameter retrievals from multispectral thermal imagery via reduced-rank multivariate regression,” in *IGARSS 2000. IEEE 2000 International Geoscience and Remote Sensing Symposium. Taking the Pulse of the Planet: The Role of Remote Sensing in Managing the Environment. Proceedings (Cat. No.00CH37120)*, vol. 4, no. 4, 2000, pp. 2–4.
50. A. Berk and G. P. Anderson, “Impact of MODTRAN 5.1 on Atmospheric Compensation,” in *International Geoscience and Remote Sensing Symposium (IGARSS)*, 2008, pp. 127–129.
51. S. Y. Kotchenova, E. F. Vermote, R. Matarrese, and F. J. Klemm, “Validation of a vector version of the 6S radiative transfer code for atmospheric correction of satellite data. Part I, path radiance,” *Applied Optics*, vol. 45, no. 26, pp. 6762–6774, 2006.
52. S. T. Fiorino, R. M. Randall, M. F. Via, and J. L. Burley, “Validation of a UV-to-RF high-spectral-resolution atmospheric boundary layer characterization tool,” *Journal of Applied Meteorology*, vol. 53, no. 1, pp. 136–156, 2014.
53. C. N. Long and D. D. Turner, “A method for continuous estimation of clear-sky downwelling longwave radiative flux developed using ARM surface measurements,” *Journal of Geophysical Research*, vol. 113, no. D18206, pp. 1–16, 2008.

54. P. Dash, F. Gottsche, F. Olesen, and H. Fischer, "Land surface temperature and emissivity estimation from passive sensor data: theory and practice," *International Journal of Remote Sensing*, vol. 23, no. 13, 2002.
55. V. Carrere and J. E. Conel, "Recovery of atmospheric water vapor total column abundance from imaging spectrometer data around 940 nm," *Remote Sensing of Environment*, vol. 440, no. 2-3, pp. 179–204, 1993.
56. A. Prata, V. Caselles, C. Coll, J. Sobrino, and C. Ottele, "Thermal remote sensing of land surface temperatures from satellites: current status and future prospects," *Remote Sensing Reviews*, vol. 12, 1995.
57. T. W. Schlatter, "Atmospheric Composition and Vertical Structure," vol. 6, pp. 1–54, 2009.
58. F. A. Kruse, "Use of airborne imaging spectrometer data to map minerals associated with hydrothermally altered rocks in the northern grapevine mountains, Nevada, and California," *Remote Sensing of Environment*, vol. 24, no. 1, pp. 31–51, 1988.
59. J. E. Conel, R. O. Green, V. Carrere, J. S. Margolis, R. E. Alley, and G. Vane, "Atmospheric water mapping with airborne visible/infrared imaging spectrometer (AVIRIS)," Joint Propulsion Laboratory, Pasadena, CA, Tech. Rep., 1988.
60. R. J. Aspinall, W. A. Marcus, and J. W. Boardman, "Considerations in collecting, processing, and analysing high spatial resolution hyperspectral data for environmental investigations," *Journal of Geographical Systems*, vol. 4, pp. 15–29, 2002.
61. B.-C. C. Gao, K. B. Heidebrecht, and A. F. H. Goetz, "Derivation of scaled surface reflectances from AVIRIS data," *Remote Sensing of Environment*, vol. 44, pp. 165–178, 1993.
62. R. O. Green, D. A. Roberts, and J. E. Conel, "Estimation of aerosol optical depth, pressure elevation, water vapor, and calculation of apparent surface reflectance from radiance measured using AVIRIS using a radiative transfer code," in *Proceedings of SPIE 1937*, 1993, pp. 2–11.
63. D. Tanré, C. Deroo, P. Duhaut, M. Herman, J. Morcrette, J. Perbos, and P. Deschamps, "Simulation of the Satellite Signal in the Solar Spectrum (5S)," 1986.
64. E. F. Vermote, D. Tanré, J. L. Deuze, M. Herman, and J. J. Morcrette, "Second Simulation of the Satellite Signal in the Solar Spectrum (6S)," Greenbelt, MD, 1994.

