Atmospheric Compensation and Surface Temperature and Emissivity Retrieval with LWIR Hyperspectral Imagery

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by
Michael Pieper
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I dedicate this thesis to my parents Adrienne and Larry who have always supported me, and Dimitris for his patient guidance over the years.
# Contents

<table>
<thead>
<tr>
<th>Chapters</th>
<th>Sections</th>
<th>Pages</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1 Introduction</strong></td>
<td>1.1 Hyperspectral Imaging Remote Sensing</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>1.2 Emissivity and Temperature Retrieval from Space</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>1.3 Objectives and Contributions</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>1.4 Organization of the Thesis</td>
<td>5</td>
</tr>
<tr>
<td><strong>2 Background</strong></td>
<td>2.1 Hyperspectral Data Format</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>2.2 Processing Fundamentals</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>2.3 LWIR Sensing Model</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>2.3.1 Atmospheric Characteristics</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>2.4 Atmospheric Compensation (AC)</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>2.4.1 AC Algorithms</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>2.5 Temperature Emissivity Separation (TES)</td>
<td>16</td>
</tr>
<tr>
<td></td>
<td>2.5.1 TES Algorithms</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td>2.6 MODerate resolution atmospheric TRANsmission model (MODTRAN)</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>2.6.1 Sensor Wavelength Calibration</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>2.7 TES based AC with LUTs</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>2.8 Generation of Synthetic Data</td>
<td>22</td>
</tr>
<tr>
<td><strong>3 Atmospheric Compensation</strong></td>
<td>3.1 At-Aperture Radiance Spectra</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>3.1.1 At-Aperture Radiance Spectra for In-scene Blackbodies</td>
<td>26</td>
</tr>
<tr>
<td></td>
<td>3.1.2 At-Aperture Radiance Spectra for In-scene Gray Bodies</td>
<td>28</td>
</tr>
</tbody>
</table>
List of Figures

1.1 Description of detection with hyperspectral imaging .................................. 2
1.2 LWIR flow diagram of atmospheric effects on ground radiance. .......................... 3

2.1 Illustration of hyperspectral data-cube [16] .................................................... 8
2.2 Simple geometric description of the GIFOV for a single detector element in a hy- 
perspectral sensor [21] ..................................................................................... 9
2.3 Hyperspectral imaging sensors measure the spectral radiance information of a scene  
to identify materials [16] ............................................................................. 10
2.4 Simplified radiative transfer model. ............................................................... 11
2.5 Example Atmospheric Transmission, Upwelling radiance, and Downwelling radi-  
ance TUD model. ....................................................................................... 14
2.6 Simulated measured and ground radiance with corresponding downwelling radi-  
ance, emissivity, and emitted ground radiance components. ............................ 17
2.7 Temperature profiles of MODTRAN atmospheres ......................................... 19
2.8 Water Vapor and Ozone atmospheric gas concentration profiles of MODTRAN at-  
mospheres. ................................................................................................. 19
2.9 Flowchart for determining best TUD model for a scene. ................................. 21
2.10 Data Generation Process ............................................................................ 23

3.1 $L_S(\lambda_k)$ of pixels with $\epsilon_G(\lambda_k) = 1$. .............................................. 27
3.2 Brightness Temperature in Kelvin of pixels with $\epsilon_G(\lambda_k) = 1$. ................. 27
3.3 Brightness Temperature of pixels with $\epsilon_G(\lambda_k) = 0.98$. .......................... 29
3.4 Brightness Temperature of pixels with $\epsilon_G(\lambda_k) = 0.8$. ............................ 29
3.5 ISAC Processing Pipeline ............................................................................. 30
3.6 ISAC scatter plot for the 11.24 $\mu$m band. ................................................... 30
3.7 ISAC model parameters ............................................................................. 33
3.8 ISAC band scatter plot for pixels with emissivities from $\epsilon_G(\lambda_k) = 1$ to 0.95 in 0.01  
increments, and ground temperatures between 287.95 K and 297.95 K in 1 K incre-  
ments ........................................................................................................ 35
3.9 ISAC full at-aperture radiance scatter plot model simulation .......................... 36
3.10 Comparison of $\Delta y$ and $\Delta y_B$ for all the spectral bands using the simulated $L_S(\lambda_k)$  
at a $T_G$ of 297.95 K. ................................................................................ 37
3.11 TUD model with water vapor multiplier of 1.45. .......................................... 38
4.1 Calculated emissivity estimates for a 295 K at-aperture radiance spectrum at increased temperature estimates. ................................................................. 55
4.2 The $W(\lambda_k, T_G)$ is used to convert from radiance to emissivity in Figure 4.1. ................................. 55
4.3 SRMSE for $\hat{\epsilon}_G(\lambda_k)$ at various temperature errors. ......................................................................................... 56
4.4 Measuring the height of the reflected $L_D(\lambda_k)$ features in $L_G(\lambda_k)$ spectra with various constant emissivity spectra. ................................................................. 57
4.5 $\hat{\epsilon}_G(\lambda_k)$ spectra for $\hat{T}_G = T_G = 295$ K and $\hat{T}_G = 294$ K and their corresponding boxcar averaging smoothing errors. ........................................................................ 60
4.6 Piece-wise linear approximation of $\hat{\epsilon}_G(\lambda_k)$ using LEC. ......................................................................................... 61
4.7 Various placements of LEC segments over atmospheric water feature to show how segment placement can affect smoothing error. ................................................................. 61
4.8 $\hat{\epsilon}_G(\lambda_k)$ spectra for $\hat{T}_G = T_G = 295$ K and $\hat{T}_G = 294$ K and their corresponding LEC smoothing errors. ......................................................................................... 62
4.9 Reflected atmospheric features transferred from $L_D(\lambda_k)$ to $\hat{\epsilon}_G(\lambda_k)$ at various $\hat{T}_G$s corresponding to Figure 4.1. ................................................................. 63
4.10 Emissivity spectra used to simulate ground radiance spectra. ......................................................................................... 67
4.11 Temperature errors for the four TES techniques. X-Limits change for each column. ......................................................................................... 69

3.12 Brightness Temperature of atmospheric compensated blackbody pixels using ISAC parameters from $\epsilon_G(\lambda_k) = 0.95$ spectra. ................................................................. 39
3.13 Brightness Temperature of atmospheric compensated pixels at varying emissivities using ISAC parameters from $\epsilon_G(\lambda_k) = 0.95$ spectra. ................................................................. 39
3.14 Interpolation over atmospheric features in brightness temperature to measure concavity. ................................................................. 40
3.15 Total atmospheric concavity of spectra at different emissivities and temperatures. ................................................................. 40
3.16 ISAC transmission estimates with constant $\epsilon_R(\lambda_k)$. ......................................................................................... 41
3.17 ISAC upwelling radiance estimates with constant $\epsilon_R(\lambda_k)$. ......................................................................................... 41
3.18 Effect of $\Delta y$ on ISAC transmission with constant $\epsilon_R(\lambda_k)$. ......................................................................................... 42
3.19 Effect of $\Delta x$ on ISAC transmission with constant $\epsilon_R(\lambda_k)$. ......................................................................................... 42
3.20 Effect of $\Delta y$ on ISAC upwelling radiance with constant $\epsilon_R(\lambda_k)$. ......................................................................................... 43
3.21 Effect of $\Delta x$ on ISAC upwelling radiance with constant $\epsilon_R(\lambda_k)$. ......................................................................................... 43
3.22 Water multiplier error for different model searching algorithms used on varying constant $\epsilon_G(\lambda_k)$ spectra. ......................................................................................... 45
3.23 Water multiplier error for water feature atmospheric compensation algorithm at varying temperatures and varying constant $\epsilon_G(\lambda_k)$ spectra. ......................................................................................... 47
3.24 Transmission estimates scaled using different water multiplier models. ......................................................................................... 49
3.25 Upwelling radiance estimates scaled using different water multiplier models. ......................................................................................... 49
3.26 Emissivity spectrum for grass. ......................................................................................... 49
3.27 Transmission and upwelling radiance scalers verse water multipliers of models. ......................................................................................... 50
3.28 $C_E(\lambda_k)$ for different water multiplier models. ......................................................................................... 50
3.29 Estimated ground radiances of ground spectra with varying emissivities using blackbody ISAC parameters with different scalings. ......................................................................................... 51
3.30 Estimated ground radiances of ground spectra with varying emissivities using grass ISAC parameters with different scalings. ......................................................................................... 51
4.12 Temperature errors for the two initial temperature estimate techniques. X-Limits change for each column. ........................................ 70

4.13 Temperature errors at 295 K with altitude for each of the signatures using boxcar TES in each error domain. ........................................ 71

4.14 Ratio of SSE for minimum error and sum of emissivity bias error and noise in the emissivity and radiance domains. ........................................ 72
(a) Emissivity Domain ........................................ 72
(b) Radiance Domain ........................................ 72

4.15 Ground temperature estimate error caused by band-averaging approximation in the emissivity and radiance domains. ........................................ 73
(a) Emissivity Domain ........................................ 73
(b) Radiance Domain ........................................ 73

4.16 $E_\epsilon$ of the emissivity bias error component for the 4 emissivity spectra in Figure 4.10 in 5 K increments. ........................................ 74
(a) Ground NESE ........................................ 75
(b) Measured NESR ........................................ 75

4.17 Noise for signature 2 ground radiance spectra at temperatures from 285 K to 305 K in 5 K increments. ........................................ 75
(a) Ground NESE ........................................ 75
(b) Measured NESR ........................................ 75

4.18 Smoothing error of $L_{DF}(\lambda_k)/\tau(\lambda_k)$ with altitude. ........................................ 76

4.19 Comparison of emissivity noise SSE and radiance noise SSE with different $\hat{T}_G$. ........................................ 76

4.20 $E_L$ and the correlation between $\tilde{\epsilon}_G(\lambda_k)$ and $\tilde{\epsilon}_b^b(\lambda_k)$ versus temperature error. ........................................ 77

4.21 Average correlation between temperature induced error and emissivity bias error with ground temperature for each of the error domains using boxcar averaging. ........................................ 78

4.22 Average correlation between temperature induced error and emissivity bias error with ground temperature for each of the error domains using LEC. ........................................ 79

4.23 Average correlation between temperature induced error and emissivity bias error with altitude for each of the error domains. ........................................ 80

4.24 Emissivity bias and temperature induced errors in the emissivity domain for the 5 noiseless ground radiance spectra simulated using signature 4, where boxcar averaging was used to minimize the emissivity and radiance smoothing errors. ........................................ 81
(a) $E_\epsilon$ minimized ........................................ 81
(b) $E_L$ minimized ........................................ 81

4.25 Emissivity bias and temperature induced errors in the emissivity domain for the 5 noiseless ground radiance spectra simulated using signature 4, where LEC was used to minimize the emissivity and radiance smoothing errors. ........................................ 81
(a) $E_\epsilon$ minimized ........................................ 81
(b) $E_L$ minimized ........................................ 81

4.26 Final $\tilde{\epsilon}_G(\lambda_k)$ found for the 5 noiseless ground radiance spectra simulated using signature 4, where boxcar averaging was used to minimize the emissivity and radiance smoothing errors. ........................................ 82
(a) $E_\epsilon$ minimized ........................................ 82
(b) $E_L$ minimized ........................................ 82

4.27 TES emissivity and temperature estimates for an at-aperture radiance spectrum at 295 K and with a band shift of $0.25 \times$ the minimum band difference. ........................................ 83

4.28 TES results for boxcar averaging in the radiance domain versus band shift. ........................................ 87
4.29 Ratio of SSE of total atmospheric mismatch error and upwelling radiance mismatch versus band shift for blackbodies. 88
4.30 TES results for boxcar averaging in the radiance domain versus band broadening. 90
4.31 Ratio of SSE of total atmospheric mismatch error and upwelling radiance mismatch versus band broadening for blackbodies. 91
5.1 Downwelling radiance estimation pipeline 96
5.2 Downsampled Downwelling Radiance MODTRAN Models 96
5.3 Sensor Calibration Correction Pipeline 98
5.4 Emissivity spectra and simulated ground radiance spectra using corresponding low emissivity spectra. 99
   (a) Emissivity Spectra 99
   (b) Simulated Ground Radiance and Blackbody Spectra 99
5.5 Simulation Pipeline 100
5.6 Best $L_D(\lambda_k)$ models. 103
   (a) Matching Calibration 103
   (b) Mismatched Calibration 103
   (c) Corrected Calibration 103
   (d) Noisy Ground Radiance Corrected Calibration 103
5.7 Ground temperature estimates of ground radiance spectra with corresponding best $L_D(\lambda_k)$ models. 107
   (a) Matching Calibration 107
   (b) Mismatched Calibration 107
   (c) Corrected Calibration 107
   (d) Noisy Ground Radiance Corrected Calibration 107
5.8 Emissivity estimates from ground radiance spectra with best $L_D(\lambda_k)$ models. 108
   (a) Matching Calibration 108
   (b) Mismatched Calibration 108
   (c) Corrected Calibration 108
   (d) Noisy Ground Radiance Corrected Calibration 108
5.9 Emissivity estimates from ground radiance spectra with true $L_D(\lambda_k)$ models. 109
   (a) Matching Calibration 109
   (b) Mismatched Calibration 109
   (c) Corrected Calibration 109
   (d) Noisy Ground Radiance Corrected Calibration 109
5.10 Calculated Emissivities using the true ground temperatures and true $L_D(\lambda_k)$ model of each stage 110
   (a) Stages of true $L_D(\lambda_k)$ model 110
   (b) Mismatched Calibration 110
   (c) Corrected Calibration 110
   (d) Noisy Ground Radiance Corrected Calibration 110
5.11 Angle error for best model for each individual signature. 111
5.12 Distance error for best model for each individual signature. 111
6.1 Transmissions for atmospheric models with water multipliers from 0.625 to 0.875 in 0.025 increments. ................................................................. 113
6.2 Temperature errors for at-aperture radiance spectra of varying temperatures and emissivities using atmospheric models of different water multipliers. .......... 114
6.3 Emissivity SSE for at-aperture radiance spectra of varying temperatures and emissivities using atmospheric models of different water multipliers. .......... 114
6.4 Emissivity spectra for at-aperture radiance spectra of varying temperatures and emissivities using an atmospheric model with a water multiplier of 0.625. ............. 115
6.5 Emissivity spectra for at-aperture radiance spectra of varying temperatures and emissivities using an atmospheric models with a water multiplier of 0.875. .......... 115
6.6 Emissivity spectra for at-aperture radiance spectra with ground temperatures of 282.94 K and varying emissivities using atmospheric models with varying water multipliers. ................................................................. 116
6.7 Emissivity spectra for at-aperture radiance spectra with ground temperatures of 302.94 K and varying emissivities using atmospheric models with varying water multipliers. ................................................................. 116
6.8 Compensation of $\hat{L}_D(\lambda_k)$ mismatch with a ground temperature error, when the reflected ground radiance of a reflector is used. ......................................................... 122
6.9 Temperature errors for corrected ground spectra of varying temperatures and emissivities using ISAC parameters derived from blackbodies and scaled using atmospheric models with varying water multipliers. .......... 123
6.10 Emissivity spectra for corrected ground spectra of varying temperatures and emissivities using unscaled ISAC parameters derived from blackbodies. .......... 123
6.11 Temperature errors for corrected ground spectra of varying temperatures and emissivities using ISAC parameters derived from grass and scaled using atmospheric models with varying water multipliers. .......... 124
6.12 Emissivity spectra for corrected ground spectra of varying temperatures and emissivities using unscaled ISAC parameters derived from grass. .......... 124
6.13 Downwelling radiance spectrum shifted down by the difference between two blackbodies. ................................................................. 125
6.14 Emissivity and temperature estimates using shifted downwelling radiance spectrum. 125
6.15 Emissivity estimates using the true downwelling radiance after AC with the true atmospheric parameters. ................................................................. 126
7.1 OLSTER scatter plot used to find blackbody-like pixels. ................................. 130
7.2 ARM OLSTER and FLAASH-IR TUD Parameters ........................................ 130
7.3 ARM OLSTER scaling using varying methods .............................................. 131
7.4 Comparison of ARM FLAASH-IR and OLSTER ground radiances for emissivity panel. ................................................................. 132
7.5 Comparison of the measured grass spectrum and the estimated $\epsilon_R(\lambda_R)$ for ARM collect. ................................................................. 132
7.6 Comparison of ARM FLAASH-IR and OLSTER panel emissivity estimates. ......... 133
## List of Tables

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.1</td>
<td>Key TES Variable List and Equation Numbers</td>
<td>93</td>
</tr>
<tr>
<td>5.1</td>
<td>Number of $L_D(\lambda_k)$ models better than true model for each stage.</td>
<td>101</td>
</tr>
<tr>
<td>5.2</td>
<td>TES error for the estimated best and true $L_D(\lambda_k)$ models for each stage.</td>
<td>101</td>
</tr>
<tr>
<td>5.3</td>
<td>Angular Error (Degrees) between the true $L_D(\lambda_k)$ model and the estimated best and true models for each stage.</td>
<td>102</td>
</tr>
<tr>
<td>5.4</td>
<td>Distance Error between the true $L_D(\lambda_k)$ model and the estimated best and true models for each stage.</td>
<td>102</td>
</tr>
<tr>
<td>5.5</td>
<td>Average Temperature Error (K)</td>
<td>104</td>
</tr>
<tr>
<td>5.6</td>
<td>Average Angular Emissivity Error (Degrees)</td>
<td>105</td>
</tr>
<tr>
<td>5.7</td>
<td>Average Distance Emissivity Error</td>
<td>105</td>
</tr>
</tbody>
</table>
# List of Acronyms

**AAC** Autonomous Atmospheric Compensation. Method of atmospheric compensation that uses the relationship between bands on the edge and center of an atmospheric feature.

**AC** Atmospheric Compensation. The process of removing atmospheric effects from the measured at-aperture radiance to obtain the ground radiance.

**ARM** Atmospheric Radiation Measurement. Site where atmospheric measurements are taken and sensors are tested.

**ARTEMISS** Automatic Retrieval of Temperature and Emissivity using Spectral Smoothness. Algorithm that determines the atmospheric parameters of a scene, and the temperatures and emissivities of each pixel.

**BRDF** Bidirectional Reflectance Distribution Function. A function of four real variables that defines how light is reflected at an opaque surface.

**CDF** Cumulative Distribution Function. The probability that a random variable $X$ will take a value less than $x$.

**CIBR** Continuum Interpolated Band Ratio. A measurement of the amount of absorption relative to an interpolation across the absorption feature.

**DRRI** Downwelling Radiance Residual Index. A temperature emissivity separation technique that finds the temperature that smooths out large atmospheric features in the emissivity estimate.

**FLAASH-IR** Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes-Infrared. Algorithm that determines the atmospheric parameters of a scene, and the temperatures and emissivities of each pixel.

**FWHM** Full Width Half Max. An expression of the extent of a function given by the difference between the two extreme values of the independent variable at which the dependent variable is equal to half of its maximum value.

**GIFOV** Ground projected Instantaneous Field Of View. The projection of a sensors pixel area onto the ground.

**HSI** Hyperspectral Imaging. An imaging sensor that measure radiation at hundreds of contiguous bands to form a spectrum.
ISAC  In-Scene Atmospheric Compensation. Method of atmospheric compensation that uses in-scene blackbody-like pixels as a reference.

ISS TES  Iterative Spectrally Smooth Temperature Emissivity Separation. A method of temperature emissivity separation where the emissivity estimate is smoothed with a running boxcar average.

LEC TES  Linear spectral Emissivity Constraint Temperature Emissivity Separation. A method of temperature emissivity separation where the emissivity estimate is smoothed with linear piecewise smoothing.

LUT  Look-Up-Table. A database of reference atmospheric models.

LWIR  Long Wave InfraRed. Region of the electromagnetic spectrum between 8 µm to 14 µm.

MODTRAN  MODerate resolution atmospheric TRANsmission. A radiative transfer algorithm used for atmospheric modeling.

NESE  Noise Equivalent Spectral Emissivity. The RMS noise of a given measurement expressed in unit of radiance.

NESR  Noise Equivalent Spectral Radiance. The RMS noise of a given emissivity measurement.


SAM  Spectral Angle Metric. The measurement of the angle between to spectra.


SNR  Signal-to-Noise Ratio. A measurement that compares the level of desired signal to the level of background noise.

SRF  Spectral Response Function. The relative efficiency of a sensor to detect a signal as a function of the wavelength of the signal.

SRMSE  “Smoothing” Root Mean Square Error. The root mean squared error of the TES smoothing error.

SR TES  Stepwise Refining Temperature Emissivity Separation. A temperature emissivity separation technique that finds the temperature that smooths out large atmospheric features in the ground radiance estimate.

SSE  Sum of Squared Errors. The sum of the squares of residuals.

TES  Temperature Emissivity Separation. Technique for determining the temperature and emissivity from the ground radiance of a pixel by finding the temperature that provides the smoothest emissivity estimate.

TIR  Thermal InfraRed. Region of the electromagnetic spectrum between 8 µm to 14 µm.
TUD  Transmission Upwelling radiance and Downwelling radiance model. A model containing the atmospheric parameters of interest for a scene.

VNIR-SWIR  Visible and Near InfraRed and Short Wave InfraRed. Region of the electromagnetic spectrum between 0.4 µm to 2.5 µm.
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Abstract of the Dissertation

Atmospheric Compensation and Surface Temperature and Emissivity Retrieval with LWIR Hyperspectral Imagery

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Michael Pieper

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Accurate estimation or retrieval of surface emissivity spectra from long-wave infrared (LWIR) or Thermal Infrared (TIR) hyperspectral imaging data acquired by airborne or space-borne sensors is necessary for many scientific and defense applications. The at-aperture radiances measured by the sensor is a function of the ground emissivity and temperature, modified by the atmosphere. Thus the emissivity retrieval process consists of two interwoven steps: atmospheric compensation (AC) to retrieve the ground radiances from the measured at-aperture radiance and temperature-emissivity separation (TES) to separate the temperature and emissivity from the ground radiances.

In-scene AC (ISAC) algorithms use blackbody-like materials in the scene, which have a linear relationship between their ground radiances and at-aperture radiances determined by the atmospheric transmission and upwelling radiances. Using a clear reference channel to estimate the ground radiances, a linear fitting of the at-aperture radiance and estimated ground radiances is done to estimate the atmospheric parameters. TES algorithms for hyperspectral imaging data assume that the emissivity spectra for solids are smooth compared to the sharp features added by the atmosphere. The ground temperature and emissivity are found by finding the temperature that provides the smoothest emissivity estimate.

In this thesis we develop models to investigate the sensitivity of AC and TES to the basic assumptions enabling their performance. ISAC assumes that there are perfect blackbody pixels in a scene and that there is a clear channel, which is never the case. The developed ISAC model explains how the quality of blackbody-like pixels affect the shape of atmospheric estimates and the clear channel assumption affects their magnitude. Emissivity spectra for solids usually have some roughness. The TES model identifies four sources of error: the smoothing error of the emissivity
spectrum, the emissivity error from using the incorrect temperature, and the errors caused by sensor noise and wavelength calibration. The ways these errors interact determines the overall TES performance. Since the AC and TES processes are interwoven, any errors in AC are transferred to TES and the final temperature and emissivity estimates. Combining the two models, shape errors caused by the blackbody assumption are transferred to the emissivity estimates, where magnitude errors from the clear channel assumption are compensated by TES temperature induced emissivity errors. The ability for the temperature induced error to compensate for such atmospheric errors makes it difficult to determine the correct atmospheric parameters for a scene. With these models we are able to determine the expected quality of estimated emissivity spectra based on the quality of blackbody-like materials on the ground, the emissivity of the materials being searched for, and the properties of the sensor. The quality of material emissivity spectra is a key factor in determining detection performance for a material in a scene.
Chapter 1

Introduction

In this chapter we give a brief description of the different types of hyperspectral imaging and explain their key difference. This is followed by a more in-depth look at LWIR hyperspectral imaging and the process and challenges of determining the ground emissivities and temperatures. Next, the objectives and contributions of the thesis are provided. Lastly, the organization of the thesis is given with a brief description of each chapter.

1.1 Hyperspectral Imaging Remote Sensing

Hyperspectral imaging (HSI) remote sensing is widely used in many civilian and military applications [14]. Each pixel of a hyperspectral imaging sensor measures the incoming radiation at many, sometimes several hundreds of, spectral bands. This set of spectral measurements, known as a radiance spectrum, contains information about the materials present in the scene and it can be exploited for detection, identification, and classification applications. Hyperspectral imaging sensors measure radiation in one of two regions of the electromagnetic spectrum, the region with wavelengths from 0.4 \( \mu \text{m} \) to 2.5 \( \mu \text{m} \), which in known as the Visible and Near InfraRed and Short Wave Infrared (VNIR-SWIR), and the region from 8 \( \mu \text{m} \) to 14 \( \mu \text{m} \), known as the Long-Wave InfraRed (LWIR) or Thermal InfraRed (TIR). The VNIR-SWIR is dominated by solar illumination, where the main source of energy in the LWIR is thermal emission. Figure 1.1 describes hyperspectral imaging in the VNIR-SWIR region where reflectance is the material property of interest used for detection. The HSI sensor produces a radiation spectrum for each pixel in the scene. The reflectance is determined from the radiance spectrum. Unique reflectance spectra are shown for soil, water, and vegetation. These unique reflectance spectra are used to identify the materials. The basic problem
CHAPTER 1. INTRODUCTION

Figure 1.1: Description of detection with hyperspectral imaging.

is the retrieval of the surface reflectance from the measured radiance spectra. This is done with a process known as atmospheric compensation, which removes atmospheric effects.

The utility of VNIR-SWIR and LWIR hyperspectral imaging is dependent on the types of materials being searched for and day vs. night operation. A material’s spectrum should be studied for unique spectral characteristics. The type of sensor should then be chosen based on the region where a material has its unique spectral characteristics. Vegetation has unique spectral characteristics in the VNIR-SWIR region, allowing for terrain classification and agricultural monitoring. Detection of camouflaged or hidden targets is also possible. Camouflaged targets are typically only made to appear to like their backgrounds visibly, while their spectra differ outside this region. These spectral differences allow for separation of the target from the background. LWIR hyperspectral sensors are useful for detecting minerals and chemicals that lack unique spectral features in the VNIR-SWIR, but have them in the LWIR. Additional benefits of LWIR sensors are their capability of collecting data at day/night because they do not require the sun as an energy source, and they are able to measure surface temperature, which is a key component for environmental models.
CHAPTER 1. INTRODUCTION

1.2 Emissivity and Temperature Retrieval from Space

In this thesis, we study hyperspectral imaging in the long-wave infrared (LWIR) region of the electromagnetic spectrum. The material property of interest in LWIR imaging is the emissivity spectrum, which is a measure of a material’s ability to emit radiation. The measured at-aperture radiance is a function of the emissivity and temperature of the surface, the reflected downwelling radiance, the path or upwelling radiance, and atmospheric transmittance. Figure 1.2 shows the components of the at-aperture radiance from the ground to the sensor. The emitted radiance of a target is determined by the material’s emissivity spectrum and temperature. The ground radiance consists of the emitted radiance and a reflected component from the atmospheric downwelling radiance. The relative contribution of the reflected component increases with decreasing emissivity. The final at-aperture radiance consists of the ground radiance affected by the atmospheric transmission on its path to the sensor, plus the atmospheric upwelling radiance.

The basic problem in LWIR is to remove the atmosphere and retrieve the emissivity and temperature of the surface. While AC is still needed to remove atmospheric effects from the at-aperture radiance spectrum, in TIR the problem is more complicated than VNIR-SWIR because the surface both reflects and emits radiation. The retrieval of ground emissivity involves two interwoven steps: (a) AC to convert at-aperture radiance to ground radiance and (b) temperature emissivity...
separation (TES) to retrieve the emissivity spectrum of the surface and its temperature from the ground radiance. When the atmospheric parameters are known, the AC and TES steps are done on each individual pixel simultaneously, however this is not a trivial task. Since the ground is characterized by its temperature and by one emissivity for each spectral band, we have one more unknown than measurements. Therefore, inversion methods have to make assumptions to bypass this difficulty. Existing TES algorithms for hyperspectral imaging data are based on the well known observation that most solid materials exhibit smoothly varying spectral emissivity compared to the sharp spectral atmospheric features (smoothness assumption). The difference in spectral roughness between the ground and atmospheric parameters can be observed in Figure 1.2.

Before AC and TES can be completed on a scene, the atmospheric parameters for a scene need to be determined. This greatly increases the complexity of the problem. The atmosphere is usually assumed to be horizontally homogeneous throughout a scene. The atmospheric transmission and upwelling radiance can be estimated using a method known as in-scene atmospheric compensation (ISAC) that utilizes materials within a scene that resemble blackbodies and have negligible reflected components [25]. The downwelling radiance is more difficult to estimate because it consists of the hemispherical emitted radiance of the entire atmosphere, even the atmosphere above the sensor. In addition, the pixels with significant reflective components have unknown emissivities. To overcome the challenge of not having an in-scene reference for the downwelling radiance, atmospheric models are generated and used for AC and TES to find the model that provides the smoothest emissivities for reflective pixels [7] [5]. Once the best atmospheric model is determined it is used for AC and TES on the entire scene.

AC and TES are underdetermined problems. The variables that control the atmospheric properties are highly variable in both time, space, and altitude. The most critical variables are the atmospheric temperature and water vapor content. In addition the radiative transfer equation that explains how these variables affect the atmospheric parameters is nonlinear [20]. The method that uses atmospheric models to find a scene’s atmospheric parameters assumes that there is a unique atmosphere that provides smooth realistic emissivities, and that this true atmosphere is present in the set of models. The models generated never fully capture the complexity of the real atmosphere. This leads to a mismatch between the model parameters and the observed parameters. A second issue is that multiple models may produce realistic results, making it difficult to pick the best model.
CHAPTER 1. INTRODUCTION

1.3 Objectives and Contributions

The objective of this thesis is to develop a model that defines the span of possible atmospheric parameters that provide smooth realistic emissivity spectra for a scene. This model will explain how all the atmospheric and ground parameter estimates are linked, and how they affect each other. A TES performance model is developed to explain the sensitivity of temperature and emissivity estimates to calibration and noise errors under varying atmospheric and ground conditions. Together these models will explain limitations of current algorithms and provide insight into ways to improve them.

1.4 Organization of the Thesis

The model was built incrementally with synthetic data so that complete atmospheric and ground truth are known, allowing for definitive conclusions to be made. The thesis is organized as follows:

Chapter 2 - Background
The basics of hyperspectral imaging are introduced along with the data format and methods used for comparing spectra. Next, the basic LWIR at-aperture radiance model is developed, and the characteristics of the atmosphere that affect the at-aperture radiance are shown. The basics of AC and TES are discussed and the popular algorithms for each are introduced. The radiative transfer algorithm used to generate atmospheric models is described, along with the algorithms that utilize these models to determine the atmospheric parameters of a scene. Lastly, the method used to generate synthetic at-aperture radiance spectra for development and testing is described.

Chapter 3 - Atmospheric Compensation
We give an in-depth analysis of in-scene atmospheric compensation (ISAC) algorithms and their ability to effectively find the blackbody-like pixels on which they are dependent. An ISAC model is developed that explains how the transmission and upwelling radiance estimates change as the blackbody-like pixels deviate from being perfect blackbodies. This model is then extended to explain how errors in AC are transferred to the ground radiance estimates.
CHAPTER 1. INTRODUCTION

Chapter 4 - Temperature Emissivity Separation
A TES performance model is developed to explain the sensitivity of temperature and emissivity estimates to varying noise, atmospheric, and ground conditions. Atmospheric parameters are presumed known to exclude errors from AC. The performance model is then extended to explain the effects of sensor calibration errors on the final estimates.

Chapter 5 - Downwelling Radiance Estimation
The ability of finding the downwelling radiance for a scene from a set of atmospheric models is studied. The analysis is done at ground level to exclude effects of AC. It is shown that the emissivity characteristics of the reflective pixels affect the determined model.

Chapter 6 - Atmospheric Mismatch Effects on Temperature Emissivity Separation
The entire AC and TES process is studied. An initial analysis of atmospheric model error on temperature and emissivity estimates is done. We show how incorrect models provide rough unrealistic emissivity results. Next, it is shown that despite errors in the ISAC atmospheric parameters, smooth emissivities are still retrievable. The developed ISAC model is used to explain the relationship required between atmospheric parameter estimates to obtain smooth emissivity estimates.

Chapter 7 - Atmospheric Compensation and Temperature Emissivity Results with Real Data
AC and TES algorithms are tested on a real data set with accurate ground truth. The algorithms tested include ISAC and an approach based entirely on atmospheric models. The ISAC model is used to explain the atmospheric parameter estimates for each approach, and their resulting ground radiance, temperature, and emissivity estimate errors.

Chapter 8 - Conclusions
Final discussion on the difficulty of AC and TES using the ISAC and TES models, and what was learned to make more effective algorithms.
Chapter 2

Background

2.1 Hypsrspectral Data Format

The basic concept behind hyperspectral imaging is that materials reflect, absorb, and emit radiation in various amounts depending on wavelength. The radiance is a measure that describes the amount of electromagnetic energy that passes through or is emitted from a particular area, and falls within a given solid angle in a specified direction. The radiance characterizes the total emission or reflection. The spectral radiance characterizes the electromagnetic radiation at a single wavelength. In theory, each material has a unique radiance spectrum. Therefore, it is possible to identify a material from its spectral radiance measurements.

A hyperspectral sensor works similarly to a digital camera. A digital camera measures light at three broad wavelength bands: red, green, and blue, for each pixel. On the other hand, the hyperspectral sensor measures radiance at several hundred fine wavelength bands. Hyperspectral imaging sensors measure radiation in one of two regions of the electromagnetic spectrum, the Visible and Near Infra-Red and Short Wave Infrared (VNIR-SWIR) region from (0.4 µm to 2.5 µm) which is dominated by solar illumination, and the LWIR region from (8 µm to 14 µm) where the main source of energy is thermal emission [21]. Just like a digital camera, a hyperspectral imaging sensor divides the imaged scene into pixels. The data collected by an HSI sensor form a data cube as shown in Figure 2.1. The face of the cube corresponds to the two spatial components, and consists of the scene divided into pixels. The third dimension is represented by the spectral component, which consist of the spectral bands. Each pixel is represented by the measured radiance spectrum for the materials located inside the pixel area, and each layer of the cube is represented by a gray scale image representing the fraction of light emitted at a specific wavelength at each pixel [15].
CHAPTER 2. BACKGROUND

The spatial footprint of each pixel is known as the Ground Projected Instantaneous Field Of View (GIFOV), the geometric projection of a single detector width $w$, onto the earth’s surface. The GIFOV depends on the width of the detector element, the focal length of the optics, and the angle and altitude of the sensor. The GIFOV for a nadir viewing angle is described in Figure 2.2. The geometric magnification of the optics is given as $m = f / H$, where $f$ is the focal length of the optics and $H$ is the altitude of the sensor. The GIFOV is defined as

$$GIFOV = w \times \frac{H}{f} = \frac{w}{m}. \quad (2.1)$$

When working with the hyperspectral data, each pixel spectrum is represented by a vector $x = [x_1, x_2, ..., x_K]^T$ in a $K$-dimensional Euclidean space where $K$ is the number of spectral bands collected by the hyperspectral sensor. To view the hyperspectral data, each vector is plotted as a point in a $K$-dimensional scatter plot. Each axis of the scatter plot is assigned a spectral band. Representing the spectra as vectors provides several methods of determining the similarity between two spectra. Pixels containing similar materials will have similar spectra. The points representing these vectors will be located closely together in the spectral space. One way of measuring the distance between the points of two spectra, $x$ and $y$, is using the Euclidean distance, given by

$$\|x - y\| = \sqrt{\sum_{k=1}^{K} (x_k - y_k)^2} \quad (2.2)$$

where $\|x\|$ is the length of $x$. A smaller distance means the spectra are more closely related. There are several factors that can affect the length of vectors, while minimally affecting the direction. The spectral angle metric (SAM) measures the angle between two vectors, and is therefore immune to length differences. The smaller the angle between the two vectors, the more similar the materials.

Figure 2.1: Illustration of hyperspectral data-cube [16].
Figure 2.2: Simple geometric description of the GIFOV for a single detector element in a hyperspectral sensor [21].

located in the pixels. The SAM is determined by

\[
\text{SAM}(x, y) = \frac{x^T y}{\|x\| \|y\|} \quad (2.3)
\]

where \(x^T y\) is the inner product between spectra \(x\) and \(y\).

2.2 Processing Fundamentals

Prior to material detection, the spectral pixel radiances in a data cube must be converted to the ground quantities of interest. This process is known as AC, and depends on the atmospheric physics in the spectral wavelength range of the sensor. In a passive VNIR-SWIR remote sensing system, the ground quantity of interest is the material reflectance. The radiation source is the illumination of the sun. The amount of radiation the sun emits at each wavelength is known as the solar spectrum. The solar spectrum is known above the earth’s atmosphere. Figure 2.3 describes how the sunlight is affected on its path to the ground and up to the sensor. As light travels toward the ground, the solar spectrum is affected by atmospheric transmission and scattering. How the atmosphere affects the sunlight varies with wavelength. The sunlight that reaches the target is either reflected, emitted, or absorbed. The reflected and emitted energy travels toward the sensor, where it is once again affected by the atmosphere. The hyperspectral sensor captures the energy which
completes the trip [16]. The reflectance spectrum is defined by

$$\text{reflectance spectrum}(\lambda) = \frac{\text{reflected radiation at band}(\lambda)}{\text{incident radiation at band}(\lambda)}$$

(2.4)

The reflectance spectrum shows the fraction of incident light that is reflected by a material as a function of wavelength [16]. It is assumed that there is no emission. This assumption is valid in the electromagnetic region dominated by solar illumination. In order to calculate the reflectance, the incident and reflected ground radiances need to be determined. These quantities are calculated by using an atmospheric model for the scene to compensate for the atmospheric transmission loses and scattering. The atmospheric model for the scene is found using the method discussed in [3].

Figure 2.3: Hyperspectral imaging sensors measure the spectral radiance information of a scene to identify materials [16].

In the LWIR region, the materials themselves are the radiation sources. The material emissivity is the desired quantity for material identification. The emissivity is a measure of an object’s ability to emit radiation at a specific wavelength. The amount of solar radiation in this region is negligible. Since the energy source is the ground, one only has to worry about atmospheric transmission losses between the ground and sensor. However, the atmosphere has thermal emission of its own. While atmospheric scattering is negligible in the LWIR, the atmosphere emits in all directions adding to the measured sensor radiance. Atmospheric parameters need to be modeled in order to compensate for the atmosphere and obtain the ground radiance. While the upward emission
simply adds to the sensor radiances, a portion of the downward emission is reflected by the ground and added to the ground radiances. The amount of reflectance increases with decreasing emissivity. Even when the ground radiances are determined, the LWIR problem is further complicated because the surface emits and reflects radiation. In addition the emitted radiation from the object is a function of its temperature and emissivity, which must be separated using a process known as temperature emissivity separation (TES) \[14\]. The rest of this thesis will only consider AC and TES in the LWIR region.

2.3 LWIR Sensing Model

To understand the extraction process of the ground material emissivity from the measured at-aperture radiances, it is important to understand the atmospheric and ground components of the at-aperture radiances. Figure 2.4 shows a simplified radiative transfer model for the at-aperture radiances of a Lambertian ground material. The monochromatic at-aperture radiances can be modeled as

\[ L_G(\lambda) = \epsilon_G(\lambda) B(\lambda, T_G) + [1 - \epsilon_G(\lambda)] L_D(\lambda) \]  \hspace{1cm} (2.5a)  
\[ L_S(\lambda) = L_G(\lambda) \tau(\lambda) + L_U(\lambda) \]  \hspace{1cm} (2.5b)  

where \( \lambda \) is the wavelength, \( \epsilon_G(\lambda) \) is the ground emissivity, \( T_G \) is the ground temperature, \( L_D(\lambda) \) is the hemispherical downwelling radiances emitted by the atmosphere, \( L_U(\lambda) \) is the upwelling radiances.
CHAPTER 2. BACKGROUND

diance emitted by the atmosphere, and $\tau(\lambda)$ is the atmospheric transmission. All radiance measurements are in units of $\mu$-flicks ($\mu$-W/cm$^2$/sr/$\mu$m). The emitted energy from a blackbody is determined by the Planck radiation function at the ground temperature

$$B(\lambda, T_G) = \frac{c_1}{\lambda^5 [\exp(c_2/(\lambda T_G)) - 1]}$$

(2.6)

where $c_1 = 1.19104 \times 10^{10}$ ($\mu$-W/cm$^2$/sr/$\mu$m)$\mu$m$^5$ and $c_2 = 14387.7$ $\mu$m K. Radiances can also be presented as brightness temperatures, defined by

$$T_B(\lambda; L_S(\lambda)) = B^{-1}(\lambda, L_S(\lambda)) = \frac{c_2}{\ln(c_1/(\lambda^5 L_S(\lambda)) + 1)}$$

(2.7)

where the brightness temperature is the inverse of the Planck function $B(\lambda, T_G)$, and is the temperature at which a blackbody emits radiance $L_S(\lambda)$ at wavelength $\lambda$ [25]. Scatter in the LWIR region is insignificant, and is therefore ignored.

A hyperspectral sensor with $K$ bands measures a band-averaged version of $L_S(\lambda)$, where the at-sensor signal model for the $k$th band is given by

$$L_S(\lambda_k) = \epsilon_G(\lambda_k) B_T(\lambda_k, T_G) + (1 - \epsilon_G(\lambda_k)) L_{D\tau}(\lambda_k) + L_U(\lambda_k)$$

(2.8)

where the band-averaged parameters are

$$L_S(\lambda_k) = \langle L_S(\lambda) \rangle_k$$

(2.9a)

$$L_U(\lambda_k) = \langle L_U(\lambda) \rangle_k$$

(2.9b)

$$B_T(\lambda_k; T_G) = \langle B(\lambda, T_G) \tau(\lambda) \rangle_k$$

(2.9c)

$$L_{D\tau}(\lambda_k) = \langle L_D(\lambda) \tau(\lambda) \rangle_k$$

(2.9d)

The triangle brackets indicate the band-averaging obtained by integrating the corresponding monochromatic term with respect to the instrument’s relative spectral response function (SRF) in band $k$. $L_{D\tau}(\lambda_k)$ is the ground component of the at-aperture radiance when there is a perfect reflector on the ground [13].

The ground radiance spectrum of a pixel contains the material properties of interest and is modeled as

$$L_G(\lambda_k) = \epsilon_G(\lambda_k) B(\lambda_k, T_G) + (1 - \epsilon_G(\lambda_k)) L_D(\lambda_k)$$

(2.10)

This is essentially Eq. (2.5b) band-averaged by the instrument’s SRF. The ground radiance spectrum consists of the thermal emitted component, which contains the ground properties of interest and a reflected component, which acts as interference. This interference makes detection with the ground radiance difficult.
CHAPTER 2. BACKGROUND

2.3.1 Atmospheric Characteristics

As the ground radiance travels up toward the sensor, it is affected by the atmosphere. The atmosphere absorbs and emits radiation. The gases present in the atmosphere between the ground and the sensor, and their temperatures and concentrations as a function of altitude, determine the atmospheric transmission $\tau(\lambda_k)$ and upwelling radiance $L_U(\lambda_k)$. The atmospheric gases with absorption features in the LWIR are water vapor and ozone. Figure 2.5 shows an example of a transmission, upwelling radiance, and downwelling radiance curves at an altitude of 0.5 km. Together the three atmospheric parameter spectra are known as a TUD model. Several observations can be made from the TUD model. The edges of the atmospheric window region are apparent at around 8 $\mu$m and 13 $\mu$m where the transmission quickly diminishes due to water and carbon dioxide absorption. There are two water features between 11.62-11.84 $\mu$m and 12.2-12.7 $\mu$m. The main ozone feature is visible in the downwelling radiance $L_D(\lambda_k)$ between 9.4-9.84 $\mu$m. Compared with the transmission and upwelling radiance which are taken on path between the sensor and ground, the downwelling radiance is constructed from the entire atmosphere including significant amounts of ozone that begin to occur above 10 km. When the imaging spectrometer altitude is below 10 km, the ozone feature is not present in $\tau(\lambda_k)$ and $L_U(\lambda_k)$. The magnitude of the downwelling radiance is significantly larger than the upwelling radiance due to the greater amount of atmosphere it is generated from.

There is substantial variation between atmospheres due to the temporal and spatial variability of the total column water vapor. The total column water vapor is the total amount of water contained in a vertical column of atmosphere. In addition, the humidity affects the continuum absorption mechanism, which is the absorption that varies smoothly with wavelength across the sharp absorption features. The transmittance can vary from nearly 1 for dry polar atmospheres to about 0.3 for very humid tropical ones. While the atmospheric transmittance is correlated with the total water vapor, this correlation is poor for the same amount of water. Transmittances can vary in some cases by up to 15% for the same water vapor amount. This shows that it is not only the total amount of water vapor which has to be considered but its distribution along the path, combined with the atmospheric temperature and pressure profiles [20].
2.4 Atmospheric Compensation (AC)

AC is the process where estimates of the atmospheric parameters $\tau(\lambda_k)$ and $L_U(\lambda_k)$ are made for a scene’s atmosphere. The process is simplified with the assumption that the atmosphere is horizontally homogeneous across the scene. With accurate estimates of these two atmospheric parameters, atmospheric transmission losses and emission are individually removed from the at-aperture radiance spectrum of each pixel, to obtain its ground radiance spectrum. The AC conversion process from at-aperture radiance to ground radiance can be described as

$$L^{AC}_G(\lambda_k) = \frac{L_S(\lambda_k) - L_U(\lambda_k)}{\tau(\lambda_k)}$$  \hspace{1cm} (2.11)$$

where errors in ground radiance estimate are caused by errors in estimating the atmospheric parameters and atmospheric variability in the scene. An additional error is caused from a band-averaging error of $L_D(\lambda)\tau(\lambda)$. Due to the high correlations between $\tau(\lambda)$ and $L_D(\lambda)$, there is a non-negligible disparity between $\langle L_D(\lambda)\tau(\lambda) \rangle_k \neq \langle L_D(\lambda) \rangle_k \langle \tau(\lambda) \rangle_k$. This prevents atmospheric transmission losses from being easily divided out. The band-averaging error is zero for a blackbody with no reflected component, but will increase as the emissivity decreases [25].
2.4.1 AC Algorithms

A brief description of AC algorithms will be given in this section, with a more in-depth description given in Chapter 3. The majority of AC algorithms estimate $\tau(\lambda_k)$ and $L_U(\lambda_k)$ using pixels within a scene that contain blackbody-like materials. These blackbody-like materials have a negligible reflected component. The at-aperture radiance spectra for pixels with blackbodies have a linear relationship between their at-aperture radiance and ground blackbody radiance spectra, which is determined by $\tau(\lambda_k)$ and $L_U(\lambda_k)$. By using a set of pixels that contain blackbody-like materials at varying temperatures, $\tau(\lambda_k)$ and $L_U(\lambda_k)$ can be estimated by fitting a line to the at-aperture radiance and estimated blackbody ground radiances scatter plots for each band. These blackbody ground radiance estimates are calculated with the band brightness temperatures of the clearest atmospheric band. With perfect blackbody pixels, the estimated atmospheric parameters are scaled versions of the true parameters. As the pixels deviate from blackbodies, the estimates deviate from the truth. Therefore, the accuracy of an AC method is dependent on the ability of the algorithm to find the best blackbody-like pixels. The main difference between AC methods is how the blackbody-like pixels in a scene are determined. We compare four algorithms:

In-Scene Atmospheric Compensation (ISAC) was the first method developed that used a linear fitting of blackbody-like pixels in each band to find estimates of $\tau(\lambda_k)$ and $L_U(\lambda_k)$. Blackbody-like pixels are found in a two step process. The clearest band with the highest emissivity is found by using the “most hits” method where the band with the most maximum pixel brightness temperatures is determined. The maximum brightness temperatures for the “most hits” pixels are used to generate ground blackbody radiances, which are then used with their at-aperture radiances to create scatter plots for each band. Lines are fitted to the blackbody-like pixels which are assumed to be at the top of each band scatter-plot [25].