65. A. Berk, L. S. Bernstein, and D. C. Robertson, "MODTRAN: A Moderate Resolution Model for LOWTRAN 7," Tech. Rep., 1989.
66. S. M. Adler-Golden, M. W. Matthew, L. S. Bernstein, R. Y. Levine, A. Berk, and S. C. Richtsmeier, "Atmospheric correction for short-wave spectral imagery based on MODTRAN4." in *Summaries of the Eighth JPL Airborne Earth Science Workshop*, R. O. Green, Ed. Jet Propulsion Lab, 1999, pp. 21–29.
67. T. Perkins, S. Adler-Golden, M. Matthew, A. Berk, G. Anderson, J. Gardner, and G. Felde, "Retrieval of atmospheric properties from hyper and multispectral imagery with the FLAASH atmospheric correction algorithm," *Proceedings of SPIE: Remote Sensing of Clouds and the Atmosphere X*, vol. 5979, 2005.
68. L. S. Bernstein, S. M. Adler-golden, X. Jin, B. Gregor, and R. L. Sundberg, "Quick Atmospheric Correction for VNIR-SWIR Spectral Imagery: Algorithm Details," pp. 2–5, 2012.
69. L. S. Bernstein, S. M. Adler-Golden, R. L. Sundberg, and A. Berk, "A New Method for Atmospheric Correction and Aerosol Optical Property Retrieval for VIS-SWIR Multi- and Hyperspectral Imaging Sensors: Quick Atmospheric Correction," in *AVIRIS Proceedings: 2004*, vol. 00, no. 1, 2004.
70. J. Gruninger, J. Lee, and R. L. Sundberg, "The application of convex cone analysis to hyperspectral and multispectral scenes," in *Proceedings of SPIE 4885: Image and Signal Processing for Remote Sensing VIII*, 2003.
71. Z. Qu, B. C. Kindel, and A. F. H. Goetz, "The High Accuracy Atmospheric Correction for Hyperspectral Data (HATCH) Model," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 41, no. 6, pp. 1223–1231, 2003.
72. F. A. Kruse, "Comparison of ATREM, ACORN, and FLAASH Atmospheric Corrections using Low-Altitude AVIRIS Data of Boulder, Colorado," in *Proc of 13th JPL Airborne Geoscience Workshop*. Pasadena, CA: Jet Propulsion Lab, 2004.
73. X. Lenot, V. Achard, and L. Poutier, "SIERRA: A new approach to atmospheric and topographic corrections for hyperspectral imagery," *Remote Sensing of Environment*, vol. 113, no. 8, pp. 1664–1677, 2009. [Online]. Available: <http://dx.doi.org/10.1016/j.rse.2009.03.016>
74. N. Keshava, "Distance Metrics and band selection in hyperspectral processing with applications to material identification and spectral libraries," in *IEEE Transactions on Geoscience and Remote Sensing*, 2004, pp. 1552–1565.
75. A. Berk, G. Anderson, and P. Acharya, "MODTRAN User's Manual," Tech. Rep., 2013.

76. C. Mattar, C. Durán-Alarcón, J. C. Jiménez-Muñoz, A. Santamaría-Artigas, L. Olivera-Guerra, and J. A. Sobrino, "Global Atmospheric Profiles from Reanalysis Information (GAPRI): a new database for earth surface temperature retrieval," *International Journal of Remote Sensing*, vol. 36, no. 19-20, pp. 5045–5060, 2015.
77. "Thermodynamic Initial Guess Retrieval (TIGR)." [Online]. Available: <http://ara.abct.lmd.polytechnique.fr/>
78. S. T. Fiorino, R. J. Bartell, M. J. Krizo, G. L. Caylor, K. P. Moore, T. R. Harris, and S. J. Cusumano, "A first principles atmospheric propagation and characterization tool: the laser environmental effects definition and reference (LEEDR)," in *Proc of SPIE 6878, Atmospheric Propagation of Electromagnetic Waves II*, 2008.
79. M. Boonmee, "Land Surface Temperature and Emissivity Retrieval from Thermal Infrared Hyperspectral Imagery," Dissertation, Rochester Institute of Technology, 2001.
80. E. D. Hernandez-Baquero, "Characterization of the Earth's Surface and Atmosphere from Multispectral and Hyperspectral Thermal Imagery," Dissertation, Rochester Institute of Technology, 2000.
81. J. H. Powell, "A Spectral Climatology for Atmospheric Compensation of Hyperspectral Imagery," Dissertation, George Mason University, 2015.
82. J. a. Hackwell, D. W. Warren, R. P. Bongiovi, S. J. Hansel, T. L. Hayhurst, D. J. Mabry, M. G. Sivjee, and J. W. Skinner, "LWIR/MWIR Imaging Hyperspectral Sensor for Airborne and Ground-Based Remote Sensing," *Proceedings of SPIE : Imaging Spectrometry II*, vol. 2819, no. 1, pp. 102–107, 1996.
83. R. G. Vaughan, W. M. Calvin, and J. V. Taranik, "SEBASS hyperspectral thermal infrared data: Surface emissivity measurement and mineral mapping," *Remote Sensing of Environment*, vol. 85, no. 1, pp. 48–63, 2003.
84. R. D. Kaiser, "Wavelength calibration and instrument line shape estimation of a LWIR hyperspectral sensor from in-scene data," *Proceedings of SPIE*, vol. 4049, no. 2000, pp. 284–287, 2000.
85. S. J. Hook, J. J. Myers, K. J. Thome, M. Fitzgerald, and A. B. Kahle, "The MODIS/ASTER airborne simulator (MASTER) - a new instrument for earth science studies," *Remote Sensing of the Environment*, vol. 76, pp. 93–102, 2001.
86. D. O'Keefe, "Oblique Longwave Infrared Atmospheric Compensation," Ph.D. dissertation, Air Force Institute of Technology, 2017.