Automatic Retrieval of Temperature and EMIssivity using Spectral Smoothness (ARTE-MISS) used a method similar to ISAC to determine initial estimates of $\tau(\lambda_k)$ and $L_U(\lambda_k)$. A known clear channel is used to generate ground blackbody radiances for every pixel, which are then used with their at-aperture radiances to create scatter plots for each band. The blackbody pixels are assumed to be at the top of each scatter plot. A line is fitted to each scatter plot removing the pixels under the line. The process is repeated until only a small number of pixels at the top of the scatter plot are left [7].

Optimized Land Surface Temperature and Emissivity Retrieval (OLSTER) uses one of the previous methods for an initial estimate of the atmospheric parameters. This initial estimate is then
used to convert all the pixels to ground radiance, which are then converted to mean-removed brightness temperature. Depending on a pixel’s emissivity relative to pixels used for the initial estimate, pixels with higher emissivities will be over corrected and have downward residual atmospheric features. Improved blackbody-like pixels are found by searching for pixels with negative concavity and positive correlation with the estimated transmission. Using the ground temperature estimates from the maximum brightness temperature of a clear channel, blackbody radiances are generated for the improved blackbody-like pixels. The blackbody radiances and their at-aperture radiances are then used to create scatter-plots for each band, and are fitted with a line for new atmospheric parameter estimates. The process is repeated until a small number of blackbody-like pixels remain [6].

Autonomous Atmospheric Compensation (AAC) uses a linear relationship between the at-aperture radiances of two close bands, where the two bands are on the edge and trough of a large water absorption feature. The slope and intercept of the relationship between the two at-aperture radiances measure the strengths of the atmospheric absorption band in terms of transmission and emission, respectively. These parameters are used to infer the entire spectral transmission and upwelling radiance by finding an atmospheric model that shares the same two band relationship [11].

2.5 Temperature Emissivity Separation (TES)

TES is the process where the temperature and emissivity of a pixel are determined from the pixel’s ground radiance spectrum. The emissivity spectrum of a pixel is required for detection because the reflected component in the ground radiance can add significant interference for low emissivity materials. Figure 2.6 shows simulated radiance spectra using the TUD model in Figure 2.5 along with Eq. (2.8) and Eq. (2.10). The spectra were simulated using the red emissivity spectrum, and a ground temperature of 295 K. The at-aperture and ground radiance have similar shapes, but slightly different magnitudes due to atmospheric affects. The emitted radiation component $\epsilon_G(\lambda_k)B(\lambda_k; T_G)$, is shown in black, and has a similar shape to the emissivity spectrum. The difference between the emitted radiation and ground radiance is the reflected radiation component from $L_D(\lambda_k)$ shown in green. The sharp reflected features from $L_D(\lambda_k)$ are easily seen in $L_G(\lambda_k)$, and the large differences in shape that they cause between the the emissivity and $L_G(\lambda_k)$ explain the challenges of detection in the ground radiance domain.

TES algorithms work on the fundamental assumption that the emissivity spectra of solid materials are smooth compared to the sharp features of atmospheric gases. With accurate atmospheric parameter estimates, the emissivity and temperature of a pixel can be estimated by finding
the temperature estimate $\hat{T}_G$, that provides the smoothest emissivity estimate $\hat{\epsilon}_G(\lambda_k)$. The emissivity estimate for a specific $\hat{T}_G$ is defined as

$$\hat{\epsilon}_G(\lambda_k) = \frac{L_S(\lambda_k) - L_U(\lambda_k) - L_D(\lambda_k) - L_{DR}(\lambda_k)}{B(\lambda_k; \hat{T}_G) - L_{DR}(\lambda_k)} \quad (2.12)$$

where $\hat{\epsilon}_G(\lambda_k)$ will contain residual atmospheric features when $\hat{T}_G \neq T_G$. The smoothness of $\hat{\epsilon}_G(\lambda_k)$ is determined by applying a smoothing algorithms to it, and calculating the difference between the original and smoothed. Atmospheric compensation is included in the emissivity calculation to avoid the band averaging error in Eq. (2.11) from dividing $L_{DR}(\lambda_k)$ by $\tau(\lambda_k)$.

### 2.5.1 TES Algorithms

A brief description of TES algorithms will be given in this section, with a more in-depth description given in Chapter 4. The main difference between the algorithms is the technique used to smooth the emissivity estimate. Iterative Spectrally Smooth (ISS) TES uses a boxcar moving average to smooth its emissivity estimate [8], and Linear spectral emissivity constraint (LEC) TES uses a linear piecewise smoothing [22].

Downwelling radiance residual index (DRRI) [17] [23] assumes a linear emissivity across large atmospheric features. For each temperature estimate, the emissivity is calculated. The emissivity is then linearly interpolated across the major atmospheric feature regions. The atmospheric residual is measured by finding the difference in emissivity between the peak emissivity and the

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**Figure 2.6:** Simulated measured and ground radiance with corresponding downwelling radiance, emissivity, and emitted ground radiance components.
CHAPTER 2. BACKGROUND

interpolated emissivity. The temperature that minimizes the total sum of atmospheric residuals for all the large atmospheric features is used to calculate the final emissivity estimate.

Stepwise refining temperature and emissivity separation (SRTES) [10] works on the ground radiance, and assumes that the emissivity is constant across key sharp atmospheric features of the downwelling radiance. An estimate of the emitted ground radiance over key atmospheric feature regions is calculated by using a constant emissivity estimate for each region to remove the reflected component from its ground radiance. A residual of each reflected component is found by interpolating across the feature in the emitted radiance, and measuring from its peak to the interpolated value. The emissivity of the peak feature band is the emissivity that provides the smallest residual. The emitted radiances with the smallest residuals are used to calculate the brightness temperature of the emitted components for each region. The average of the brightness temperatures is used as the final temperature estimate, and is used to calculate the entire emissivity spectrum.

2.6 MODerate resolution atmospheric TRANsmission model (MODTRAN)

MODTRAN is the standard atmospheric infrared/visible/ultraviolet radiance and transmission band model for lower altitudes. It is able to rapidly predict the atmospheric emission, thermal scatter, and solar scatter for arbitrary, refracted paths above the curved earth, incorporating the effects of molecular absorbers and scatterers, aerosols, and clouds. The band models have a spectral resolution of 0.1 cm\(^{-1}\) from 1 to 50,000 cm\(^{-1}\) (0.2 - 10,000 \(\mu\)m) [1].

There are 6 standard atmospheric profiles in MODTRAN that are used to generate atmospheric TUD models. These models are for different latitudes and seasons. Each atmospheric profile model includes profiles of temperature, water vapor concentration, and ozone concentration versus altitude. The 6 atmospheric temperature profile models are shown in Figure 2.7. The models show high temperature variability, but have similar overall trends. The gas concentration models are shown in Figure 2.8. The water profiles show a large amount of variability below 4 km, and are nearly identical after 6 km. The ozone profiles are not as variable, and have negligible concentrations below 10 km [1].

The inputs to MODTRAN used to generate the LWIR TUD models are a set of 3 atmospheric profile models. This set includes a temperature model and the water and ozone gas models. There are multiplier factors for the two gas models so that a greater number of possible atmospheres
can be generated. Collection parameters such as ground altitude, sensor wavelength range, sensor altitude, and sensor scan angle are specified. The sensor wavelength region is typically 7.5 to 14 $\mu$m for LWIR sensors. The TUD model is generated in a two step process. High resolution transmission and upwelling radiance spectra are generated by setting the ground temperature to nearly 0 and the ground reflectance to 0, thus eliminating the ground radiance. A high resolution reflected hemispherical downwelling radiance is generated by setting the ground reflectance to 1 and the sensor altitude directly above the ground, thus eliminating the atmospheric effects above the ground. The three are combined to form the TUD model. A look-up-table (LUT) or database of TUD models can be generated by repeating the process with permutations of the 6 profile models and varying the water and ozone multipliers \[1\].


CHAPTER 2. BACKGROUND

2.6.1 Sensor Wavelength Calibration

In order to use the high resolution MODTRAN TUD models for AC and TES, the TUD models need to be downsampled using the band SRF. A preflight spectral and radiometric calibration of the hyperspectral sensor is typically accomplished to obtain accurate measurements of the SRF, consisting of the bands centers $\lambda_k$ and FWHM. These measured wavelength calibration parameters can change over time. Factors such as mechanical vibration and temperature changes can cause spectral shifts $\lambda_k + \Delta$ and band broadening $s \times \text{FWHM}$ \[12\]. The result is the supplied SRF is only an estimate of the wavelength calibration $\hat{\lambda}_k$. The calibration error typically remains constant in the along-track direction but depending on the quality of the sensor can change in the across-track direction \[12\]. These wavelength calibration errors cause a mismatch between the atmospheric parameters in the TUD model and the at-aperture radiance spectra. These mismatches affect the AC and TES results. To minimize the mismatch effects, algorithms that utilize MODTRAN TUD models need to have wavelength calibration correction.

2.7 TES based AC with LUTs

While the transmission and upwelling radiance of a scene can be estimated using in-scene blackbody-like pixels, a similar technique is not possible for the downwelling radiance. The downwelling radiance is constructed from the entire atmosphere, even the unmeasured portion above the sensor. The only evidence of the downwelling radiance comes from reflective pixels with unknown emissivities. Due to the lack of in-scene knowledge needed to create a downwelling radiance estimate, a LUT of TUD models is generated. The best fitting model for a scene is found using a method similar to the one shown in Figure 2.9. Reflective pixels with a downwelling radiance component are found in a scene. Using one of the TES smoothing techniques, the pixels are processed with each of the TUD models in the LUT. The model that provides the smoothest emissivity estimates for the reflective pixels is chosen as the atmospheric model for the scene. This atmospheric model is then used for AC and TES processing of the entire scene. Since atmospheric models are being utilized, an algorithm needs to contain sensor calibration correction.

Automatic Retrieval of Temperature and EMissivity using Spectral Smoothness (ARTEMISS) finds the best atmospheric model in a TUD LUT by using ISSTES. The TUD-LUT is generated by directly estimating the columnar water vapor and ozone amount directly from the ARTEMISS ISAC transmission described in Section 2.4.1. The relationship between the three-band ratio
CHAPTER 2. BACKGROUND

![Flowchart for determining best TUD model for a scene.](image)

Figure 2.9: Flowchart for determining best TUD model for a scene.

of the transmission around the 11.7 \( \mu \text{m} \) and the column water vapor is used to generate a smaller more precise TUD LUT. The size of the TUD LUT can be further decreased by finding TUD models whose transmission have a large SAM with the ARTEMISS ISAC transmission. Reflective pixels are found by putting the pixels into bins based on ground temperature estimates, a small number of pixels are then chosen from each bin excluding pixels with smooth brightness temperature spectra. Wavelength calibration is done by splitting the ARTEMISS ISAC transmission into sections that are normalized to vectors of unit length. The high resolution MODTRAN TUD models are split into the same number of overlapping sections, and are downsampled with different band shifts and FWHM multipliers, which are then also normalized. The optimum wavelength calibration parameters are found for each section by finding the downsampling that provides the largest SAM with the corresponding ARTEMISS ISAC transmission section [7].

Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes-InfraRed (FLAASH-IR) also finds the best atmospheric model in a TUD LUT by using ISSTES. However, a wide boxcar running average of around \( \approx 0.3 \mu \text{m} \) (typically \( \approx 7 \) channels) is used, or combined with a 3-channel averaging. The wide averaging window removes the fine spectral features from wavelength miscalibration. The TUD LUT is formed by specifying a three-dimensional grid of atmospheric parameters, such as surface air temperature, water vapor column density, and ozone column density scale factors. TES is run on between 10-20 pixels of varying brightness and spectral shape, where reflective pixels are included. FLAASH-IR also includes its own wavelength calibration correction technique [2].
CHAPTER 2. BACKGROUND

2.8 Generation of Synthetic Data

The testing of atmospheric compensation and TES algorithms on actual data requires a great deal of accurate atmospheric and ground truth to make concrete conclusions about algorithm performance. In addition, to understand the performance limitations of the algorithms and their causes under different conditions, one would have to collect a great deal of data and truth under these conditions. These varying atmospheric and ground conditions include:

- Ground emissivity spectra of different magnitudes and roughness;
- Varying ground temperatures;
- Instrument noise effects; and
- Varying atmospheric conditions and sensor altitudes.

Due to the difficulty of collecting data with accurate ground truth, there is not a significant amount of data available for in-depth performance testing. For this reason in-depth testing requires the generation of at-aperture radiance spectrum, where the truth is perfectly known.

Synthetic data was generated to have the properties of the Spatially Enhanced Broadband Array Spectrograph System (SEBASS). SEBASS has been around since the late 1990s. The sensor consists of a $128 \times 128$ pixel focal plane, where one dimension is the spectral dimension and the other is one of the spatial dimensions. The second spatial dimension of the data cube is generated by the motion of the plane. The spectral resolution is $0.05 \, \mu m$ from $7.5$ to $13.6 \, \mu m$. Figure 2.5 shows a TUD model generated with MODTRAN using the Mid-Latitude Summer atmospheric profiles with a water multiplier of $0.75$, an ozone multiplier of $1$, at an altitude of $0.5$ km, and downsampled to the $128$ band SEBASS resolution $[24] \ [5]$. This TUD model was used to generate a majority of the radiance spectra throughout the thesis.

The at-aperture radiance generation process is shown in Figure 2.10. The first step of the process is generating high-resolution atmospheric parameters with MODTRAN within the wavelength range of $7.5$ to $14 \, \mu m$. The inputs to MODTRAN include atmospheric temperature and gas profiles. These models provide the temperature and gas concentrations with altitude. The gas concentrations can be scaled by using a multiplier factor. Additional inputs include the sensor and ground altitudes, and the sensor wavelength range.

With the atmospheric parameters, the next step is to generate the high-resolution at-aperture radiance spectra. Using the high-resolution atmospheric parameters, an emissivity spec-
trum with the same resolution, and a ground temperature, the forward at-aperture radiance model
described in Eqs. (2.5a) and (2.5b) is used to generate the high-resolution at-aperture radiance spec-
trum. The last step involves downsampling the high-resolution at-aperture radiance spectrum to the
resolution of the sensor of interest. This is done using a sensor model which includes the spectral
response function and noise signal model of the sensor. The spectral response function consists of
the band centers $\lambda_k$, the band FWHMs, and assumes each band has a Gaussian response.

Noise effects are studied by adding noise to a single noiseless at-aperture radiance spec-
trum to generate 10,000 noisy spectra [13]. The measured at-aperture noise equivalent spectral
radiance (NESR) of this noise is determined with a Dyson imaging spectrometer signal model for
each at-aperture radiance spectrum. The Dyson signal model takes into account the optical effi-
ciency of the sensor based upon the number of mirrors, the mirror reflectance, the transmission of
the refractive elements, and the grating efficiency. Noise components include the focal plane array
dark current, read out noise, quantization noise, and the self emission of the optics. In order to min-
imize the emission of the optics, the sensor is placed in a dewar at 80K. The at-aperture radiance is
converted to the electronic signal read by the sensor, so that the signal-to-noise ratio (SNR) can be
determined. With the SNR, the NESR of the at-aperture radiance can be determined using

\[ \text{NESR}(\lambda_k) = \frac{L_S(\lambda_k)}{\text{SNR}(\lambda_k)} \]  

(2.13)

With this realistic NESR random white Gaussian noise can be added to the synthetic at-aperture radiance spectra [14].

Wavelength calibration error can be included by downsampling the atmospheric parameters used with AC and TES with a SRF that is slightly mismatched to the one used to downsample the at-aperture radiance spectra. The wavelength calibration mismatch involves a slight shift in the sensor band centers, \( \lambda_k + \Delta \), which is determined by using a fraction of the minimum change in wavelength between bands. A band broadening mismatch can be added by scaling the sensor’s FWHM. The wavelength calibration mismatch can then be varied to observe effects on the AC and TES results.
Chapter 3

Atmospheric Compensation

Atmospheric compensation (AC) is the process where atmospheric transmission losses and emissions are removed from the at-aperture radiance pixel spectra using Eq. 2.11 to obtain the ground radiance pixel spectra. The difficulty of atmospheric compensation lies in determining accurate estimates of the atmospheric transmission and upwellling radiance for a scene. Any errors in estimating the atmospheric parameters are transferred to TES and the final temperature and emissivity estimates. Atmospheric compensation algorithms are used to determine the atmospheric parameters for a scene, which are then used for atmospheric compensation of the pixel spectra. There are three main types of atmospheric compensation algorithms: in-scene, model based, and hybrid algorithms.

All three types of algorithms attempt to find the atmospheric scene parameters that most accurately remove the sharp atmospheric features found in at-aperture radiance spectra. Pixels containing blackbody-like materials, with a minimal reflected downwelling radiance component, have smooth blackbody-like ground radiance spectra. These blackbody-like pixels provide a way of determining the atmospheric parameters. The accuracy of the atmospheric parameters are determined by how closely the blackbody-like pixels in a scene resemble blackbodies, and how effectively an algorithm can find the best blackbody-like pixels.

In this chapter, an in depth analysis of in-scene atmospheric compensation (ISAC) algorithms is done. The goal of this study is to determine which algorithm is most effective at finding the most blackbody-like pixels in a scene. An overall ISAC model is developed to explain how the quality of the determined blackbody-like pixels affects the final transmission and upwelling radiance estimates. The model is then extended to explain how errors in the atmospheric estimates are transferred to ground radiance estimates after AC.
CHAPTER 3. ATMOSPHERIC COMPENSATION

3.1 At-Aperture Radiance Spectra

The in-scene blackbody-like pixels used by atmospheric compensation algorithms to determine the atmospheric parameters are found directly from the at-aperture radiances. A scene consists of blackbody \( \epsilon_{G}(\lambda_k) = 1 \), grey body \( \epsilon_{G}(\lambda_k) \approx 1 \), and reflective \( \epsilon_{G}(\lambda_k) < 1 \) materials. A description of the at-aperture radiance spectra of these three types of materials will be discussed in the following sections, to provide an understanding of their spectral characteristics. Understanding these characteristics will help with the classification of the types of materials in a pixel from their at-aperture radiance spectra, and allow for the identification of blackbody-like pixel spectra.

3.1.1 At-Aperture Radiance Spectra for In-scene Blackbodies

The spectral characteristics of blackbodies in a scene are dependent on their temperatures relative to the temperature of the atmosphere between the ground and sensor. The at-aperture radiance equation, Eq. (2.8), for a blackbody on the ground can be expressed as

\[
L_S(\lambda_k) = B(\lambda_k, T_G)\tau(\lambda_k) + L_U(\lambda_k)
\]

(3.1)

The atmospheric absorbance is \( 1 - \tau(\lambda_k) \). The upwelling radiance can then be expressed in terms of absorbance by

\[
L_U(\lambda_k) = B(\lambda_k, T_U)(1 - \tau(\lambda_k))
\]

(3.2)

where \( T_U \) is an effective atmospheric temperature for the upwelling radiation between the ground and sensor [25]. Using Eq. (3.2), Eq. (3.1) can be expressed as

\[
L_S(\lambda_k) = B(\lambda_k, T_G) - \left( B(\lambda_k, T_G) - B(\lambda_k, T_U) \right)(1 - \tau(\lambda_k))
\]

(3.3)

where we can easily see that the resulting \( L_S(\lambda_k) \) is determined by the interaction of \( T_G \) and \( T_U \).

Using Eq. (3.1) and the atmospheric parameters in Figure 2.5, Figure 3.1 shows the simulated \( L_S(\lambda_k) \) for blackbodies at ground temperatures between 287.95 K and 297.95 K in 1 K increments. The effective atmospheric temperature is 292.95 K. When \( T_G = T_U \), the atmospheric absorption and emission are equal, and \( L_S(\lambda_k) \) is a smooth blackbody spectrum. The temperature at which the atmospheric absorption and emission are equal will be defined as \( T_E \). For blackbodies \( T_U \) and \( T_E \) are equal, however \( T_E \) will increase as the emissivity of the pixel decreases. When \( T_G > T_U \) the atmospheric absorption is greater than the emission and absorption features are visible in \( L_S(\lambda_k) \). When \( T_G < T_U \) the atmospheric absorption is less than the emission and emission features are visible in \( L_S(\lambda_k) \).

26
CHAPTER 3. ATMOSPHERIC COMPENSATION

Figure 3.1: $L_S(\lambda_k)$ of pixels with $\epsilon_G(\lambda_k) = 1$.

We are able to see the interaction of the atmospheric absorption more clearly by converting the simulated $L_S(\lambda_k)$ to brightness temperature, using Eq. (2.7) at the center wavelength $\lambda_k$ at each band. The brightness temperature of a blackbody pixel will be constant for all $\lambda_k$ when $T_G = T_E$. Figure 3.2 shows the brightness temperature of the at-aperture radiance spectra in Figure 3.1. The brightness temperature is flat for the red spectrum where $T_G = T_U$. Absorption and emission are clearly visible above and below $T_U$ respectively.

The ground temperature of blackbodies can be estimated from the brightness temperatures of clear bands $\lambda_C$, where $\tau(\lambda_C) \approx 1$ and $L_U(\lambda_C) \approx 0$. This simplifies Eq. (3.1) to

$$L_S(\lambda_C) \approx B(\lambda_C, T_G) \quad (3.4)$$

so that the estimated ground temperature is

$$\hat{T}_G = T_B(\lambda_C; B(\lambda_C, T_G)) \approx T_G \quad (3.5)$$

Analysis of TUD models generated with MODTRAN suggest that clear wavelengths are located at $\lambda_C = 8.87, 9.21$ or $10.07 \mu m$, as shown in Figure 2.5. It is shown in Figure 3.2 that the brightness temperature provides $\hat{T}_G$ estimates closest to $T_G$ at clear bands.

Depending on the temperature of the blackbody, either the maximum or minimum brightness temperature gives the best estimate. When absorption occurred with $T_G > T_E$, the maximum brightness temperature provided the best temperature estimate with a $\hat{T}_G < T_G$. When emission occurred with $T_G < T_E$, the minimum brightness temperature provided the best temperature estimate with a $\hat{T}_G > T_G$. 

27
CHAPTER 3. ATMOSPHERIC COMPENSATION

3.1.2 At-Aperture Radiance Spectra for In-scene Gray Bodies

The at-aperture radiance of gray bodies with an $\epsilon_G(\lambda_k) \approx 1$ can be defined as

$$L_S(\lambda_k) \cong \epsilon_G(\lambda_k)B(\lambda_k,T_G)\tau(\lambda_k) + L_U(\lambda_k)$$  \hspace{1cm} (3.6)

The downwelling radiance is ignored since $[1 - \epsilon_G(\lambda_k)]L_D\tau \approx 0$. Similar to Eq. (3.3), the at-aperture radiance for a gray body can be represented as an interaction of atmospheric absorption and emission,

$$L_S(\lambda_k) = \epsilon_G(\lambda_k)B(\lambda_k,T_G) - \left( \epsilon_G(\lambda_k)B(\lambda_k,T_G) - B(\lambda_k,T_U) \right)(1 - \tau(\lambda_k))$$  \hspace{1cm} (3.7)

where $\epsilon_G(\lambda_k)$ weights the ground radiance. The weighting of the ground radiance means that a larger $T_G$ is required for equilibrium and that $T_E > T_U$.

For clear bands $\lambda_C$, the at-aperture radiance of gray blackbodies in Eq. (3.6) simplifies to

$$L_S(\lambda_C) \approx \epsilon_G(\lambda_C)B(\lambda_C,T_G)$$  \hspace{1cm} (3.8)

and the ground temperature can then be estimated using the brightness temperature, where

$$\hat{T}_G = T_B(\lambda_C; \epsilon_G(\lambda_C)B(\lambda_C,T_G)) \approx T_G$$  \hspace{1cm} (3.9)

where $\epsilon_G(\lambda_C) < 1$ has the effect of slightly lowering the ground temperature estimate.

Using Eqs. (2.8) and (2.10) and the atmospheric parameters in Figure 2.5, at-aperture radiance spectra were simulated for grey bodies with a constant emissivity of $\epsilon_G(\lambda_k) = 0.98$ at ground temperatures between 287.95 K and 297.95 K in 1 K increments. Figure 3.3 shows the brightness temperature of the simulated $L_S(\lambda_k)$. The lack of atmospheric features in 4th spectrum from the top shows that $T_E$ is approximately 2 K higher than $T_U$. Compared to Figure 3.2, it can be seen that the reduced emissivity lowered all the brightness temperatures. There is a slight ozone feature visible between 9 and 10 $\mu m$ from the small reflected downwelling radiance.

3.1.3 At-Aperture Radiance Spectra for In-scene Reflective Materials

As the emissivity of a pixel decreases, the pixel becomes more reflective, and the at-aperture radiance is defined as Eq. (2.8) where the atmospheric emission component consists of $L_U(\lambda_k) + (1 - \epsilon_G(\lambda_k))L_D\tau(\lambda_k)$. As $\epsilon_G(\lambda_k)$ decreases a majority of $L_S(\lambda_k)$ consists of the atmospheric emission, and $T_E$ will increase with the decreasing $\epsilon_G(\lambda_k)$. Typically reflective pixels will not be hot enough to reach $T_E$, and will have emissive features.
CHAPTER 3. ATMOSPHERIC COMPENSATION

Figure 3.3: Brightness Temperature of pixels with $\epsilon_G(\lambda_k) = 0.98$.

Figure 3.4: Brightness Temperature of pixels with $\epsilon_G(\lambda_k) = 0.8$.

Using Eqs. (2.8) and (2.10) and the atmospheric parameters in Figure 2.5 at-aperture radiance spectra were simulated for reflective pixels with a constant emissivity of $\epsilon_G(\lambda_k) = 0.8$ at ground temperatures between 287.95 K and 297.95 K in 1 K increments. Figure 3.4 shows the brightness temperature of the simulated $L_S(\lambda_k)$. The brightness temperatures appear extremely emissive, and the $\hat{T}_G$ estimates at $\lambda_C$ are far below $T_G$.

3.2 In-Scene Atmospheric Compensation (ISAC)

ISAC is a method where the transmission and upwelling radiance of a scene’s atmosphere are estimated using blackbody or gray body materials of varying temperatures that are present in the scene. It is assumed that blackbody-like materials such as water and vegetation are present in the scene. The estimated transmission, $\hat{\tau}(\lambda_k)$, and upwelling radiance, $\hat{L}_U(\lambda_k)$, are then used in Eq. (2.11) for the atmospheric compensation of each pixel. Pixels that contain materials such as water and vegetation have $\epsilon_G(\lambda_k) \approx 1$ and are key candidates for blackbody like pixels. When $\epsilon_G(\lambda_k) \approx 1$, the at-aperture radiance is approximately given by Eq. (3.6), and the simplified measured radiance equation is a linear function for each wavelength band, of the independent variable $B(\lambda_k, T_G)$, where $\tau(\lambda_k)$ and $L_U(\lambda_k)$ are the slope and y-intercept [25].

Figure 3.5 shows a standard ISAC processing pipeline. Pixels that contain possible blackbody materials are found within the scene. Ground temperature estimates, $\hat{T}_G$, of these pixels are determined using the brightness temperature of a clear reference band $\lambda_R$, which are then used to
CHAPTER 3. ATMOSPHERIC COMPENSATION

Figure 3.5: ISAC Processing Pipeline

Figure 3.6: ISAC scatter plot for the 11.24 µm band.

generate a blackbody ground reference spectrum, \( B(\lambda_k, \hat{T}_G) \), for each pixel. The accuracy of these estimates depends on the emissivity and transmission of the reference band for each pixel. Scatter plots of \( B(\lambda_k, \hat{T}_G) \) vs. \( L_S(\lambda_k) \) are created for each band, such as the scatter plot shown in Figure 3.6. The blackbody pixels for this case are shown in green. The scatter plots follow the linear trend described by Eq. (3.6). By fitting a line to the blackbody pixels in each scatter plot, estimates of the transmission \( \hat{\tau}(\lambda_k) \), and upwelling radiance \( \hat{L}_U(\lambda_k) \) can be determined for each band. These individual band estimates are combined to create the transmission and upwelling radiance spectral estimates. These estimates are proportional to the true atmospheric parameters, where \( \hat{\tau}(\lambda_R) = 1 \) and \( \hat{L}_U(\lambda_R) = 0 \).

The difficulty of ISAC lies in determining which of the pixels in a scene are closest to being blackbodies, and what are their corresponding ground temperatures. There are several ISAC algorithms, whose main differences are the techniques used to find the blackbody-like pixels. The quality of the estimated atmospheric parameters for each method depend on the how well the in-scene blackbody like pixels resemble actual blackbodies, the accuracy of their ground temperature
estimates, and the ability of the method to find the best blackbody pixels in a scene. Models will be created in Sections 3.4 and 3.5 to analyze the accuracy of each of the methods to determine the best in-scene blackbody-like pixels.

### 3.3 Full At-Aperture Radiance Scatter Plot Model

The atmospheric parameters are determined from the band scatter-plots. The quality of these estimates is determined by how much blackbody-like pixels deviate from the position of true blackbodies. To understand how deviations in a pixel’s emissivity from being blackbody affect its position relative to blackbodies of the same temperature, a scatter plot model was developed using the complete at-aperture radiance equation. A similar model neglecting the downwelling radiance is discussed in [25].

Using the complete at-aperture radiance model, the coordinates of a point in the scatter plot are written as,

\[ x = B \left\{ \lambda_k, T_B(\lambda_R, L_S(\lambda_R)) \right\} \]  
\[ y = L_S(\lambda_k) = \epsilon_G(\lambda_k)B(\lambda_k, T_G)\tau(\lambda_k) + [1 - \epsilon_G(\lambda_R)]L_{DR}(\lambda_k) + L_U(\lambda_k) \]  

where the atmospheric parameters \( \tau(\lambda_k) \), \( L_U(\lambda_k) \), and \( L_{DR}(\lambda_k) \) are common to all points. The only quantities that differ between pixels are the ground quantities \( T_G \), \( \epsilon_G(\lambda_k) \), and \( \epsilon_G(\lambda_R) \). An analysis of how reductions in \( \epsilon_G(\lambda_k) \), and \( \epsilon_G(\lambda_R) \) of pixel causes changes in its position relative to a blackbody pixel of the same \( T_G \) reveals a protocol for selecting the reference channel \( \lambda_R \), and determining the possible location of blackbody pixels.

Figure 3.7 shows the at-aperture scatter plot model components. We assume that there is a set of perfect blackbody pixels at varying temperatures. Using a clear transmission channel for \( \lambda_R \), we plot the blackbody pixels for each band. These blackbody pixels follow the black blackbody line, whose slope and y-intercept are the optimum ISAC band estimates of the transmission and upwelling radiance, and are specified as \( \hat{\tau}_B(\lambda_k) \) and \( \hat{L}_{UB}(\lambda_k) \) respectively. A pixel is chosen with a ground temperature \( T_G \), and a blackbody with the same \( T_G \) is found on the line, represented as the black dot \( (x_B, y_B) \). This is the starting location of the pixel if it was a blackbody. The final pixel position \( (x, y) \) is determined by \( \epsilon_G(\lambda_R) \) and \( \epsilon_G(\lambda_k) \). As \( \epsilon_G(\lambda_R) \) decreases there will be a leftward \( \Delta x \), and as \( \epsilon_G(\lambda_k) \) decreases there will be a downward \( \Delta y \). The vertical drop in blackbody line over \( \Delta x \) is \( \Delta y_B \). The final distance of the pixel from the blackbody line can be found by comparing \( \Delta y \) and \( \Delta y_B \).
CHAPTER 3. ATMOSPHERIC COMPENSATION

The decrease in the at-aperture radiance caused by $\epsilon_G(\lambda_k) < 1$ for any band can be written as

$$\Delta y = \Delta L_S(\lambda_k, \epsilon_G(\lambda_k)) = \left(1 - \epsilon_G(\lambda_k)\right)\left(B(\lambda_k, T_G)\tau(\lambda_k) - L_{D_T}(\lambda_k)\right)$$  (3.12)

where this is the amount that the pixel moves down in the scatter plot.

The leftward movement from the blackbody line caused by $\epsilon_G(\lambda_R) < 1$ is the difference between two blackbody radiances,

$$\Delta x = \Delta B(\lambda_k, T_G) = B(\lambda_k, \hat{T}_{GB}) - B(\lambda_k, \hat{T}_G)$$  (3.13)

where $\hat{T}_{GB}$ is the estimated ground temperature of a blackbody with ground temperature $T_G$ after atmospheric effects, defined as

$$\hat{T}_{GB} = T_B[\lambda_R, B(\lambda_R, T_G)\tau(\lambda_R) + L_U(\lambda_R)]$$  (3.14)

and $\hat{T}_G$ is the estimated ground temperature of a pixel at $T_G$ with $\epsilon_G(\lambda_R) < 1$, defined as

$$\hat{T}_G = T_B[\lambda_R, L_S(\lambda_R)] = T_B[\lambda_R, B(\lambda_R; T_G)\tau(\lambda_R) + L_U(\lambda_R) - \Delta L_S(\lambda_R; \epsilon_G(\lambda_R))]$$  (3.15)

The $\Delta y$ of a blackbody for the equivalent $\Delta x$ is

$$\Delta y_B = \Delta x \hat{\tau}_B(\lambda_k)$$  (3.16)

where the pixel lies compared to the blackbody line is determined by the relation between $\Delta y$ and $\Delta y_B$. A pixel will lie below the blackbody line if

$$\Delta L_S(\lambda_k, \epsilon_G(\lambda_k)) > \Delta B(\lambda_k, T_G)\hat{\tau}_B(\lambda_k)$$  (3.17)

The variability of the downwelling radiance between bands affects $\Delta L_S(\lambda_k, \epsilon_G(\lambda_k))$, and determines the placement of a pixel relative to the blackbody line for each band.

3.3.1 Relationship between True and ISAC Blackbody Atmospheric Parameters

The ISAC parameters found using perfect blackbodies are proportional to the true parameters, where $\hat{\tau}_B(\lambda_R) = 1$ and $\hat{L}_{UB}(\lambda_R) = 0$. The scaling procedure of the ISAC parameters to the true parameters is discussed in [25]. The ISAC transmission found using blackbodies $\hat{\tau}_B(\lambda_k)$ can be scaled to the true transmission $\tau(\lambda_k)$ using

$$\tau(\lambda_k) = \frac{\tau(\lambda_R)}{\hat{\tau}_B(\lambda_R)} \hat{\tau}_B(\lambda_k)$$  (3.18)

32
CHAPTER 3. ATMOSPHERIC COMPENSATION

The shape of \( \hat{\tau}_B(\lambda_k) \) and \( \tau(\lambda_k) \) are identical, so only a simple scalar to match \( \tau(\lambda_R) \) and \( \hat{\tau}_B(\lambda_R) \) is needed. The scaling of the ISAC upwelling radiance found using blackbodies \( \hat{L}_{UB}(\lambda_k) \) is done using

\[
L_U(\lambda_k) = \hat{L}_{UB}(\lambda_k) + \frac{\hat{\tau}_B(\lambda_k)}{\tau_B(\lambda_R)} C_T(\lambda_k)
\]

(3.19a)

\[
C_T(\lambda_k) = \alpha(\lambda_k, \lambda_R)[\hat{\tau}_B(\lambda_R) - \tau(\lambda_R)] - \beta(\lambda_k, \lambda_R)[\hat{L}_{UB}(\lambda_R) - L_U(\lambda_R)]
\]

(3.19b)

\[
\beta(\lambda_k, \lambda_R) = \frac{B'(\lambda_k, T_r)}{B'(\lambda_R, T_r)}
\]

(3.19c)

\[
\alpha(\lambda_k, \lambda_R) = \left[ \frac{B(\lambda_k, T_r)}{B(\lambda_R, T_r)} - \beta(\lambda_k, \lambda_R) \right] B(\lambda_R, T_r)
\]

(3.19d)

where the function \( B'(\lambda_k, T_r) \) is \( dB/dT \), and \( T_r \) is a reference temperature within the temperature bounds of the scene. Enough radiance needs to be added to \( \hat{L}_{UB}(\lambda_k) \) to compensate for the reduction in the transmission of \( \hat{\tau}_B(\lambda_k) \).

### 3.3.2 Determining a Reference Band and Ground Temperature

The accuracy of the ISAC parameters is determined by how well the ground radiance of a blackbody-like pixel, \( B(\lambda_k, \hat{T}_G) \), can be approximated. This approximation is dependent on the estimated ground temperature, \( \hat{T}_G \), and the \( \lambda_R \) used to make the estimate. If the wrong \( \lambda_R \) is chosen, the shape and scale of the atmospheric parameters will be affected. The goal is to find a band and pixels where Eq. (2.8) simplifies to \( L_S(\lambda_R) \approx B(\lambda_R, T_G) \), and \( \hat{T}_G \approx T_G \). This simplification
CHAPTER 3. ATMOSPHERIC COMPENSATION

requires that, $\lambda_R$ be one of the clear atmospheric bands $\lambda_C$ where $\tau(\lambda_R) \approx 1$. The difficulty lies in finding the clear band where pixels have $\epsilon_G(\lambda_R) \approx 1$, when the material properties of the ground are unknown.

The at-aperture radiance of a pixel tends to have absorption features only when the ground temperature is warmer than the apparent atmospheric upwelling temperature and $\epsilon_G(\lambda_k) \approx 1$, as shown in Section [3.1]. For these warm blackbody-like pixels, the maximum brightness temperature gives the best $\hat{T}_G$. To find the blackbody like pixels, the ground temperature is estimated for each pixel by finding its maximum band brightness temperature using Eq. [2.7]. The band that supplies the most maximum pixel brightness temperatures is chosen as the reference band $\lambda_R$, and only the pixels that share this band as their maximum are kept for further searching of possible blackbodies. This method is known as the “most hits” method used by Young in [25]. The reference band will typically correspond to one of the $\lambda_C$, where the product $\tau(\lambda_k)\epsilon_G(\lambda_k)$ is the largest. However, this doesn’t necessarily mean that $\epsilon_G(\lambda_R)$ has the highest emissivity, due to the brightness temperature depending on both $\tau(\lambda_k)$ and $\epsilon_G(\lambda_k)$. When $\lambda_R$ does not correspond with one of the $\lambda_C$, a majority of the pixels are cold or reflective. The reference band can then be chosen as the $\lambda_C$ with the most hits, if there are enough pixels over a wide enough temperature range. It is difficult to find cold blackbody pixels using brightness temperature because they are emissive like the unwanted reflective pixels.

ISAC assumes the “most hits” blackbody-like pixels are likely to be near or slightly below the blackbody line. The “most hits” method provides pixels where $\epsilon_G(\lambda_R)$ is likely to be the highest emissivity of a spectrum, and $\hat{T}_G$ is the most accurate ground temperature estimate. The accurate $\hat{T}_G$ minimizes $\Delta x$, while $\epsilon_G(\lambda_R)$ provides an upper emissivity bound so that the $\epsilon_G(\lambda_k) \leq \epsilon_G(\lambda_R)$ provides a $\Delta y$ below the blackbody line.

The main limitations of the “most hits” method is that it rejects the cold blackbody like pixels, and only does ISAC on the warm portion of a scene’s temperature range. In addition, the best blackbody like pixels will be ignored if they do not share the “most hits” band.

3.4 Determining Blackbody-Like Pixels from Scatter Plots

The Young and ARTEMISS ISAC methods attempt to determine blackbody-like pixels directly from the band scatter plots. They use the assumption that the blackbody like pixels are at the top of the band scatter plots, and use different methods to determine the top pixels. Where Young uses the “most hits” method to determine $\lambda_R$ and remove pixels with low $\epsilon(\lambda_R)$ that can
be above blackbodies, ARTEMISS simply uses the clear 10.1 \( \mu m \) channel. To test the validity of the assumption that blackbodies are at the top of the scatter plot, several tests were done to study the location of near-blackbody pixels relative to true blackbody pixels. The simplest method is to generate a set of at-aperture radiance spectra at varying emissivities and temperatures, choose a clear reference channel \( \lambda_R \) to estimate \( \hat{T}_G \), and create the \( B(\lambda_k, \hat{T}_G) \) vs. \( L_S(\lambda_k) \) band scatter plots. The locations of the near-blackbodies relative to the true blackbodies can be studied in each band scatter plot.

At-aperture radiance spectra were simulated using Eqs. 2.8 and 2.10 and the atmospheric parameters in Figure 2.5. The at-aperture radiance spectra were simulated at ground temperatures between 287.95 K and 297.95 K in 1 K increments, for constant emissivities of \( \epsilon_G(\lambda_k) = 1, 0.99, 0.98, 0.97, 0.96, \) and 0.95. Figure 3.8 shows a scatter plot at the 9.43 \( \mu m \) band using the simulated spectra with a \( \lambda_R \) of 10.1 \( \mu m \). The blackbodies are in black, and the pixels of \( \epsilon_G(\lambda_k) = 0.95 \) are in red. The pixels for each emissivity follow a linear trend, and move further up and left from the blackbody line as the emissivity decreases. The plot shows that for this band, one can not expect blackbody pixels to be near the top of the scatter plot. The problem with this method is that a scatter plot needs to be analyzed for each of the bands, and the overall trend across the large number of bands is difficult to visualize.

Figure 3.8: ISAC band scatter plot for pixels with emissivities from \( \epsilon_G(\lambda_k) = 1 \) to 0.95 in 0.01 increments, and ground temperatures between 287.95 K and 297.95 K in 1 K increments

The full at-aperture scatter plot model was used to visualize how the distance of a pixel
relative to the blackbody line changes with emissivity across the entire spectral range. Figure 3.9 shows the simulation process used to make the comparison. The first step involved simulating the at-aperture radiance spectra, using the process described to make the band scatter plot in Figure 3.8. Using the perfect blackbody spectra, the \( T_{GB} \) were estimated with a \( \lambda_R \) of 10.1 \( \mu m \), and blackbody lines were created for each band. ISAC fitting was then used on the blackbody lines for each band to form the \( \hat{T}_{B} \) and \( \hat{L}_{UB} \) spectra. Next, the at-aperture radiance spectra corresponding to a single \( T_G \) were selected. Using the blackbody spectra, \( L_S(\lambda, \epsilon_G(\lambda_k)) = 1 \) and \( L_S(\lambda, \epsilon_G(\lambda_k) < 1) \), the \( \Delta y \) for each spectrum was determined. The \( \hat{T}_{GB} \) and \( \hat{T}_G \) were then estimated for the the at-aperture radiance spectra and used to generate ground blackbody references. Using \( \Delta y_{B} \) and the differences between the blackbody and the near-blackbody ground references \( \Delta y_{B} \) was determined. The location of a pixel relative to the blackbody line was found by comparing \( \Delta y \) and \( \Delta y_{B} \).

Figure 3.10 shows a comparison of the \( \Delta y \) and \( \Delta y_{B} \) of each band for \( L_S(\lambda_k) \) spectra generated at a \( T_G \) of 297.95 K and constant emissivities of \( \epsilon_G(\lambda_k) \) of 0.95 to 1. The \( \Delta y \) for each emissivity are in blue, with \( \epsilon_G(\lambda_k) = 1 \) at the bottom and \( \epsilon_G(\lambda_k) = 0.95 \) at the top. The \( \Delta y_{B} \) using the maximum transmission band at 10.1 \( \mu m \) as \( \lambda_R \), are in red. The \( \Delta y_{B} \) using the maximum brightness temperature bands as \( \lambda_R \), are in green. The corresponding colored dots are at the \( \lambda_R \) bands. It can be seen when \( \epsilon_G(\lambda_k) = \epsilon_G(\lambda_R) \) the blue lines are below the red lines for a majority of the bands, meaning the pixel is above the blackbody line. Red and blue lines corresponding to different emissivities can be compared. Lower emissivity blue lines are above higher emissivity red lines, meaning when \( \epsilon_G(\lambda_k) < \epsilon_G(\lambda_R) \) a pixel will be below the blackbody line.

The green lines using the maximum brightness temperature have a \( \lambda_R \) in the ozone feature region. The \( \lambda_R \) are in the large dip of the ozone feature in \( \Delta y_{B} \), so that the green lines are below


CHAPTER 3. ATMOSPHERIC COMPENSATION

Figure 3.10: Comparison of $\Delta y$ and $\Delta y_B$ for all the spectral bands using the simulated $L_S(\lambda_k)$ at a $T_G$ of 297.95 K.

The blue lines for a majority of the bands when $\epsilon_G(\lambda_k) = \epsilon_G(\lambda_R)$. An ozone band will only have a maximum brightness temperature at low altitudes where there is no ozone absorption and the transmission is relatively high. Using the ozone band at higher altitudes would result in scale and shape changes in the estimated atmospheric parameters. The maximum brightness temperature bands change between the constant emissivity spectra, meaning the “most hits” method could miss the best blackbody pixels which have a maximum brightness temperature at 10.1 $\mu m$.

The results show that when the clearest band is used as $\lambda_R$, $\epsilon_G(\lambda_k) < \epsilon_G(\lambda_R)$ is required for pixels to be below the perfect blackbodies. Any pixel with $\epsilon_G(\lambda_k) \geq \epsilon_G(\lambda_R)$ will be above the perfect blackbodies. The “most hits” method attempts to minimize pixels with $\epsilon_G(\lambda_k) > \epsilon_G(\lambda_R)$, but is susceptible to pixels with $\epsilon_G(\lambda_k) = \epsilon_G(\lambda_R)$ being above the blackbodies.

3.5 Optimized Land Surface Temperature and Emissivity Retrieval (OLSTER)

OLSTER is a hybrid AC algorithm developed in [6]. An initial pass of an ISAC algorithm is used to determine atmospheric parameters. This initial pass should be free of low emissivity pixels. The resulting atmospheric parameters are based on the median emissivity $\epsilon_M(\lambda_k)$ of the high emissivity pixels in the scene. The atmospheric parameters are scaled if they happen to have
non-physical values. The initial atmospheric parameters are used to convert the pixels in the scene to ground radiance, which are then converted to brightness temperature. The resulting brightness temperatures show over compensation of the atmosphere when $\epsilon_G(\lambda_k) > \epsilon_M(\lambda_k)$, and under compensation when $\epsilon_G(\lambda_k) < \epsilon_M(\lambda_k)$. The higher emissivity pixels are determined by finding the pixels with negative concave atmospheric compensation features. Negative concave features have a downward shape. Pixels with positive concave features are removed raising the median emissivity. The process is repeated till a small number of blackbody-like pixels are left. These blackbody-like pixels are then used to create band scatter plots which are fitted to estimate the atmospheric parameters.

![Figure 3.11: TUD model with water vapor multiplier of 1.45.](image)

The OLSTER assumption was tested with at-aperture radiance spectra that were simulated with the TUD model in Figure 3.11. The TUD model was created by increasing the MODTRAN water multiplier from 0.75 to 1.45 to see if OLSTER could work on a scene with a high water vapor concentration. The at-aperture radiance spectra were simulated at ground temperatures between 262.95 K and 322.95 K in 1 K increments, for constant emissivities of $\epsilon_G(\lambda_k) = 1, 0.99, 0.98, 0.97, 0.96, 0.95, 0.9$, and 0.8. The median emissivity was assumed to be $\epsilon_M(\lambda_k) = 0.95$, and the fitting of the band scatter plots of the corresponding emissivity spectra were used as the initial ISAC atmospheric parameters. The determined atmospheric parameters were used to correct the simulated at-aperture radiance spectra, which were then converted to brightness temperature. Figure 3.12 shows the brightness temperatures for the corrected blackbody pixels. It can be seen that the average brightness temperatures of a spectrum depends on its $T_G$, however the atmospheric fea-
CHAPTER 3. ATMOSPHERIC COMPENSATION

tures from the correction are nearly identical between the spectra. Figure 3.13 shows the corrected brightness spectra that correspond to constant emissivities of $\epsilon_G(\lambda_k) = 0.9$ to 1 in 0.01 increments at a $T_G$ of 297.87 K. The corrected spectrum for $\epsilon_G(\lambda_k) = 0.95$ is perfectly smooth, the concavity is negative and decreases with increasing emissivity, and the concavity is positive and increasing with decreasing emissivity.

Figure 3.12: Brightness Temperature of atmospheric compensated blackbody pixels using ISAC parameters from $\epsilon_G(\lambda_k) = 0.95$ spectra.

Figure 3.13: Brightness Temperature of atmospheric compensated pixels at varying emissivities using ISAC parameters from $\epsilon_G(\lambda_k) = 0.95$ spectra.