REPORT DOCUMENTATION PAGE					Form Approved OMB No. 0704-0188	
The public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing the burden, to the Department of Defense, Executive Service Directorate (0704-0188). Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to any penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.						
PLEASE DO NOT RETURN YOUR FORM TO THE ABOVE ORGANIZATION.						
1. REPORT DATE (DD-MM-YYYY) 21-12-2017		2. REPORT TYPE Dissertation			3. DATES COVERED (From - To) Sep 2014 - Sep 2017	
4. TITLE AND SUBTITLE In-Scene Atmospheric Compensation of Thermal Hyperspectral Imaging with Applications to Simultaneous Shortwave Data Collection				5a. CONTRACT NUMBER		
				5b. GRANT NUMBER		
				5c. PROGRAM ELEMENT NUMBER		
6. AUTHOR(S) Lane, Cory T., Lt Col				5d. PROJECT NUMBER 17P406		
				5e. TASK NUMBER		
				5f. WORK UNIT NUMBER		
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/EN) 2950 Hobson Way Wright-Patterson AFB, OH 45433					8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) National Air & Space Intelligence Center Dr. Allan Yarbrough (NASIC/GSIR) 4180 Watson Way Wright-Patterson AFB, OH 45433					10. SPONSOR/MONITOR'S ACRONYM(S) NASIC	
					11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION/AVAILABILITY STATEMENT Distribution Statement A. Approved for Public Release; Distribution Unlimited						
13. SUPPLEMENTARY NOTES						
14. ABSTRACT Compensating for the effects of the Earth's atmosphere is necessary to analyze hyperspectral remote sensing data of the Earth's surface. A new algorithm, the Combined Hyperspectral Atmospheric Effects Removal Method (CHAERM) is designed to provide in-scene atmospheric compensation of LWIR hyperspectral imagery with a priority on expediency suitable for operational contexts. CHAERM's methodology consists of a high-emissivity material screen, followed by a new method of decoupling the effects of continuum absorption and line absorption in the radiative transfer of the atmosphere. Spectral similarity is calculated in a way that allows rapid matching to a large meteorologically consistent database, the Global Atmospheric Profiles from Reanalysis Information (GAPRI) dataset, containing 4,846 realistic atmospheric states. Additionally, the GAPRI database has been modified to account of surface elevation variability and different aerosol loading based on geography. CHAERM's capabilities are demonstrated using simulated hyperspectral datasets and show promising results. RMS residuals in retrievals of transmission and path radiance spectra have been shown to be consistently at or below 10% of the mean value in the band.						
15. SUBJECT TERMS Atmospheric Correction; Hyperspectral Imaging; Thermal Infrared; Meteorological Database						
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT UU	18. NUMBER OF PAGES 159	19a. NAME OF RESPONSIBLE PERSON Dr. Kevin Gross, AFIT/ENP	
a. REPORT U	b. ABSTRACT U	c. THIS PAGE U			19b. TELEPHONE NUMBER (Include area code) (937) 255-3636 x4558, kevin.gross@afit.edu	

Reset