The concavity was measured by finding the peak bands of the initial $\hat{\tau}(\lambda_k)$, and interpolating between the peak bands across the atmospheric features of the corrected brightness temperature. Figure 3.14 shows the interpolation between peaks across the atmospheric features. The total atmospheric concavity is then measured by subtracting the interpolated brightness temperature from the corrected brightness temperature and taking the sum of the difference for all the bands.

The blackbody pixels are found by creating a scatter plot of the total atmospheric concavity versus the ground temperature estimate of each pixel. Such a scatter plot is shown in Figure 3.15 for at-aperture radiance spectra simulated at ground temperatures between 282.87 K and 302.87 K in 1 K increments, for constant emissivities of $\epsilon_G(\lambda_k) = 1$ to 0.9 in 0.01 increments. The blackbody pixels in red have the most negative total atmospheric concavity, and are easily separable from the rest of the pixels for all ground temperatures.
CHAPTER 3. ATMOSPHERIC COMPENSATION

Figure 3.14: Interpolation over atmospheric features in brightness temperature to measure concavity.

Figure 3.15: Total atmospheric concavity of spectra at different emissivities and temperatures.

3.6 Fitting Blackbody Pixels

When the ISAC linear fitting is done for each band, it is important that the fitting is uniform across the entire temperature range of the scene. If a majority of the blackbody pixels are at one condensed temperature range, a simple linear fitting may go through the cloud of points instead of going along the atmospheric linear trend of the entire temperature range. For this reason, it is important to control the fitting across the entire temperature range. The original ISAC method divided the temperature range into bins, where each bin contained a similar number of pixels. The linear trend was removed from each band scatter plot by subtracting a least-squares regression line of all the “most hits”. A cumulative distribution function (CDF) was then created for the pixels in bin. The CDF of the bin was then compared to a modeled CDF to determine which pixels at the top of the distribution were blackbodies and not caused by noise. The maximum difference between the calculated and modeled CDF for each bin were used as weights for weighted least-squares regression of the determined blackbody pixels in all of the bins [25].

We created a uniform sampling of pixels for each temperature, by dividing the pixels in the scene into bins that were 0.25 K wide using their reference band brightness temperatures. The OLSTER method was then used to find the best blackbody pixels in each bin. A maximum of 50 suspected pixels were taken from each bin. An upper bound threshold was used to make sure that bins without any high quality blackbody pixels were not used. The concavity threshold for
CHAPTER 3. ATMOSPHERIC COMPENSATION

Figure 3.16: ISAC transmission estimates with constant $\epsilon_R(\lambda_k)$.

Figure 3.17: ISAC upwelling radiance estimates with constant $\epsilon_R(\lambda_k)$.

OLSTER was 0. An ISAC least-squares regression line was then fitted to each band scatter plot using the blackbody pixels found in all the bins to determine estimates of the transmission and upwelling radiance.

3.7 Spectral Shape Effects on Atmospheric Parameters

ISAC finds the most blackbody-like pixels in a scene. Typically the emissivity spectra of materials within these pixels will deviate from true blackbodies. The band fitting of these non-blackbody pixels will give atmospheric parameter estimates that deviate from the estimates made with true blackbody pixels. We assume that all the pixels used for the band fitting have the same ground reference emissivity $\epsilon_R(\lambda_k)$. Figures 3.16 and 3.17 show the ISAC estimates for $\hat{\tau}(\lambda_K)$ and $\hat{L}_U(\lambda_K)$ found by fitting at-aperture radiance spectra with various constant $\epsilon_R(\lambda_k)$. The at-aperture radiance spectra are the same as the spectra used in Section 3.5. The estimates for true blackbodies are in black, and the estimates for constant emissivities of 0.9 to 0.1 in 0.2 increments are in green, blue and red respectively. As the emissivity decreases, $\hat{\tau}(\lambda_K)$ decreases after $9.25 \mu m$ and $\hat{L}_U(\lambda_K)$ increases. Fitting at-aperture radiance spectra with non-constant emissivity spectra would provide atmospheric estimates with greater deviation from the true blackbody estimates.

A model was created to explain how band fitting of at-aperture radiance spectra with a non-blackbody $\epsilon_R(\lambda_k)$ causes a deviation from the true blackbody estimate. The model was created by using the full at-aperture radiance scatter plot model in Section 3.3. The deviations of $\hat{\tau}(\lambda_K)$
CHAPTER 3. ATMOSPHERIC COMPENSATION

Figure 3.18: Effect of $\Delta y$ on ISAC transmission with constant $\epsilon_R(\lambda_k)$.

Figure 3.19: Effect of $\Delta x$ on ISAC transmission with constant $\epsilon_R(\lambda_k)$.

and $\hat{L}_U(\lambda_K)$ from the true blackbody estimates are described by

$$\hat{\tau}(\lambda_k) = \frac{\hat{\tau}_B(\lambda_k) - \tau_{\Delta y}(\lambda_k)}{1 - \tau_{\Delta x}(\lambda_k)} \quad (3.20a)$$

$$\hat{L}_U(\lambda_k) = \hat{L}_{UB}(\lambda_k) - L_{\Delta y}(\lambda_k) + L_{\Delta x}(\lambda_k)\hat{\tau}(\lambda_k) \quad (3.20b)$$

where $\tau_{\Delta y}(\lambda_k)$ and $L_{\Delta y}(\lambda_k)$ are the slope and intercept of $\Delta y(\lambda_k)$ vs. $B(\lambda_k, \hat{T}_{GB})$, and $\tau_{\Delta x}(\lambda_k)$ and $L_{\Delta x}(\lambda_k)$ are the slope and intercept of $\Delta x(\lambda_k)$ vs. $B(\lambda_k, \hat{T}_{GB})$. Figures 3.18 and 3.19 show $\tau_{\Delta y}(\lambda_k)$ and $\tau_{\Delta x}(\lambda_k)$ respectively, for various $\epsilon_R(\lambda_k)$ and $\epsilon_R(\lambda_R)$. The $\tau_{\Delta y}(\lambda_k)$ in Figure 3.18 which depend on the individual band $\epsilon_R(\lambda_k)$ have atmospheric features which increase with decreasing emissivity. They become increasingly curved with decreasing emissivity causing the drop in $\hat{\tau}(\lambda_K)$ found in Figure 3.16. The $\tau_{\Delta x}(\lambda_k)$ in Figure 3.19 which depends on only $\epsilon_R(\lambda_R)$ are smooth and increases with decreasing emissivity. The $\tau_{\Delta x}(\lambda_k)$ are fairly flat, and close to $1 - \epsilon_R(\lambda_R)$.

Figures 3.20 and 3.21 show $L_{\Delta y}(\lambda_k)$ and $L_{\Delta x}(\lambda_k)$ respectively, for various $\epsilon_R(\lambda_k)$ and $\epsilon_R(\lambda_R)$. Similar to $\tau_{\Delta y}(\lambda_k)$, there are atmospheric features in $L_{\Delta y}(\lambda_k)$, but it becomes increasingly negative with decreasing emissivity. The $L_{\Delta x}(\lambda_k)$ are smooth, become increasingly negative with decreasing emissivity, and have a dip that increases with decreasing emissivity.
Since $\tau_{\Delta y}$ and $L_{\Delta y}$ depend on the individual band $\epsilon_R(\lambda_k)$, they can be expressed as,

\[
\tau_{\Delta y}(\lambda_k) = (1 - \epsilon_R(\lambda_k))\beta(\lambda_k)
\]

\[
L_{\Delta y}(\lambda_k) = -1(1 - \epsilon_R(\lambda_k))L_D(\lambda_k) - \frac{\tau_{\Delta y}(\lambda_k)}{\tau_{\Delta y}(\lambda_R)}C_{\Delta y}(\lambda_R)
\]

\[
C_{\Delta y}(\lambda_R) = \left(1 - \epsilon_R(\lambda_R)\right)\left(\alpha(\lambda_k, \lambda_R)[1 - \tau(\lambda_R)] + \beta(\lambda_k, \lambda_R)L_U(\lambda_R)\right)
\]

\[
L_{\Delta y}(\lambda_k) = -1\left(1 - \epsilon_R(\lambda_k)\right)\left(L_D(\lambda_k) + \beta(\lambda_k)C_T(\lambda_k)\right)
\]

where $\alpha(\lambda_k, \lambda_R)$ and $\beta(\lambda_k, \lambda_R)$ are defined in Eqs. (3.19c) and (3.19d) respectively. Both $\tau_{\Delta x}$ and $L_{\Delta x}$ are functions that depend on the difference between two blackbodies. They can be expressed as

\[
\tau_{\Delta x}(\lambda_k) = 1 - \epsilon_R(\lambda_R)B_{\Delta x}(\lambda_k)
\]

\[
B_{\Delta x}(\lambda_k) = \left[\frac{B(\lambda_R, \hat{T}_R)/B(\lambda_R, \hat{T}_R)}{B(\lambda_k, \hat{T}_R)/B(\lambda_k, \hat{T}_RB)}\right]^{\frac{\epsilon_R(\lambda_k)}{\lambda_R L_R(\lambda_R)}}
\]

\[
L_{\Delta x}(\lambda_k) = -1(B(\lambda_k, \hat{T}_R) - \epsilon_R(\lambda_R)B_{\Delta x}(\lambda_k)B(\lambda_k, \hat{T}_RB))
\]

where $L_{RB}(\lambda_R)$ and $L_R(\lambda_R)$ are at-aperture radiances at $\lambda_R$ at a reference temperature $T_r$ for a perfect blackbody and $\epsilon_R(\lambda_R)$ respectively. $\hat{T}_R$ and $\hat{T}_{RB}$ are their corresponding brightness temperatures. $T_r$ is a temperature within the temperature bounds of the scene.
Using Eq. (3.21a), Eq. (3.20a) can be expressed as

\[
\hat{\tau}(\lambda_k) = \frac{\epsilon_R(\lambda_k)}{\epsilon_R(\lambda_R)B_{\Delta x}(\lambda_k)} \hat{\tau}_B(\lambda_k)
\]

(3.23)

The blackbody like pixels used for the band fitting will have high \(\epsilon_G(\lambda_R)\). This means that \(B_{\Delta x}(\lambda_k)\) will be close to 1 and that \(\hat{\tau}(\lambda_k)\) and \(\tau_B(\lambda_k)\) will be related by

\[
\hat{\tau}(\lambda_k) \approx \frac{\epsilon_R(\lambda_k)}{\epsilon_R(\lambda_R)} \hat{\tau}_B(\lambda_k)
\]

(3.24)

where the shape of the transmission estimate is affected by the ratio of \(\epsilon_R(\lambda_k)\) relative to \(\epsilon_R(\lambda_R)\).

### 3.8 Determining Atmospheric Models

The atmospheric parameters determined by ISAC are relative to the data and will differ from the truth. Figure 3.16 shows ISAC transmission estimates of the true transmission shown in Figure 3.11. The ISAC reference band at 9.25 \(\mu\)m always has a transmission of 1 and an upwelling radiance of 0. In addition, the ISAC transmission and upwelling radiances will be higher and lower than their respective truths. An atmospheric model needs to be found that provides parameters that are closer in magnitude and shape to the truth. This model is found by comparing the ISAC parameters and blackbody pixels to a look-up-table (LUT) of atmospheric models. When the correct model is found it can be used directly on the data, or used to scale the ISAC parameters.

Several methods were tested to determine an accurate atmospheric model. When comparing data to models it is important that the downsampling of the models accurately match the data. The methods will be tested under ideal conditions where the downsampling of the models perfectly match the SRF. At-aperture radiance spectra were simulated using the atmospheric parameters in Figure 2.5 at temperatures between 287.94 K to 297.94 K in 1 K increments, using constant emissivity spectra of 1 to 0.95 in 0.01 increments and 0.95 to 0.8 in 0.05 increments. A set of models with water multiplier factors from 0.1 to 2 in 0.025 increments were then used to determine the correct multiplier of 0.75.

#### 3.8.1 ARTEMISS

ARTEMISS finds the atmospheric model that has the closest angular match with the ISAC transmission [7]. The ISAC transmission was determined for each set of constant emissivity at-aperture radiance spectra. These ISAC transmissions were then compared to the transmissions
of each of the atmospheric models with varying water multipliers. The atmospheric model that provides the smallest angle is then chosen. Figure 3.22 shows the multiplier error of the atmospheric model with the smallest angle in blue. The correct model is found down to a constant emissivity of 0.97 and the multiplier error increases as the emissivity of the ISAC pixels decrease.

![Figure 3.22: Water multiplier error for different model searching algorithms used on varying constant $\epsilon_G(\lambda_k)$ spectra.](image)

3.8.2 Autonomous Atmospheric Compensation (AAC)

AAC uses the assumption that the difference in radiance between close bands of black-body pixels is mainly caused by atmospheric features. The bands used by this method typically consist of a band on the edge of a sharp atmospheric feature and a band in the trough of the feature. The water feature between 11.62 and 11.84 $\mu$m is used with the edge band $\lambda_E$ being at 11.62 $\mu$m and the trough band $\lambda_T$ being at 11.73 $\mu$m. It is assumed that their is a linear relationship between the at-aperture radiance of these two bands, and that an atmospheric model can be found that shares the same relationship.

The linear relationship between the two feature bands is found by taking the ratio of the at-aperture radiance at two wavelengths and moving all terms to the right except $L_S(\lambda_E)$, where.

$$L_S(\lambda_E) = \frac{L_G(\lambda_E)}{L_G(\lambda_T)} \frac{\tau(\lambda_E)}{\tau(\lambda_T)} L_S(\lambda_T) + L_U(\lambda_E) - \frac{L_G(\lambda_E)}{L_G(\lambda_T)} \frac{\tau(\lambda_E)}{\tau(\lambda_T)} L_U(\lambda_T) \quad (3.25)$$

and by assuming that the ground radiance of the two feature bands $L_G(\lambda_E)$ and $L_G(\lambda_T)$ are equal,
the relationship is simplified to

\[ L_S(\lambda_E) = \frac{\tau(\lambda_E)}{\tau(\lambda_T)} L_S(\lambda_T) + L_U(\lambda_E) - \frac{\tau(\lambda_E)}{\tau(\lambda_T)} L_U(\lambda_T) \]  

(3.26)

In matrix notation the relationship between \( L_S(\lambda_E) \) and \( L_S(\lambda_T) \) is

\[ L_S(\lambda_E) = T_i \cdot L_S(\lambda_T) + P_d \]  

(3.27a)

\[ T_i = \frac{\tau(\lambda_E)}{\tau(\lambda_T)} \]  

(3.27b)

\[ P_d = L_U(\lambda_E) - T_i L_U(\lambda_T) \]  

(3.27c)

Using a method similar to ISAC, a scatter plot of the two band radiances for several pixels at varying temperatures is created, and a line is fitted to the points to determine \( T_i \) and \( P_d \). An atmospheric model is then found that shares similar \( T_i \) and \( P_d \). The AAC fitting was done for the at-aperture radiance spectra at each constant emissivity. Figure 3.22 shows the water multiplier error of the atmospheric model with the closest \( T_i \) in red and the closest \( P_d \) in green. The closest \( T_i \) model remains constant as the emissivity decreases where \( P_d \) increases. The black line shows multiplier error of the atmospheric model that provides the fitting with the minimum SSE to the scatter plots. There is a sharp dip at an emissivity of 0.96.

The assumption that the blackbody radiances of the two feature bands is constant provides a bias error that causes the water multiplier error of the atmospheric model. The determined \( T_i \) was 1.1245 however the \( T_i \) for the true model was 1.111. A correction factor for this bias can be found by finding the slope of \( B(\lambda_E, T_G)/B(\lambda_T, T_G) \). The slope for the water feature between 11.62 and 11.84 µm was 1.0121. Dividing the determined \( T_i \) by the correction factor provided the true \( T_i \).

### 3.8.3 Water Feature Atmospheric Compensation

Water feature atmospheric compensation finds the atmospheric model that best compensates the water absorption feature between 11.62 and 11.84 µm. Atmospheric compensation is done on the absorption feature and converted to brightness temperature. The model that provides the brightness temperature with the smallest standard deviation is chosen. Figure 3.23 shows the water multiplier errors of the atmospheric models that provide the smoothest brightness temperatures for each at-aperture radiance spectrum at a constant emissivity and specific temperature. The results for the perfect blackbody spectra are in green, and have the smallest multiplier error. There is a slight increase in error at the apparent atmospheric temperature of 292.94 K due to the lack of absorption features in the at-aperture radiance spectrum. As the emissivity decreases the multiplier error
CHAPTER 3. ATMOSPHERIC COMPENSATION

increases. The model multiplier error is heavily dependent on the emissivity and the ground temperature relative to the atmospheric temperature. There is a positive multiplier error when the ground temperature is less than the apparent atmospheric temperature and a negative multiplier error when it is higher.

![](image)

Figure 3.23: Water multiplier error for water feature atmospheric compensation algorithm at varying temperatures and varying constant $\epsilon_G(\lambda_k)$ spectra.

3.8.4 LUT Challenges

There are several challenges that come with using an atmospheric model directly from a LUT. It is assumed that the true atmospheric model is present in the LUT. The atmospheric models need to be downsampled to the current SRF of the sensor. If the true model is not present in the LUT, the closest model can differ in several ways. The model closest in overall shape to the ISAC parameter may be of an incorrect magnitude. A model that matches the $T_r$ of the water features in blackbody spectra may not match the atmospheric parameters outside the feature. In addition, if a collect is taken at a low altitude, even if the model transmission and upwelling radiance match the true atmosphere, the model downwelling radiance might not match the truth. Due to the high dimensional space of possible atmospheres in a scene and the high accuracy required for AC and TES to function, it is difficult to find a model that works. LUT are typically large in size to increase the likelihood that the true model is present.
CHAPTER 3. ATOMICHE COMPENSATION

3.9 Scaling ISAC Parameters

Before the ISAC parameters can be used for atmospheric compensation they need to be scaled using the closest atmospheric model. The scaling procedure we use is discussed in [25], and it was shown in Section 3.3.1 how the ISAC parameters found with perfect blackbodies can be scaled to the truth. The ISAC parameters found using any high emissivity ground reference material can be scaled using any atmospheric model. The scaled ISAC transmission is determined using

\[ \hat{\tau}_S(\lambda_k) = \frac{\tau_M(\lambda_R)}{\hat{\tau}(\lambda_R)} \hat{\tau}(\lambda_k) \]  

(3.28)

where \( \tau_M(\lambda_R) \) is the atmospheric transmission of a model at \( \lambda_R \). The scaled ISAC upwelling radiance is determined using

\[ \hat{L}_{US}(\lambda_k) = \hat{L}_U(\lambda_k) + \frac{\hat{\tau}(\lambda_k)}{\hat{\tau}(\lambda_R)} C_S(\lambda_k) \]  

(3.29a)

\[ C_S(\lambda_k) = \alpha(\lambda_k, \lambda_R)[\hat{\tau}(\lambda_R) - \tau_M(\lambda_R)] - \beta(\lambda_k, \lambda_R)[\hat{L}_U(\lambda_R) - L_{UM}(\lambda_R)] \]  

(3.29b)

where \( L_{UM}(\lambda_R) \) is the upwelling radiance of a model at \( \lambda_R \), and \( \alpha(\lambda_k, \lambda_R) \) and \( \beta(\lambda_k, \lambda_R) \) are defined in Eqs. (3.19c) and (3.19d) respectively.

Figures 3.24 and 3.25 show the scaled ISAC parameters using a blackbody and grass as \( \epsilon_R(\lambda_k) \). The parameters shown are unscaled and scaled with the 0.75 and 1 water multiplier models. The spectrum for grass is shown in Figure 3.26. The shape deviation between the red and blue ISAC parameters is caused by the deviation of grass from being a perfect blackbody. As the water multiplier increases, the transmission is scaled down and the upwelling radiance increases. Figure 3.27 shows how the \( \tau_M(\lambda_R) \) and \( L_{UM}(\lambda_R) \) used for scaling change with the water multiplier of the model.

3.10 Atmospheric Compensation with Scaled ISAC Parameters

There will always be discrepancies between the ISAC parameters and the true atmospheric model. The main discrepancy of the ISAC parameters is the change in shape caused by \( \epsilon_R(\lambda_k) \) and how this causes deviation from the shape of the true model. The atmospheric model LUT has a limited number of possible atmospheres, and may not contain an exact match to the scene. When an atmospheric model is used for atmospheric compensation the main discrepancies are the amount of deviation between the true model and its closest match in the LUT, and how closely it matches the ISAC parameters so it can be found. Additional error is caused by calibration mismatch of the sensor.
and the atmospheric models in the LUT. Due to the extensive number of possible atmospheres, it is possible that the mismatch between the closest atmospheric model and the truth exceeds that of the ISAC parameters. When atmospheric compensation is done with the ISAC parameters, the ISAC parameters are only scaled using \( \tau_M(\lambda_R) \) and \( L_{UM}(\lambda_R) \) and maintain their shape. The effects of choosing the correct atmospheric model for scaling on atmospheric compensation will be studied to determine how much of an effect it has on the estimated ground radiance.

The ISAC parameter model for any emissivity material was discussed in Section \ref{sec:isac}. The estimated ground radiance after atmospheric compensation with the scaled ISAC parameters can be
CHAPTER 3. ATMOSPHERIC COMPENSATION

described with the ISAC model as

\[
\hat{L}_G(\lambda_k) = \left[ L_{AC}^G(\lambda_k) \tau(\lambda_R) + C_E(\lambda_k) \right] \frac{\epsilon_R(\lambda_R) B_{\Delta x}(\lambda_R)}{\tau_R(\lambda_R)} + \frac{L_{\Delta y}(\lambda_k)}{\tau_S(\lambda_k)} - L_{\Delta x}(\lambda_k) \tag{3.30a}
\]

\[
L_{AC}^G(\lambda_k) = \epsilon_G(\lambda_k) B(\lambda_k, T_G) + (1 - \epsilon_G(\lambda_k)) \frac{L_{DR}(\lambda_k)}{\tau(\lambda_k)} \tag{3.30b}
\]

\[
C_E(\lambda_k) = \alpha(\lambda_k, \lambda_R)[\tau_M(\lambda_R) - \tau(\lambda_R)] - \beta(\lambda_k, \lambda_R)[L_{UM}(\lambda_R) - L_U(\lambda_R)] \tag{3.30c}
\]

where \(L_{AC}^G(\lambda_k)\) is the atmospheric compensated ground radiance using the true atmospheric parameters, and \(C_E(\lambda_k)\) is the residual \(C\) needed to get \(L_{US}(\lambda_k)\) to \(L_U(\lambda_k)\). The estimated ground radiance consists of \(L_{AC}^G(\lambda_k)\) whose shape is affected by \(\epsilon_R(\lambda_k)\), and a constant additional radiance that consists of the other three terms. Figure 3.28 shows how \(C_E(\lambda_k)\) changes for different water multipliers.

![Figure 3.28: \(C_E(\lambda_k)\) for different water multiplier models.](image)

Atmospheric compensation using ISAC parameters with varying \(\epsilon_R(\lambda_k)\) and scaling multipliers were tested on at-aperture radiance spectra simulated with constant \(\epsilon_G(\lambda_k)\) of 1, 0.8, and 0 with ground temperatures of 282.94 K to 302.94 K in 5 K increments. Figure 3.29 shows the \(\hat{L}_G(\lambda_k)\) using parameters found with an \(\epsilon_R(\lambda_k)\) of 1 that are unscaled and scaled with the 0.75 and 1 water multiplier models. The model with a water multiplier of 0.75 was the true model. The true ground radiance is also shown in black as a reference. The estimated ground radiances for blackbodies appear to all look like blackbodies despite the scaling used. The scaling causes a shifting of the spectra, which is caused by the \(C_E(\lambda_k)/\tau_M(\lambda_R)\) term. The other two additive terms are 0 because \(\epsilon_R(\lambda_k) = 1\). The \(\hat{L}_G(\lambda_k)\) using the true model with a water multiplier of 0.75 is identical to \(L_{G}(\lambda_k)\) because there is no reflected component to cause a band-averaging error. As \(\epsilon_G(\lambda_k)\) decreases, there
Figure 3.29: Estimated ground radiances of ground spectra with varying emissivities using black-body ISAC parameters with different scalings.

is a larger discrepancy between \( L_G(\lambda_k) \) and the true \( \hat{L}_G(\lambda_k) \) due to the increased reflected component and band-averaging error. The shift between the different scaled \( \hat{L}_G(\lambda_k) \) remains constant. The \( \hat{L}_G(\lambda_k) \) for the at-aperture radiance spectra with a \( \epsilon_G(\lambda_k) = 0 \) can be thought as the reflected downwelling radiances for atmospheric parameters with the corresponding scaling, \( \hat{L}_D(\lambda_k) \). As \( \hat{L}_{US}(\lambda_k) \) increases with increasing water multiplier, the corresponding \( \hat{L}_D(\lambda_k) \) decreases.

Figure 3.30: Estimated ground radiances of ground spectra with varying emissivities using grass ISAC parameters with different scalings.

Figure 3.30 shows the \( \hat{L}_G(\lambda_k) \) using parameters found with the grass spectrum as \( \epsilon_R(\lambda_k) \) that are unscaled and scaled with the 0.75 and 1 water multiplier models. The atmospheric com-
CHAPTER 3. ATMOSPHERIC COMPENSATION

penetration will make at-aperture radiance spectra with grass appear to be blackbodies. At-aperture radiance spectra with blackbodies will be over compensated, and there will be slight shape effects in the corrected spectra, as seen in the spectra with $\epsilon_G(\lambda_k) = 1$. The scaling causes additional shifting from $C_E(\lambda_k)$ and the other two terms are no longer zero because $\epsilon_R(\lambda_k) \neq 1$.

Errors in the scaling parameters cause a shifting determined by the sum of the three additive parameters to the true atmospheric compensated ground radiance $L_{GAC}(\lambda_k)$. These parameters have little effect on the overall shape of the ground radiance spectra. The effects of using these corrected ground radiances on the emissivities found with TES will be studied in Chapter 6.

3.11 Summary

We presented the basis of ISAC algorithms and how they utilize in-scene blackbody-like pixels to estimate the atmospheric transmission and upwelling radiance. The major difference between ISAC algorithms is how they attempt to determine the most blackbody-like pixels in the scene. We tested several algorithms, and found that the only method that was capable of finding the most blackbody-like pixels in a scene when the atmosphere contained a large amount of water vapor was OLSTER.

A numerical model was developed to explain the errors that occur in the ISAC atmospheric estimates from the assumptions that perfect blackbody pixels are used for the linear fitting and that the reference channel is perfectly clear. Using a case with perfect blackbodies as a reference, where the atmospheric estimates $\hat{\tau}_B(\lambda_k)$ and $\hat{L}_{UB}(\lambda_k)$ are directly related to the truth, a scatter plot model was developed to explain how decreases in $\epsilon_G(\lambda_k)$ caused deviations from the reference. Unlike previous models the scatter plot model included effects from the downwelling radiance.

Using the assumption that all the blackbody-like pixels shared the same emissivity $\epsilon_R(\lambda_k)$, the scatter plot model was used to develop a numerical model that explained how changes in $\epsilon_R(\lambda_k)$ affected the final atmospheric estimates relative to $\hat{\tau}_B(\lambda_k)$ and $\hat{L}_{UB}(\lambda_k)$. The model explains how the shape of $\epsilon_R(\lambda_k)$ affected the atmospheric estimates. It was also explained how the assumption of a perfectly clear channel introduces a scaling error into the atmospheric estimates, that needs to be corrected. Methods were discussed that determined a reference model to apply the scaling. Lastly, the developed model was used to understand how the ISAC errors from fitting with a non-blackbody $\epsilon_R(\lambda_k)$ and scaling errors were transferred to ground radiance estimates. Shape errors in the atmospheric estimates from $\epsilon_R(\lambda_k)$ affected the shape, where scaling errors provided slight shifts in the estimates.
Chapter 4

Temperature Emissivity Separation

Separation of emissivity and temperature from TIR measurements is not a trivial task. Since the surface is characterized by its temperature and by one emissivity for each spectral band, we have one more unknown than measurements. Therefore, inversion methods have to make assumptions to bypass this difficulty. Existing TES algorithms for hyperspectral imaging data are based on the well known observation that most solid materials exhibit smoothly varying spectral emissivity compared to the spectral atmospheric transmission features (smoothness assumption). Two algorithms based on this assumption are the Automatic Retrieval of Temperature and Emissivity using Spectral Smoothness (ARTEMISS) method [8] and the Linear Emissivity Constraint (LEC) TES algorithm [22].

The purpose of this chapter is to evaluate the sensitivity of these TES algorithms to (a) violations of the smoothness assumption, (b) errors in the estimation of ground temperature, (c) sensor noise, (d) sensor altitude, and (e) sensor calibration. The sensitivity to atmospheric parameter estimation is important, but they are not considered in this chapter. Thus, in this work we assume perfect knowledge of atmospheric transmission, upwelling radiance, and downwelling radiance. To have perfect knowledge of all parameters and spectra required for this study we use synthetic data generated by a forward at-aperture radiance signal model. Furthermore, we have developed an error model which we use to explain the results obtained by Monte-Carlo simulations. The model and results were published in [19]. Although, these results were obtained by ignoring these practical limitations, the conclusions are very useful because provide upper-bounds on the performance of the evaluated TES algorithms.

The analysis and model presented in this chapter complement and extend similar work by other authors. Ingram and Muse [13] were the first to provide a sensitivity analysis of ARTEMISS
TES algorithm to deviations from the smoothness assumption and sensor noise using the ASTER library \cite{4} and a white Gaussian sensor noise model. Borel \cite{7} investigated the sensitivity of the TES algorithm to atmosphere and sensor changes using synthetic data as part of the entire ARTEMIS process. Wang et al. \cite{22} discuss the accuracy and sensitivity of their method, to errors introduced by the algorithm assumption, instrument noise, and uncertainties of atmospheric downwelling radiance. An empirical evaluation of TES algorithms with real data has been reported by \cite{2}.

The chapter is organized as follows. An in-depth description of TES techniques is given in Section 4.1 with the smoothing techniques used in Section 4.2. The performance model of the TES algorithms is explained in Section 4.3. Sections 4.4 present the TES results, and Section 4.5 gives an explanation of the results using the performance model. Section 4.6 adds calibration mismatch to the performance model and provides simulation results. Finally, a summary is given in Section 4.7. At the end of the chapter in Table 4.1 is a list of the key variables, and the equations numbers in which they are defined.

### 4.1 Temperature-Emissivity Separation (TES) Procedure

TES algorithms solve the underdetermined problem of estimating the emissivity spectrum and ground temperature from the at-aperture radiance, and use the assumption that the thermal infrared spectra of the solids being searched for tend to be smooth. The spectral features of solids are wide compared to the sharp features of the atmospheric gases which need to be removed. With the assumption that the emissivity spectrum for a solid material should be smooth, TES finds the \( \hat{T}_G \) where \( \hat{\epsilon}_G(\lambda_k) \) is smoothest, and the residual atmospheric spectral features are minimized. In order for the atmospheric features to be completely removed, accurate estimates of \( \tau(\lambda_k) \), \( L_U(\lambda_k) \), and \( L_{D\tau}(\lambda_k) \) are required, along with accurate sensor calibration \cite{7}.

Given an estimate of the ground temperature, we can calculate a ground emissivity estimate \( \hat{\epsilon}_G(\lambda_k) \) as

\[
\hat{\epsilon}_G(\lambda_k) = \frac{L_S(\lambda_k) - L_U(\lambda_k) - L_{D\tau}(\lambda_k)}{W(\lambda_k, \hat{T}_G)}
\]  
(4.1)

where the factor to convert from radiance to emissivity is

\[
W(\lambda_k, \hat{T}_G) = B(\lambda_k, \hat{T}_G) \tau(\lambda_k) - L_{D\tau}(\lambda_k)
\]  
(4.2)
and is used extensively throughout the paper. To reduce the computation required for the band-averaging of $B_\tau(\lambda_k, \hat{T}_G)$ in Eq. (2.12) for each $\hat{T}_G$ iteration, it is approximated as $B(\lambda_k, \hat{T}_G)\tau(\lambda_k)$. This approximation only slightly effects the temperature and emissivity estimates [7].

To understand the effects of using an incorrect $\hat{T}_G$ to calculate $\hat{\epsilon}_G(\lambda_k)$, we plot the $\hat{\epsilon}_G(\lambda_k)$ spectra were calculated with a span of $\hat{T}_G$ from 290 K to 300 K in 0.5K increments for the at-aperture radiance spectrum in Figure 2.6, the true $T_G$ is 295 K. The $\hat{\epsilon}_G(\lambda_k)$ spectra calculated for $\hat{T}_G$ equal to 290 K, 295 K, and 300 K are in green, red, and magenta respectively. The red $\hat{\epsilon}_G(\lambda_k)$ spectrum for $\hat{T}_G = T_G$ is smooth, and perfectly matches $\epsilon_G(\lambda_k)$. However, if $\hat{T}_G \neq T_G$, the residual effects of the sharp atmospheric features are present, and grow as the temperature deviation increases [7]. The corresponding weighting factors $W(\lambda_k, \hat{T}_G)$ are shown in Figure 4.2.

Since the true spectrum $\epsilon_G(\lambda_k)$ is not available, we determine the smoothness of $\hat{\epsilon}_G(\lambda_k)$ using a smoothed estimate $\hat{\epsilon}_G^s(\lambda_k)$ in place of $\epsilon_G(\lambda_k)$. This “smoothing” root mean square error (SRMSE) is defined by

$$E_G(T_G) = \sqrt{\frac{1}{k_2 - k_1 + 1} \sum_{k=k_1}^{k_2} \left[ \epsilon_G(\lambda_k) - \hat{\epsilon}_G^s(\lambda_k) \right]^2}$$

where $\hat{\epsilon}_G(\lambda_k)$ is a smoothed emissivity estimate using a specific smoothing algorithm, and $k_1$ and $k_2$ are the limits of the wavelengths of interest.
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

Figure 4.3: SRMSE for $\hat{\epsilon}_G(\lambda_k)$ at various temperature errors.

$k_2$ are the range of spectral bands. The goal is to find the $\hat{T}_G$ which provides the minimum SRMSE

$$\min_{T_G} E_\epsilon(T_G)$$

and use the corresponding smoothest $\hat{\epsilon}_G(\lambda_k)$ for detection and identification. While $\hat{T}_G$ is a key component for climatology, its only importance for target detection is its accuracy directly determines the accuracy of $\hat{\epsilon}_G(\lambda_k)$.

TES algorithms differ by the type of smoothing algorithm that is applied to $\hat{\epsilon}_G(\lambda_k)$ and the form of SRMSE that is being minimized, both are discussed in Sections 4.2 and 4.1.2 respectively. The $\hat{T}_G$ that provides the minimum SRMSE is found using any numerical optimization technique with a single variable, such as golden section or gradient decent. Figure 4.3 shows the smoothing error versus temperature error for the $\hat{\epsilon}_G(\lambda_k)$ spectra in Figure 4.1. The minimum was found using the Matlab function “fminsearch”, which uses unconstrained nonlinear optimizations starting at an initial $\hat{T}_G$. The SRMSE as a function of temperature was studied, and it was determined that there is a single well-defined minimum for ground temperature within realistic bounds. To speed up the optimization, we select the initial $\hat{T}_G$ very carefully.

### 4.1.1 Ground Temperature Estimate Initialization

The TES algorithm requires an initial value for $\hat{T}_G$. To increase the accuracy of the initial estimate, the at-aperture radiance is converted to ground radiance with Eq. (2.11). The initial $\hat{T}_G$ is then determined by finding the maximum band brightness temperature in $\hat{L}_G(\lambda_k)$ using Eq. (2.7). Figure 4.4 shows four ground radiance spectra all at 295 K. These spectra from top to bottom have
**Figure 4.4:** Measuring the height of the reflected $L_D(\lambda_k)$ features in $L_G(\lambda_k)$ spectra with various constant emissivity spectra.

constant emissivity spectra of 1, 0.9, 0.7, and 0 respectively. The top spectrum is a perfect blackbody, and the bottom spectrum is a perfect reflector of $L_D(\lambda_k)$. As $\epsilon_G(\lambda_k)$ decreases, $L_G(\lambda_k)$ approaches $L_D(\lambda_k)$. The blackbody at the top has a constant brightness temperature of 295 K, and as the $\epsilon_G(\lambda_k)$ decreases, the brightness temperature will decrease to the brightness temperature of $L_D(\lambda_k)$. Finding the band in $L_G(\lambda_k)$ with the maximum brightness temperature $\lambda_B$, will occur when $\epsilon_G(\lambda_B)$ is the highest emissivity and closest to being blackbody. This maximum brightness temperature is the closest to $T_G$. When calculating $\hat{\epsilon}_G(\lambda_k)$ with the maximum brightness temperature, $\hat{\epsilon}_G(\lambda_B)$ will equal 1, with the others $0 \leq \epsilon(\lambda_k) \leq 1$. The maximum brightness temperature provides a lower bound of $\hat{T}_G$. A $\hat{T}_G$ less than the maximum brightness temperature would provide unrealistic emissivities with $\hat{\epsilon}_G(\lambda_B) > 1$.

TES will find the $\hat{T}_G$ with the minimum smoothing error more quickly with a better initial $\hat{T}_G$. As the maximum emissivity of a pixel decreases and is further from being a blackbody, the initial $\hat{T}_G$ based on the maximum band brightness temperature decreases in accuracy. We observed that the ground radiance spectra in Figure 4.4 decrease as the emissivity decreases, therefore the maximum brightness temperature will also decrease, providing more inaccurate temperature estimates. As the emissivity of a pixel decreases, the sharp reflected gas features become more visible. The heights of these reflected features are dependent on the heights of the corresponding features in the downwelling radiance and the reflectance $[1 - \epsilon_G(\lambda_k)]$ across the features, as shown in Eq. (2.10). The ground temperature affects the base radiance of the reflected feature, but not the height of the feature. 


CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

Since the emissivity is directly related to the height of reflected downwelling features, a large feature can be used to estimate the emissivity at the feature band. This can be done using a method similar to the Continuum Interpolated Band Ratio (CIBR) method [9]. The height of the large water feature between 12.2-12.7 $\mu$m is measured for both the ground and downwelling radiance spectra in Figure 4.4. The height of the feature is measured from the feature’s peak to a line that is linearly interpolated across the base of the feature. The emissivity at a feature band can be estimated by comparing the height of a reflected feature in the ground radiance, $H_G$, to a reference height of the same feature from an accurate estimate of the downwelling radiance $H_D$ [18]. Knowing that the height of the reference occurs at an emissivity of 1, the ratio of the two heights can be used to estimate the emissivity at the feature band $\lambda_f$ using

$$\hat{\epsilon}_G(\lambda_f) = 1 - \frac{H_G}{H_D} \tag{4.5}$$

Intuitively, if $H_G = H_D$ then $\hat{\epsilon}_G(\lambda_f) = 0$, and if $H_G = 0$ then $\hat{\epsilon}_G(\lambda_f) = 1$. The estimated emissivity is then used to estimate the ground temperature.

$$\hat{T}_G = B^{-1}\left(\lambda_f; \frac{\hat{L}_G(\lambda_f) - [1 - \hat{\epsilon}_G(\lambda_f)]L_D(\lambda_f)}{\hat{\epsilon}_G(\lambda_f)}\right) \tag{4.6}$$

where $B(\lambda_f, T_G)$ is solved for and its brightness temperature is determined.

### 4.1.2 Radiance and Emissivity Domain Error Calculations

To measure the smoothness of $\hat{\epsilon}_G(\lambda_k)$ for a temperature estimate $\hat{T}_G$, we compare it to a smoothed estimate $\hat{\epsilon}_G^s(\lambda_k)$ in place of $\epsilon_G(\lambda_k)$, the difference between the two is defined as

$$\tilde{\epsilon}_G(\lambda_k) = \hat{\epsilon}_G(\lambda_k) - \hat{\epsilon}_G^s(\lambda_k) \tag{4.7}$$

where $\tilde{\epsilon}_G(\lambda_k)$ is the smoothing error in the emissivity domain [7].

The smoothing error can also be found in the radiance domain, where the smoothed at-aperture radiance $\hat{L}_S^s(\lambda_k)$ is calculated using $\hat{\epsilon}_G^s(\lambda_k)$ as follows

$$\hat{L}_S^s(\lambda_k) = \hat{\epsilon}_G^s(\lambda_k)B(\lambda_k, \hat{T}_G)\tau(\lambda_k) + [1 - \hat{\epsilon}_G^s(\lambda_k)]L_D(\lambda_k) + L_U(\lambda_k) \tag{4.8}$$

this smoothed at-aperture radiance is then compared to the at-aperture radiance

$$\hat{L}_S(\lambda_k) = L_S(\lambda_k) - \hat{L}_S^s(\lambda_k) \tag{4.9}$$
where $\tilde{L}_S(\lambda_k)$ is the error in the radiance domain \[7\]. It can be shown that the error in the emissivity and radiance domain are related by

$$\tilde{L}_S(\lambda_k) = \tilde{\epsilon}_G(\lambda_k)W(\lambda_k, \hat{T}_G) \quad (4.10)$$

The “smoothing” root mean square error (SRMSE) is defined in the emissivity domain as

$$E_\epsilon(T_G) = \sqrt{\frac{1}{k_2 - k_1 + 1} \sum_{k=k_1}^{k_2} \tilde{\epsilon}_G(\lambda_k)^2} \quad (4.11)$$

and in the radiance domain as

$$E_L(T_G) = \sqrt{\frac{1}{k_2 - k_1 + 1} \sum_{k=k_1}^{k_2} \tilde{L}_S(\lambda_k)^2} \quad (4.12)$$

The range of spectral bands used to calculate the total error is specified by $k_1$ and $k_2$ \[7\]. The TES temperature error of $\hat{T}_G$ is defined as

$$\tilde{T}_G = \hat{T}_G - T_G \quad (4.13)$$

### 4.2 Smoothing Techniques

The type of TES algorithm is determined by the smoothing technique it uses. The quality of the smoothing technique and the TES results are determined by how well they capture the true emissivity spectrum $\epsilon_G(\lambda_k)$ and smooth the sharp reflected atmospheric features. We next discuss the two most popular smoothing techniques.

#### 4.2.1 Boxcar Averaging

The simplest smoothing technique used by ARTEMISS \[7\] is a boxcar moving average low-pass filter defined as

$$\tilde{\epsilon}_s^G(\lambda_k) = \frac{1}{2M + 1} \sum_{m=-M}^{M} \tilde{\epsilon}_G(\lambda_k-m) \quad (4.14)$$

where $\tilde{\epsilon}_s^G(\lambda_k)$ is the smoothed emissivity spectrum, and the boxcar width is $J = 2M + 1$. The smoothing is done on each of the bands, and shows the greatest effect at the bands where the peaks of atmospheric features occur, and $\tilde{\epsilon}_G(\lambda_k)$ is least smooth.

Figure 4.5 shows two estimated emissivity spectra from the ground radiance spectrum in Figure 2.6. The red spectrum is the emissivity estimate where $\hat{T}_G = T_G = 295$ K, so that
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

Figure 4.5: $\hat{\epsilon}_G(\lambda_k)$ spectra for $\hat{T}_G = T_G = 295$ K and $\hat{T}_G = 294$ K and their corresponding boxcar averaging smoothing errors.

$\hat{\epsilon}_G(\lambda_k) = \epsilon_G(\lambda_k)$. The blue spectrum is the emissivity estimate where $\hat{T}_G = 294$ K, the reflected atmospheric features are clearly visible above 11 $\mu$m. A 3-band boxcar average was used to smooth both of the estimated spectra, but the difference between $\hat{\epsilon}_G(\lambda_k)$ and $\hat{\epsilon}_G^s(\lambda_k)$ is not easily visible. The errors between $\hat{\epsilon}_G$ and $\hat{\epsilon}_G^s(\lambda_k)$ for the two estimates are plotted in colors corresponding to their $\hat{\epsilon}_G(\lambda_k)$. Similar to Figure 4.3 it is clear that the error increases when $\hat{T}_G \neq T_G$, and that the largest errors occur at the locations of the reflected atmospheric features.

4.2.1.1 Linear Emissivity Constraint (LEC)

Linear spectral emissivity constraint is a piece-wise linear approximation of the emissivity spectrum, described in [22]. The $K$ hyperspectral bands are split into $M$ segments of width $J$, where $m$ is the segment index. The entire emissivity spectrum, can then be fitted by a series of $M$ lines as shown in Figure 4.6. Representing each segment of the smoothed emissivity spectrum as a linear equation

$$\epsilon_G^s(\lambda_k) = a_m \lambda_k + b_m, \quad m = 1, \ldots, M \quad (4.15)$$

where $a_m$ and $b_m$ are the sets of linear coefficients for each of the $M$ segments, and the $k$s are the bands within each segment $m$. The size of the segments, $J$, need to be at least 3-bands or greater for effective smoothing. Since the segments are non-overlapping, their placement relative to atmospheric feature peaks is important. If a segment is on the edge of a feature, the feature will not be smoothed out, as shown in Figure 4.7. The blue segment that crosses the peak will smooth out...
the feature and produce a higher error. However, the green segments are fitted to the edges of the feature, producing a small error.

\[ \lambda (\mu m) \]
\[ \begin{array}{c}
9.2 \\
9.4 \\
9.6 \\
9.8 \\
\end{array} \]

\[ \begin{array}{c}
0.63 \\
0.64 \\
0.65 \\
0.66 \\
\end{array} \]

\[ \hat{\epsilon}_G(\lambda_k) \]
LEC

\[ \lambda (\mu m) \]
\[ \begin{array}{c}
12.2 \\
12.4 \\
12.6 \\
12.8 \\
\end{array} \]

\[ \begin{array}{c}
0.91 \\
0.92 \\
0.93 \\
0.94 \\
0.95 \\
\end{array} \]

\[ \hat{\epsilon}_G(\lambda_k) \]
LEC Across
LEC Edge

Figure 4.6: Piece-wise linear approximation of \( \epsilon_G(\lambda_k) \) using LEC.

Figure 4.7: Various placements of LEC segments over atmospheric water feature to show how segment placement can affect smoothing error.

The best linear coefficients \( a_m \) and \( b_m \) for each of the \( M \) segments are found by solving the linear regression equation for each segment

\[ A_m^T C_m \approx \hat{\epsilon}_G^{(m)}, \quad m = 1, \ldots, M \]  (4.16)

where

\[ C_m = \begin{bmatrix} a_m & b_m \end{bmatrix}^T \]  (4.17a)

\[ A_m^T = \begin{bmatrix} \lambda_1^{(m)} & \lambda_2^{(m)} & \ldots & \lambda_J^{(m)} \\
1 & 1 & \ldots & 1 \end{bmatrix} \]  (4.17b)

\[ \hat{\epsilon}_G^{(m)} = \begin{bmatrix} \hat{\epsilon}_G(\lambda_1)^{(m)} & \hat{\epsilon}_G(\lambda_2)^{(m)} & \ldots & \hat{\epsilon}_G(\lambda_J)^{(m)} \end{bmatrix}^T \]  (4.17c)

and \( m \) specifies the segment number with corresponding \( \lambda_j \) and \( \hat{\epsilon}_G(\lambda_j) \).

The linear regression coefficients can then be determined by using a set of least squares equations on each segment

\[ C_m = (A_m^T A_m)^{-1} A_m^T \hat{\epsilon}_G^{(m)} \]  (4.18)

The linear coefficients can then be used to build the smoothed emissivity spectrum, given by

\[ \begin{bmatrix} \hat{\epsilon}_G^{s}(\lambda_1)^{(m)}, \hat{\epsilon}_G^{s}(\lambda_2)^{(m)}, \ldots, \hat{\epsilon}_G^{s}(\lambda_J)^{(m)} \end{bmatrix} = A_m^T C_m, \quad m = 1, \ldots, M \]  (4.19)
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

Figure 4.8: $\hat{\epsilon}_G(\lambda_k)$ spectra for $\hat{T}_G = T_G = 295$ K and $\hat{T}_G = 294$ K and their corresponding LEC smoothing errors.

Figure 4.8 shows the same two estimated emissivity spectra in Figure 4.5. A 3-band LEC was used to smooth both of the estimated spectra, but the difference between $\hat{\epsilon}_G(\lambda_k)$ and $\hat{\epsilon}_s^G(\lambda_k)$ is not easily visible. The errors between $\hat{\epsilon}_G(\lambda_k)$ and $\hat{\epsilon}_s^G(\lambda_k)$ for the two estimates are plotted in colors corresponding to their $\hat{\epsilon}_G(\lambda_k)$. It is clear that the error increases when $\hat{T}_G \neq T_G$, and that the largest errors occur at the bands affected by the reflected atmospheric features. Comparing Figure 4.5 and 4.8 it can be observed that the smoothing error for LEC is smaller with the error features being a lot sharper than the boxcar average. The smoothing error at the large emissivity trough near 9.5 $\mu$m when $\hat{T}_G = T_G$ is visibly reduced with LEC smoothing. This means that the LEC smoothing is able to more accurately capture the shape of $\epsilon_G(\lambda_k)$.

4.3 Performance Model

Ideally the minimum SRMSE should correspond to the case when $\hat{T}_G = T_G$; however, typically this is not the case due to $\epsilon_G(\lambda_k)$ not being perfectly smooth. To understand the causes of this temperature error, we developed a performance model for the TES algorithm. The first part of the performance model includes an emissivity estimate model that explains how $\hat{\epsilon}_G(\lambda_k)$ deviates from $\epsilon_G(\lambda_k)$ with ground temperature estimation errors. Next, a system noise model was developed to show how noise at the at-aperture radiance transfers to the emissivity estimate. Due to the linearity of the emissivity estimate model and the additive noise, the smoothed emissivity
estimate is the sum of the individual smoothed components. The final performance model consists of the errors between the original and smoothed components. The emissivity estimate model, noise model, and three smoothing errors will be discussed in this section. Later in Sections 4.4 and 4.5, simulation results will be presented and explained with the performance model respectively.

4.3.1 Emissivity Estimation Model

The effect of an inaccurate $\hat{T}_G$ on $\hat{\epsilon}_G(\lambda_k)$, can be shown by rewriting Eq. (4.1) as

$$\hat{\epsilon}_G(\lambda_k) \approx \epsilon_G(\lambda_k) + \epsilon_G(\lambda_k)A(\lambda_k)$$  \hspace{1cm} (4.20a)

$$\approx \epsilon_G(\lambda_k) + \epsilon_{\tilde{T}}(\lambda_k)$$  \hspace{1cm} (4.20b)

where

$$A(\lambda_k) = \frac{B(\lambda_k, T_G) - B(\lambda_k, \hat{T}_G)}{W(\lambda_k, \hat{T}_G)}$$  \hspace{1cm} (4.20c)

where $\epsilon_{\tilde{T}}(\lambda_k)$ is the emissivity error induced onto $\epsilon_G(\lambda_k)$ by a ground temperature estimation error. There is an approximation error caused by using the approximation $B_\tau(\lambda_k, T_G) \approx B(\lambda_k, \hat{T}_G)\tau(\lambda_k)$, which was discussed in Section 4.1. This approximation is only significant at extremely small ground temperature errors. Figure 4.9 shows $A(\lambda_k)$, the atmospheric features which are scaled by $\epsilon_G(\lambda_k)$ and transferred to the $\hat{\epsilon}_G(\lambda_k)$ of the corresponding $\hat{T}_G$ estimates in Figure 4.1. The scaling effects by $\epsilon_G(\lambda_k)$ are most noticeable by the smaller size of the ozone feature between 9.4-9.84 $\mu$m.
4.3.2 Effects of Sensor Noise

When the at-aperture radiance is measured by the imaging spectrometer, measurement noise is introduced. We assume additive Gaussian noise, which is independent in each band [13]. The resulting measured at-aperture radiance is defined as

\[ L_M(\lambda_k) = L_S(\lambda_k) + n_M(\lambda_k) \]  

where \( n_M(\lambda_k) \) is the measurement noise. The measured at-aperture noise equivalent spectral radiance, NESR(\( \lambda_k \)) for a Dyson imaging spectrometer was discussed in Section 2.8.

When atmospheric compensation is done on \( L_M(\lambda_k) \) using Eq. (2.11), the resulting noisy ground radiance is defined as

\[ \hat{L}_G^n(\lambda_k) = L_M(\lambda_k) - L_U(\lambda_k) = \hat{L}_G(\lambda_k) + n_G(\lambda_k) \]  

and \( n_G(\lambda_k) \) is the measurement noise at ground level, and is defined as

\[ n_G(\lambda_k) = n_M(\lambda_k)/\tau(\lambda_k) \]  

The bands with lower transmission will have increased noise comparatively, due to their reduced ground signal.

The effect of measurement noise on the ground emissivity estimate is

\[ \hat{\epsilon}_G^n(\lambda_k) = \hat{\epsilon}_G(\lambda_k) + n_\epsilon(\lambda_k) \]

where \( n_\epsilon(\lambda_k) \) is the measurement noise in the ground emissivity domain,

\[ n_\epsilon(\lambda_k) = n_M(\lambda_k)/W(\lambda_k, \hat{T}_G) \]

The measurement noise \( n_M(\lambda_k) \) is divided by the radiance to emissivity conversion factor. Examples of the conversion factor are shown in Figure 4.2. The dips located at the bands of larger atmospheric features mean these bands have less energy and will be comparatively noisier. In addition, the noise level is directly dependent on \( \hat{T}_G \) in \( W(\lambda_k, \hat{T}_G) \). The noise equivalent spectral emissivity is NESE(\( \lambda_k \)) = NESR(\( \lambda_k \))/\( W(\lambda_k, \hat{T}_G) \).

Substituting Eq. (4.20b) for \( \hat{\epsilon}_G(\lambda_k) \), the noisy emissivity estimate model is

\[ \hat{\epsilon}_G^n(\lambda_k) = \epsilon_G(\lambda_k) + \epsilon_{\hat{T}_G}(\lambda_k) + n_\epsilon(\lambda_k) \]
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

4.3.3 Smoothing Errors

Due to the linearity of the smoothing techniques, the smoothed noisy emissivity estimate is

\[ \hat{\epsilon}_G^{sn}(\lambda_k) = \epsilon_G^s(\lambda_k) + \epsilon_{T_G}^s(\lambda_k) + n^s(\lambda_k) \]

(4.27)

where it is the sum of the three smoothed contributions of \( \hat{\epsilon}_G^{sn}(\lambda_k) \).

The total smoothing error for the noisy emissivity estimate can be represented as the difference between the three components in \( \hat{\epsilon}_G^{sn}(\lambda_k) \) and \( \hat{\epsilon}_G^{n}(\lambda_k) \) so that

\[ \tilde{\epsilon}_G^{n}(\lambda_k) = \tilde{\epsilon}_G^{b}(\lambda_k) + \tilde{\epsilon}_{T_G}(\lambda_k) + \tilde{n}_e(\lambda_k) \]

(4.28)

The interaction of these three smoothing errors can be used to explain the final ground temperature and emissivity estimates. These three errors and their corresponding radiance errors are described below.

- Emissivity Bias Error

The assumption that the emissivity spectrum is perfectly smooth introduces a bias error. The emissivity bias error is defined as

\[ \tilde{\epsilon}_G^{b}(\lambda_k) = \epsilon_G(\lambda_k) - \epsilon_G^s(\lambda_k) \]

(4.29)

where \( \tilde{\epsilon}_G^{b}(\lambda_k) \) is the smoothing error from directly applying the smoothing criteria to \( \epsilon_G(\lambda_k) \). The bias error is independent of \( \hat{T}_G \), and can only be reduced by having a smoothing criteria that more accurately captures \( \epsilon_G(\lambda_k) \). The red \( \tilde{\epsilon}_G(\lambda_k) \) spectra in Figures 4.5 and 4.8 are for \( \hat{T}_G = T_G \), so \( \tilde{\epsilon}_G(\lambda_k) = \epsilon_G(\lambda_k) \). The corresponding red error spectra in each figure show \( \tilde{\epsilon}_G^{b}(\lambda_k) \) for a 3-band wide boxcar moving average and LEC respectively. If the size, \( J \), of the smoothing functions were increased, the total amount of smoothing to \( \epsilon_G(\lambda_k) \) would increase along with the emissivity bias error.

- Temperature Induced Emissivity Error

The smoothing error that is incurred when \( \hat{T}_G \neq T_G \) is defined as

\[ \tilde{\epsilon}_{T_G}(\lambda_k) = \epsilon_{T_G}(\lambda_k) - \epsilon_{T_G}^s(\lambda_k) \]

(4.30)

and will consist mostly of the smoothing error incurred from the effects of the sharp reflected atmospheric features in \( A(\lambda_k) \), when \( \epsilon_G(\lambda_k) \) is relatively smooth. The temperature induced emissivity error will always be zero when \( \hat{T}_G = T_G \).
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

- Emissivity Noise Error

The smoothing error that is introduced from noise is defined as

\[
\tilde{n}_\epsilon(\lambda_k) = n_\epsilon(\lambda_k) - n^*_\epsilon(\lambda_k)
\]  

(4.31)

with the majority of emissivity noise error occurring at the bands with sharp atmospheric features. These sharp atmospheric features were introduced into the noise during the conversion of the measurement noise to the emissivity domain, as described in Section 4.3.2.

- Radiance Error

The following three error components can be converted to their corresponding radiance domain errors using the conversion in Eq. (4.10)

\[
\tilde{L}_M(\lambda_k) = \tilde{L}_G^b(\lambda_k)W(\lambda_k, \hat{T}_G) = \tilde{L}_M^b(\lambda_k) + \tilde{L}_G(\lambda_k) + \tilde{n}_M(\lambda_k)
\]

(4.32)

4.4 Ground Temperature Estimation Error Results

The goal of this work is to evaluate TES techniques under a variety of conditions and explain how these conditions cause the resulting ground temperature estimation errors using the developed TES performance model. The model tests the optimal performance limitations of the TES techniques, caused by the assumption that an emissivity spectrum is perfectly smooth. Perfect knowledge of the atmospheric parameters and sensor calibration is assumed. Adding meaningful atmospheric compensation errors would require a detailed error model for atmospheric compensation algorithms, which currently is not available.

The TES techniques were tested on at-aperture radiance spectra generated using the process discussed in Section 2.8. The atmospheric parameters used were generated with MODTRAN using the Mid-Latitude Summer atmospheric profiles with a water multiplier of 0.75 and an ozone multiplier of 1. The \( L_S(\lambda) \) spectra were downsampled to the spectral resolution of the SEBASS sensor, which has 128 bands from 7.6 \( \mu \)m to 13.5 \( \mu \)m [24]. It was assumed that the spectral response for each of the 128 bands was Gaussian. The \( k_1 \) and \( k_2 \) used to determine the SRMSE were the bands closest to 8.25 \( \mu \)m and 13.1 \( \mu \), which correspond to SEBASS bands 11 and 116 respectively.

The four emissivity spectra used to simulate the at-aperture radiance spectra are shown in Figure 4.10. These few spectra were chosen to span the variety of spectra that might be found in a material library. The emissivity spectra range in smoothness with signature 1 being extremely
smooth, and signature 3 having many sharp characteristics. The spectra also range in the magnitude of their emissivities, with signature 1 having a high emissivity around 0.9 and signature 4 having an emissivity below 0.4. With these few emissivity spectra it was hoped to learn how different emissivities affect TES.

![Emissivity spectra](image)

Figure 4.10: Emissivity spectra used to simulate ground radiance spectra.

A total of four TES techniques were tested. These techniques included TES boxcar averaging minimizing the SRMSE in the emissivity and ground radiance domain, and LEC also minimizing the two SRMSE. Both the boxcar averaging and LEC used 3-bands for their smoothing, to provide similar smoothing and minimize the total amount of emissivity bias error.

To study how well the TES techniques worked under different ground temperature and atmospheric conditions, the four TES techniques were tested under two different conditions, for each of the four emissivity spectra. In the first test, the atmospheric parameters for a sensor altitude of 0.5 km were used to generate five noiseless at-aperture radiance spectra with ground temperatures between 285 K to 305 K in 5 K increments. In the second test, noiseless at-aperture radiance spectra were simulated at a ground temperature of 295 K with atmospheric parameters at sensor altitudes from 0 to 10 km in 0.5 km increments. The effects of noise were studied by generating 10,000 noisy spectra for each noiseless at-aperture radiance spectrum. The ground temperature estimation results are studied because ground temperature errors directly correlate with emissivity errors, and it is simpler to analyze a single variable. These tests will be further discussed and their results presented in the next two sections.
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

4.4.1 TES Results at constant Altitude Varying Ground Temperature

In this test, the atmospheric parameters for a sensor altitude of 0.5 km were used to generate five noiseless at-aperture radiance spectra with ground temperatures between 285 K to 305 K in 5 K increments. The purpose of this test was to determine how ground temperature and emissivity affects the temperature estimates for each TES technique, when atmospheric parameters remain constant. The $\hat{T}_G$ errors for the 4 emissivity spectra using the 4 TES techniques are shown in Figure 4.11. The temperature errors in each column are for an emissivity signature, and each row is for a TES technique. The x-limits are consistent for each column, but vary across columns. The TES smoothing techniques and their error metrics are specified on the right. In each of the 16 plots, the red line is the temperature error for the noiseless ground radiances, the solid blue line is the average error for the noisy ground radiances, and the blue dashed lines are error bounds that contain the 50%, 80%, and 90% confidence intervals for $\hat{T}_G$. The green line is just a reference for zero temperature error.

Several key observations can be made from the 12 TES temperature error plots corresponding to the relatively smooth emissivity signatures excluding the third emissivity signature:

- The ground temperature estimation error increases as $T_G$ increases.
- TES techniques that minimize the ground radiance error have a larger average temperature error that is less variable than their counterparts that minimize the emissivity domain error.
- The LECTES techniques have larger average and more variable temperature errors than the boxcar TES technique.
- The ground temperature error increases with decreasing ground emissivity.

The third emissivity signature has several sharp features which affected its TES temperature error results compared to the other emissivity signatures. The boxcar TES technique that minimized the ground radiance error had a lower average temperature error with less variability than its emissivity error counterpart which had the highest average temperature error.
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

Figure 4.11: Temperature errors for the four TES techniques. X-Limits change for each column.
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

4.4.1.1 Ground Temperature Initialization Results

Figure 4.12 shows the initial $\hat{T}_G$ estimate errors for the simulated at-aperture radiance in the previous section, using the maximum brightness and feature based methods. The format of the plots are the same as Figure 4.11. The $\hat{T}_G$ error using the maximum brightness temperature increases as the ground temperature increases, and increase as the maximum emissivities of each signature decreases with increasing signature number, as shown in Figure 4.10. The initial temperature estimates using the feature based method show a significant improvement over the maximum brightness temperature for the relatively smooth emissivity signatures, and the $\hat{T}_G$ errors do not increase much with increasing ground temperature. The $\hat{T}_G$ errors are significantly higher for the last signature with the lowest emissivity due to the increased band-averaging error of the atmospheric compensation conversion to ground radiance.

Figure 4.12: Temperature errors for the two initial temperature estimate techniques. X-Limits change for each column.
4.4.2 TES Results at Constant Ground Temperature and Varying Altitude

In this test, noiseless at-aperture radiance spectra were simulated at a ground temperature of 295 K with atmospheric parameters at sensor altitudes from 0 to 10 km in 0.5 km increments. The purpose of the test was to determine how increased atmospheric effects with increasing altitude affect the temperature estimates for each TES technique, when the ground temperature remains constant. Figure 4.13 shows the $\hat{T}_G$ errors versus sensor altitude for the four emissivity spectra using boxcar averaging TES in both of the error domains. The temperature errors in each column are for an emissivity signature, and each row is for a TES technique. The x-limits are consistent for each column, but vary across columns.

Several key observations can be made from the TES temperature error verse sensor altitude plots:

- The ground temperature estimation error increases with altitude.
- The variability of the ground temperature estimate errors increase with sensor altitude.

Figure 4.13: Temperature errors at 295 K with altitude for each of the signatures using boxcar TES in each error domain.
In the emissivity error domain there is a bias error between the noiseless temperature errors and the average temperature errors of the noisy at-aperture radiance spectra. This bias error increases with sensor altitude.

4.5 Explanation of Experimental Results

TES finds the ground temperature estimate that provides the minimum SRMSE. The $\hat{T}_G$ that provides the minimum SRMSE is determined by the interaction of the temperature induced emissivity error with both the emissivity bias and noise errors. When $\hat{T}_G = T_G$, the total error will be the sum of $\tilde{e}_b^G(\lambda_k)$ and $\tilde{\epsilon}_n(\lambda_k)$. Any errors in $\hat{T}_G$ are caused by shifting $\hat{T}_G$ from $T_G$ to create a $\tilde{\epsilon}_{\hat{T}_G}(\lambda_k)$ that reduces the overall error. Figures 4.14a and 4.14b correspond to the boxcar averaging temperature errors versus altitude plots in Figure 4.13. The two figures show the ratio between the minimum error and sum of the emissivity bias and noise errors for the emissivity and radiance domains respectively. Except for the signature 1 which was the smoothest, the error ratios were less than one, meaning that $\tilde{\epsilon}_{\hat{T}_G}(\lambda_k)$ reduced the total error by introducing a ground temperature error. The reason that signature 1 had a ratio greater than one can be explained by it’s smoothness and the error of the model from the resampling approximation.

Figure 4.14: Ratio of SSE for minimum error and sum of emissivity bias error and noise in the emissivity and radiance domains.

In this section, we use the performance model to explain the observations made from
the results in the previous section. The sections are organized as follows. Section 4.5.1 shows the ground temperature errors caused by the TES band-averaging approximations. Sections 4.5.2 and 4.5.3 use the performance model to provide explanations of the observations made in the TES tests for constant altitude and varying temperature and constant temperature and varying altitude respectively. Section 4.5.4 shows the amount of correlation between the temperature induced and emissivity bias error components, and how this affects the total error. Lastly, Section 4.5.5 uses the performance model to describe how the ground temperature and emissivity errors are linked.

### 4.5.1 Temperature Error Caused by Resampling Approximation

In Section 4.1, it was explained that the TES emissivity estimate in Eq. (4.1) used $B(\lambda_k, \hat{T}_G)\tau(\lambda_k)$ to approximate $B(\lambda_k, \hat{T}_G)$. Using this approximation gives a slight deviation in the $\hat{T}_G$ that provides the minimum error. Figures 4.15a and 4.15b show errors between the $\hat{T}_G$ found by doing TES with and without the approximation. The errors are positive, meaning that TES with the approximation gives a better estimate of the ground temperature, but with an additional smoothing error.

![Figure 4.15: Ground temperature estimate error caused by band-averaging approximation in the emissivity and radiance domains.](image)

The gain in smoothing error is typically small, and is only comparable to the other errors when the emissivity signature is extremely smooth. Signature 1 was the smoothest, and had the smallest emissivity bias error, as shown in Figure 4.16. The small emissivity bias error caused the
ratios for signature 1 in Figures 4.14a and 4.14b to be greater than one. The minimum smoothing error consisted of a very small emissivity bias error which could not be reduced, the noise, and the additional error from the band-averaging approximation.

### 4.5.2 Constant Altitude Varying Ground Temperature Analysis

In Figure 4.11 it was shown that the ground temperature estimate error increases as the ground temperature of a spectrum increases. The temperature induced emissivity error attempts to reduce the emissivity bias error of a spectrum which remains constant with temperature. As the ground temperature of a spectrum increases, the estimate of the ground temperature should also increase. This increase in $\hat{T}_G$ means that the weighting factor $W(\lambda_K)$ in $\bar{\epsilon}_G(\lambda_k)$ will also increase. The increase in $W(\lambda_K)$ requires a larger temperature error for $\bar{\epsilon}_G(\lambda_k)$ to compensate $\epsilon_b G(\lambda_k)$ the same amount.

The TES techniques that minimize the emissivity error have a smaller average and are more variable than their counterparts that minimize the radiance domain error. In the emissivity domain, the temperature induced error is more sensitive to the temperature errors at the bands where large atmospheric features are present. Figure 4.9 shows how the large atmospheric features are more pronounced with changes in $\hat{T}_G$. The error in the emissivity domain equally weights each of the bands, so that the bands with large features that supply the greatest smoothing error can be utilized to find a more accurate $\hat{T}_G$. Any small changes in $\hat{T}_G$ will cause the temperature induced error to quickly increase the total error. A disadvantage is that the large feature bands are more
susceptible to noise error, as a result $\hat{T}_G$ in the emissivity domain will have a higher variability. Figure 4.17a shows the ground NESE for the 5 ground radiance spectra simulated using emissivity signature 2. It can be observed that the noise at the feature bands is more pronounced than the other bands.

Figure 4.17: Noise for signature 2 ground radiance spectra at temperatures from 285 K to 305 K in 5 K increments.

In the radiance domain the large atmospheric feature bands are weighted less, suppressing the noisier bands and reducing the variability of the estimates. Figure 4.17b shows the at-aperture NESR for the same spectra used in Figure 4.17a and that the feature bands are not pronounced. The reduced weighting of the large feature bands reduces the amount of change in these bands with changes in $\hat{T}_G$. This prevents large increases in error with increases in $\hat{T}_G$, reducing the temperature sensitivity and the overall accuracy of $\hat{T}_G$.

The increase in the ground temperature error with decreasing ground emissivity can be explained similarly to the increase in the ground temperature estimate error with the increasing ground temperature. The temperature induced emissivity error has the emissivity spectrum as a scalar term, as seen in Eq (4.20a). This scalar term reduces the ability of temperature induced emissivity error to reduce the emissivity bias error of a spectrum. When the magnitude of an emissivity spectrum decreases, a larger temperature error is needed for $\tilde{\epsilon}_{\hat{T}_G}(\lambda_k)$ to compensate $\tilde{\epsilon}_G(\lambda_k)$ the same amount.
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

4.5.3 Constant Ground Temperature and Varying Altitude

The increase in the ground temperature error with increasing altitude can be explained by how the smoothness of the temperature induced emissivity error changes with the decrease in transmission. The smoothness of $\tilde{e}_{\tilde{T}_G}(\lambda_k)$ depends mostly on the smoothness of $A(\lambda_k)$ in Eq. (4.20a) which contains the sharp atmospheric features. The transmission can be factored out of $A(\lambda_k)$, so that

$$A(\lambda_k) = \frac{B(\lambda, \tilde{T}_G) - B(\lambda, \hat{T}_G)}{B(\lambda, \tilde{T}_G) - L_{D_T}(\lambda_k)/\tau(\lambda_k)}$$

(4.33)

where all the terms are smooth except for $L_{D_T}(\lambda_k)/\tau(\lambda_k)$. The roughness of $\tilde{e}_{\tilde{T}_G}(\lambda_k)$ will mostly depend on the roughness of $L_{D_T}(\lambda_k)/\tau(\lambda_k)$, and will change with $\tau(\lambda_k)$ due to band-averaging error. Figure 4.18 shows the smoothing error of $L_{D_T}(\lambda_k)/\tau(\lambda_k)$ at altitudes of 0 km to 10 km in 0.5 km increments. A $\hat{T}_G$ of 296 K was used with a $\tilde{T}_G$ of 295 K. It can be seen that the features of the smoothing error are sharper for the ground spectrum in green, compared to the 10 km smoothing error spectrum in red. This reduction in smoothing error with altitude means that a larger temperature error is needed for $\tilde{e}_{\tilde{T}_G}(\lambda_k)$ to compensate $\tilde{e}_{\hat{T}_G}(\lambda_k)$ the same amount.

The decrease in transmission with increasing altitude reduces the amount of energy at the emissivity level. The reduction in signal increases the NESE. The increase in noise causes an increase in the variability of the ground temperature estimate errors.

The bias errors in the emissivity domain between the noiseless temperature errors and the average temperature errors of the noisy at-aperture radiance spectra are caused by the noise in the
emissivity domain being dependent on $\hat{T}_G$, as shown in Eq. (4.25). An increase in $\hat{T}_G$ allows for a reduction of the noise error and the overall error, causing a bias temperature error when noise is added. Figure 4.19 shows a comparison of the SSE of the noise in the emissivity and radiance domain versus $\hat{T}_G$ for an at-aperture radiance spectrum simulated using signature 4, at a temperature of 295 K, and a sensor altitude of 0.5 km. As $\hat{T}_G$ increases there is a large reduction in the emissivity noise SSE. When the emissivity noise error is converted to the radiance domain, the multiplication by the $W(\lambda_k, \hat{T}_G)$ keeps the radiance noise SSE fairly constant, as shown in Figure 4.19.

4.5.4 Correlation Between Error Components from Smoothing Technique

A ground temperature estimation error occurs when there is a correlation between the temperature induced error and the emissivity bias error. This correlation allows for the temperature induced error to compensate for some of the emissivity bias error, and reduce the total smoothing error. While the amount of correlation between these errors is important, the final ground temperature estimate error is determined by the $\hat{T}_G$ at which the largest amount of emissivity error is compensated without adding additional error. Figure 4.20 shows the $E_L$ and the correlation between $\bar{\epsilon}_{\hat{T}_G}(\lambda_k)$ and $\bar{\epsilon}_{G}^{b}(\lambda_k)$ versus temperature error for an at-aperture radiance spectrum with signature 4 at 295 K. When there is a negative correlation there is a slight reduction in $E_L$ before $\bar{\epsilon}_{\hat{T}_G}(\lambda_k)$ causes an increase. The correlation tends to be larger for larger ground temperatures, lower emissivities, and in the radiance domain.

![Figure 4.20: $E_L$ and the correlation between $\bar{\epsilon}_{\hat{T}_G}(\lambda_k)$ and $\bar{\epsilon}_{G}^{b}(\lambda_k)$ versus temperature error.](image)

Figure 4.21 corresponds to the results in Figure 4.11 and shows the correlation between
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

the temperature induced errors and emissivity bias error using boxcar averaging at the $\hat{T}_G$ for the 5 temperatures at an altitude of 0.5 km. Key observations are the negative correlation that becomes more negative with increasing ground temperature, and that the radiance error correlation is more negative than the emissivity. This increase in correlation with temperature can be attributed to $W(\lambda_k, \hat{T}_G)$ increasing with temperature and reducing the atmospheric features in $A(\lambda_k)$. The more negative correlation of the radiance can be explained by the conversion of the errors from the emissivity to radiance domain. The temperature induced error is heavily dependent on $A(\lambda_k)$ which contains the atmospheric components, and the emissivity bias error in the emissivity domain is dependent only on the emissivity signature and the smoothing technique. When the emissivity bias error is converted to the radiance domain, it is multiplied by $W(\lambda_k, \hat{T}_G)$ which also contains atmospheric features. For the most part the radiance results had higher temperature errors than the emissivity results, except in signature 3 which was not smooth.

![Figure 4.21: Average correlation between temperature induced error and emissivity bias error with ground temperature for each of the error domains using boxcar averaging.](image)

The improved smoothing of LEC reduced the temperature induced error allowing for the increased temperature error to further compensate. The correlation for signature 3 was unique in that the radiance temperature errors were positively correlated and gave negative temperature
errors. This is further evidence of how a high emissivity bias error can cause surprising interactions between the errors.

Figure 4.22: Average correlation between temperature induced error and emissivity bias error with ground temperature for each of the error domains using LEC.

Figure 4.23 corresponds to the results in Figure 4.13 and shows the correlation between the temperature induced error and emissivity bias error using boxcar averaging at $\hat{T}_G$ with spectra simulated at varying altitudes and a ground temperature of 295 K for each of the error domains. Similar to the rest of the correlation plots, the radiance correlation is more negative than the emissivity. The changes in correlation with altitude follow the changes in temperature errors with altitude fairly well except for signature 1. The reduction of the atmospheric features in the temperature induced error with altitude allowed for the more negative correlation. Signature 1 showed a sharp increase in correlation in the first km, then remained fairly constant. This first km corresponds to the region where the temperature error from the resampling approximation showed the greatest increase, and was comparable to the temperature error for signature 1. In addition, the magnitudes of the correlations for each signature correspond to the reductions of the SSE seen in Figures 4.14a and 4.14b.

The emissivity bias error and temperature induced error for the 4 TES techniques are shown in Figures 4.24a to 4.25b using the 5 simulated noiseless ground radiance spectra for signature 4 at the 5 temperatures. Figure 4.24a shows the emissivity bias error in red, and in blue are the 5 temperature induced errors using the 5 temperatures found with the TES technique that minimized $E_{\epsilon}$ with boxcar averaging. We see that the temperature induced error has features in
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

![Figure 4.23: Average correlation between temperature induced error and emissivity bias error with altitude for each of the error domains.](image)

the opposite direction of the emissivity bias error to reduce \( E_\epsilon \). If the temperature estimates were further increased, the large atmospheric feature would quickly increase \( \tilde{\epsilon}_G(\lambda_k) \). Figure 4.24b shows the emissivity bias and temperature induced errors with the TES technique that minimized \( E_L \) with boxcar averaging. Since the emissivity bias error is weighted differently for each \( \hat{\epsilon}_G(\lambda_k) \), there are 5 red emissivity bias error spectra. The weighting also made the size of the atmospheric feature at 12.6 µm comparable to the rest of the error features. This allowed for further increasing of \( \hat{T}_G \) to further compensate for the emissivity bias error.

Figures 4.25a and 4.25b show the emissivity bias and temperature induced errors for the TES techniques that use LEC to minimizing \( E_\epsilon \) and \( E_L \) respectively. The smoothing errors for LEC were smaller and sharper than boxcar averaging. Due to the sharpness of the features and how well their positions corresponded between errors, \( \hat{T}_G \) could be further increased to compensate for the emissivity bias error.

### 4.5.5 Temperature and Emissivity Error Relationship

The relationship between temperature error and emissivity error is shown by the emissivity estimate model in Section 4.3.1. Eq. (4.20b) shows the relationship for noiseless spectra, and Eq. (4.26) shows the relationship for noisy spectra. The emissivity estimate error for a \( \hat{T}_G \) is the sum of the emissivity error and noise error given in Eqs. (4.20a) and (4.25) respectively.

The effects of temperature errors on emissivity estimates are shown in Figures 4.26a and
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

Figure 4.24: Emissivity bias and temperature induced errors in the emissivity domain for the 5 noiseless ground radiance spectra simulated using signature 4, where boxcar averaging was used to minimize the emissivity and radiance smoothing errors.

Figure 4.25: Emissivity bias and temperature induced errors in the emissivity domain for the 5 noiseless ground radiance spectra simulated using signature 4, where LEC was used to minimize the emissivity and radiance smoothing errors.

4.26b using the 5 simulated noiseless ground radiance spectra for signature 4. Figure 4.26a shows the 5 emissivity estimates using the 5 temperatures found using the TES technique that utilized
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

Boxcar averaging and minimized the radiance error $E_L$. We observe from the figure that due to the temperature error $\hat{T}_G > 0$ the $\hat{\epsilon}_G(\lambda_k)$ are shifted below $\epsilon_G(\lambda_k)$. The amount of shifting $\hat{\epsilon}_G(\lambda_k)$ increases as the temperature of the ground radiance spectrum increases and $\hat{T}_G$ increases. The green and magenta $\hat{\epsilon}_G(\lambda_k)$s are for the 285 K and 305 K spectra respectively. The temperature errors were small enough that any effect from the large atmospheric feature at 12.6 µm is barely visible. Figure 4.26 shows the 5 emissivity estimates using the 5 temperatures found using the TES technique that utilized boxcar averaging and minimized $E_L$. The larger temperature errors compared to minimizing the emissivity error $E_\epsilon$ are shown by the larger shift down of the $\hat{\epsilon}_G(\lambda_k)$ spectra, and the increased visibility of the effect of the atmospheric feature at 12.6 µm.

![Figure 4.26: Final $\hat{\epsilon}_G(\lambda_k)$ found for the 5 noiseless ground radiance spectra simulated using signature 4, where boxcar averaging was used to minimize the emissivity and radiance smoothing errors.](image)

4.6 Wavelength Calibration Mismatch

When atmospheric models are used for AC and TES, the atmospheric model parameters need to be sampled to the current SRF of the sensor. These downsampled atmospheric parameters are then used in the AC and TES equation given by

$$\hat{\epsilon}_G(\hat{\lambda}_k) = \frac{L_S(\hat{\lambda}_k) - L_U(\hat{\lambda}_k) - L_D \tau(\hat{\lambda}_k)}{W(\hat{\lambda}_k, \hat{T}_G)}$$

(4.34a)

$$W(\hat{\lambda}_k, \hat{T}_G) = B(\hat{\lambda}_k, \hat{T}_G) \tau(\hat{\lambda}_k) - L_D \tau(\hat{\lambda}_k)$$

(4.34b)
where \( \hat{\lambda}_k \) specifies that the component is downsampled using the estimated SRF for each band. The SRF of the sensor changes over time from mechanical vibration and temperature changes causing spectral shifts and band broadening of the sensor’s SRF. Downsampling the true atmospheric model to an inaccurate sensor SRF causes a mismatch between the atmosphere in the at-aperture radiance and the atmosphere used for TES. This mismatch error is transferred to the emissivity estimate, and prevents any temperature estimate from providing a smooth emissivity estimate without residual atmospheric features. The additional roughness added from the wavelength calibration mismatch creates an additional bias error that causes further temperature estimation error.

Figure 4.27 shows TES temperature and emissivity estimates for an at-aperture radiance spectrum at 295 K and with a band shift of \( 0.25 \times \) the minimum band difference. The true spectrum is in red, and the magenta spectrum is the TES result without calibration error. The roughness of the emissivity spectrum caused a 1.72 K temperature error, and dropped the emissivity estimate. The green spectrum is the calculated emissivity at the true ground temperature of 295 K with with the wavelength calibration error. The large features from the wavelength calibration mismatch are easily visible. The blue spectrum is the emissivity spectrum found with TES. The atmospheric features are still visible and caused a temperature error of \(-1.75\) K.

To understand how wavelength calibration errors affect TES under different ground temperature and emissivity conditions, emissivity estimate and TES performance models were developed. Similar to the models developed for perfect calibration, these wavelength calibration error models are a sum of several components. A majority of the components are similar between both
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

the models, with additional components for the wavelength calibration mismatch.

4.6.1 Wavelength Calibration Emissivity Estimation Model

When there is a wavelength calibration error, the measured at-aperture radiance spectrum can be expressed as

$$
\hat{\epsilon}_G^a(\hat{\lambda}_k) = \epsilon_G(\lambda_k) + \epsilon_{\hat{T}_G}(\hat{\lambda}_k) + \epsilon_A(\hat{\lambda}_k) + n_e(\hat{\lambda}_k) \tag{4.35}
$$

where \( \hat{\lambda}_k \) specifies that the component is effected by the mismatched SRF for each band. When \( \hat{\lambda}_k = \lambda_k \), the model reduces to the perfect calibration model in Eq. (4.26). The following are the emissivity estimate components:

- **Emissivity**
  
The emissivity component consists of the true emissivity spectrum \( \epsilon_G(\lambda_k) \).

- **Temperature Induced**
  
The temperature induced component is nearly identical to \( \epsilon_{\hat{T}_G}(\lambda_k) \) except for \( W(\hat{\lambda}_k, \hat{T}_G) \) in the denominator, where

$$
\epsilon_{\hat{T}_G}(\hat{\lambda}_k) = \epsilon_G(\lambda_k)A(\hat{\lambda}_k) \tag{4.36a}
$$

$$
A(\hat{\lambda}_k) = \frac{B(\lambda_k, T_G) - B(\lambda_k, \hat{T}_G)}{W(\hat{\lambda}_k, \hat{T}_G)} \tag{4.36b}
$$

the residual atmospheric features induced by temperature errors will be slightly altered by the mismatch.

- **Atmospheric Mismatch**
  
The atmospheric mismatch component is the only component that is unique to the wavelength calibration emissivity estimation model, where

$$
\epsilon_A(\hat{\lambda}_k) = \frac{\epsilon_G(\lambda_k)\left( B(\lambda_k, \hat{T}_G)\tau(\lambda_k) - B(\hat{\lambda}_k, \hat{T}_G)\tau(\hat{\lambda}_k) \right) + \left( L_U(\lambda_k) - L_U(\hat{\lambda}_k) \right) + \left( 1 - \epsilon_G(\lambda_k) \right)\left( L_D(\lambda_k) - L_D(\hat{\lambda}_k) \right)}{W(\hat{\lambda}_k, \hat{T}_G)} \tag{4.37}
$$

It shows how the mismatch in the atmospheric parameters caused by wavelength calibration error affects the emissivity estimate.
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

• Noise

The noise component is nearly identical to \( n_\epsilon(\lambda_k) \) except for \( W(\hat{\lambda}_k, \hat{T}_G) \) in the denominator, where

\[
n_\epsilon(\hat{\lambda}_k) = n_M(\lambda_k)/W(\hat{\lambda}_k, \hat{T}_G)
\] (4.38)

and the atmospheric features in the emissivity noise are slightly altered by the mismatch.

• Emissivity Estimate Error

The emissivity error consists of the sum of \( \tilde{\epsilon}_G(\hat{\lambda}_k) \), \( \epsilon_A(\hat{\lambda}_k) \), and \( n_\epsilon(\hat{\lambda}_k) \).

4.6.2 Smoothing Error

Due to the linearity of the smoothing techniques, the smoothed noisy emissivity estimate is

\[
\tilde{\epsilon}_G^s(\hat{\lambda}_k) = \epsilon_G(\lambda_k) + \tilde{\epsilon}_G(\hat{\lambda}_k) + \epsilon_A(\hat{\lambda}_k) + n_s(\hat{\lambda}_k)
\] (4.39)

where it is the sum of the four smoothed components of \( \tilde{\epsilon}_G^n(\hat{\lambda}_k) \).

The total smoothing error for the noisy emissivity estimate can be represented as the difference between the three components in \( \tilde{\epsilon}_G^n(\hat{\lambda}_k) \) and \( \tilde{\epsilon}_G^s(\hat{\lambda}_k) \) so that

\[
\tilde{\epsilon}_G^b(\hat{\lambda}_k) = \tilde{\epsilon}_G^n(\hat{\lambda}_k) - \tilde{\epsilon}_G^s(\hat{\lambda}_k)
\] (4.40)

The interaction of these four smoothing errors can be used to explain the final ground temperature and emissivity estimates. These four errors and their corresponding radiance errors are described below.

• Emissivity Bias Error

The assumption that the emissivity spectrum is perfectly smooth introduces a bias error. The emissivity bias error is the same as for the perfect calibration model in Eq. (4.29).

• Temperature Induced Emissivity Error

The smoothing error that is incurred when \( \hat{T}_G \neq T_G \) is defined as

\[
\tilde{\epsilon}_{\hat{T}_G}(\hat{\lambda}_k) = \epsilon_{\hat{T}_G}(\hat{\lambda}_k) - \epsilon_{\hat{T}_G}(\hat{\lambda}_k)
\] (4.41)

and will consist mostly of the smoothing error incurred from the effects of the sharp reflected atmospheric features in \( A(\hat{\lambda}_k) \), when \( \epsilon_G(\lambda_k) \) is relatively smooth. The atmospheric features will be slightly altered compared to \( \tilde{\epsilon}_{\hat{T}_G}(\lambda_k) \) due to the calibration error.
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

- Atmospheric Mismatch Error
  The smoothing error introduced by calibration mismatch in the atmospheric features is
  \[ \tilde{\epsilon}_A(\hat{\lambda}_k) = \epsilon_A(\hat{\lambda}_k) - \epsilon_A^s(\hat{\lambda}_k) \]  
  where most of the error will be along bands with atmospheric features.

- Emissivity Noise Error
  The smoothing error that is introduced from noise is
  \[ \tilde{n}_e(\hat{\lambda}_k) = n_e(\hat{\lambda}_k) - n_e^s(\hat{\lambda}_k) \]  
  with the majority of emissivity noise error occurring at the bands with sharp atmospheric features. These sharp atmospheric features will be slightly altered compared to \( \tilde{n}_e(\lambda_k) \) due to the calibration error.

- Radiance Error
  The following four error components can be converted to their corresponding radiance domain errors using the conversion in Eq. (4.10)
  \[ \tilde{\mathcal{L}}_M(\hat{\lambda}_k) = \tilde{\mathcal{L}}_b(\hat{\lambda}_k) W(\hat{\lambda}_k, \hat{T}_G) \]
  \[ = \tilde{\mathcal{L}}_M^b(\hat{\lambda}_k) + \tilde{\mathcal{L}}_{TG}(\hat{\lambda}_k) + \tilde{\mathcal{L}}_A(\hat{\lambda}_k) + \tilde{n}_M(\hat{\lambda}_k) \]  

4.6.3 Spectral Shift Results and Analysis

The effects of spectral shifts on TES were tested. At-aperture radiance spectra were simulated for the four emissivity signatures at three temperatures, the atmospheric parameters at 0.5 km, and downscaled to the SRF of SEBASS. The inputs to TES were the shifted wavelengths, and atmospheric parameters downscaled to the shifted SRF. The shift \( \lambda_k + \Delta \) was determined by using a fraction of the minimum change in wavelength between bands. TES results using boxcar averaging in the radiance domain for fractional shifts of \(-0.25\) to \(0.25\) were found, and are shown in Figure 4.28. Each row of plots correspond to a ground temperature, with the columns being the fraction band shift versus ground temperature estimation error, total smoothing error, emissivity bias error and temperature induced error correlation, and atmospheric error and temperature induced error correlation. The correlation between the two sets of errors was determined by subtracting the average from each smoothing error, and calculating the SAM in Eq (2.3) between the demeaned smoothing error spectra.
The ground temperature estimation errors have a parabolic shape with a peak that increases with temperature, which matches the results with the perfect calibration model [19]. The peak is not centered at zero due to the atmospheric features not being symmetrical. The amount of change in the temperature error increases as the emissivity of the signature decreases, and becomes negative at large band shifts. The temperature errors at the greatest band shifts are nearly identical for each ground temperature.

When the emissivity of a material is close to one, the downwelling radiance component of $\epsilon_A(\lambda_k)$ is approximately 0. The upwelling radiance and transmission components are highly
negatively correlated. The upwelling radiance can be represented as
\[ L_U(\lambda_k) = B(\lambda_k, T_A)(1 - \tau(\lambda_k)) \] (4.45)
where \( T_A \) is the apparent temperature of the atmosphere and \( (1 - \tau(\lambda_k)) \) is the atmospheric emission. The upwelling radiance mismatch from wavelength calibration error can then be represented as
\[ L_U(\lambda_k) - L_U(\hat{\lambda}_k) = \left[ B(\lambda_k, T_A) - B(\hat{\lambda}_k, T_A) \right] - \left[ B(\lambda_k, T_A)\tau(\lambda_k) - B(\hat{\lambda}_k, T_A)\tau(\hat{\lambda}_k) \right] \] (4.46)
where the first part is small and smooth and the second part is related to the transmission mismatch component of \( \epsilon_A(\hat{\lambda}_k) \). When \( \hat{T}_G \approx T_A \) and \( \epsilon_G(\lambda_k) \approx 1 \), the second part of the \( L_U(\lambda_k) \) is canceled out by the transmission mismatch component. Figure 4.29 shows the ratio of the SSE of \( \epsilon_A(\hat{\lambda}_k) \) for a blackbody material and the \( L_U(\lambda_k) \) component versus band shift for three \( T_G \) when \( T_A \approx 294 \) K. All the ratios are close to 0 meaning that the upwelling and transmission mismatch components nearly cancel each other out. The ratio increases as \( T_G \) deviates from \( T_A \). The cancellation of the atmospheric mismatch errors for materials close to being blackbody explains why the temperature and smoothing errors for signatures 1 and 2 are small and change little with band shifting error. There is less cancellation as the emissivity decreases, and the downwelling mismatch component increases. This increases the atmospheric mismatch error, which is somewhat compensated by the temperature induced error.

![Figure 4.29: Ratio of SSE of total atmospheric mismatch error and upwelling radiance mismatch versus band shift for blackbodies.](image)

The right two columns in Figure 4.28 show the correlation between the temperature induced error and the emissivity bias and atmospheric mismatch errors in the radiance domain. When
the correlation is negative, that component is being compensated by the temperature induced error. The wavelength calibration error has little effect on the emissivity bias error in the radiance domain. At small atmospheric mismatch errors the emissivity bias error is greater and will have a negative correlation. The atmospheric mismatch error increases with increasing band shift and decreasing emissivity. When the atmospheric mismatch becomes greater than the emissivity bias error it will have a negative correlation. The emissivity bias error increases with temperature in the radiance domain due to the conversion factor. This increase in the emissivity bias error means that a greater atmospheric error is required for a negative correlation. Signatures 1 and 2 for the 305 K case never reached the point where the atmospheric error was greater.

4.6.4 Band Broadening Results and Analysis

The effect of spectral band broadening on TES was tested. The same simulated at-aperture radiance spectra from the previous section were used. The inputs to TES were the sensor wavelengths, and atmospheric parameters downsampled to the band broadened SRF. The band broadening consisted of multiplying the sensor FWHM by a scaler. TES results using boxcar averaging in the radiance domain for band broadening scaling of -0.95 to 1.05 were found, and are shown in Figure 4.30. Each row of plots correspond to a ground temperature, with the columns being the band broadening scalers versus ground temperature estimation error, total smoothing error, emissivity bias error and temperature induced error correlation, and atmospheric error and temperature induced error correlation.

The ground temperature estimation errors from band broadening are a lot greater than the errors from band shifts. The temperature error increases with decreasing emissivity, and becomes increasingly negative and positive as the band broadening is less than and greater than one respectively. Figures 4.31 shows the ratio of the SSE of $\epsilon_A(\hat{\lambda}_k)$ for a blackbody material and the $L_U(\lambda_k)$ component versus band broadening for three $T_G$ when $T_A \approx 294$ K. Similar to the band shifting, the upwelling and transmission mismatch components nearly cancel each other out, and the ratio increases as $T_G$ deviates from $T_A$.

The total smoothing errors in the second column do not change much with band broadening, meaning that the temperature induced error is compensating for the atmospheric mismatch error and causing the large temperature errors. The ability for the temperature induced error to compensate for the emissivity bias and atmospheric errors is shown by the correlation between them in the last two columns. The correlation with the atmospheric error is almost $-1$ for all the band
Figure 4.30: TES results for boxcar averaging in the radiance domain versus band broadening.

broadening scalers except around 1, explaining how the temperature induced error is able to compensate for most of it. Band broadening changes the smoothing of the SRF, which will mostly just change the height of atmospheric features. Where band shifts will actually change the shape of the atmospheric features. By not changing the shape of the features, the correlation of the temperature induced and atmospheric error components is allowed to be extremely high.
CHAPTER 4. TEMPERATURE EMISSIVITY SEPARATION

Figure 4.31: Ratio of SSE of total atmospheric mismatch error and upwelling radiance mismatch versus band broadening for blackbodies.

4.7 Summary

A performance model was created for the TES algorithms that utilize the emissivity smoothness assumption. The model explains how any correlation between the emissivity bias error from an emissivity spectrum not being perfectly smooth and the emissivity error induced by a ground temperature estimation error causes a temperature error. This ground temperature error directly translates to an emissivity error. It was shown that factors such as increasing ground temperatures, increasing altitude, and decreasing emissivity increase the ground temperature estimation error.

The ground temperature estimation errors were compared for TES using boxcar averaging and LEC. The LEC approach reduced the emissivity bias error by fitting the emissivity spectra more accurately, however the fitting improvement did not translate to improved ground temperature estimates. Unlike the other emissivity signatures, the signature with large features had a greatly reduced average ground temperature error in the radiance domain compared to its errors in the emissivity domain. This showed that better smoothing does not necessarily translate to more accurate estimates, and that a better understanding of the interactions between the two errors is needed for the development of improved TES algorithms.

The performance model was extended to include the effects of band shifting and broadening wavelength calibration errors. These wavelength calibration errors caused atmospheric mismatch errors. It was shown that the upwelling and transmission atmospheric mismatch errors are
negatively correlated, and nearly cancel each other out when the emissivity of a material is close to one. As the emissivity decreases the total atmospheric error increases. The transmission error decreases while the upwelling error remains constant, reducing the amount of cancellation. The downwelling radiance error also increases as the reflected component of a pixel increases. When the atmospheric mismatch error exceeds the emissivity bias error, the temperature induced error compensates for a fraction of it. This compensation further increases the temperature and emissivity errors. The band broadening calibration error had an extremely high correlation between its temperature induced and atmospheric errors. This large correlation allowed for more effective temperature induced compensation, causing increased temperature and emissivity errors.
## Chapter 4. Temperature Emissivity Separation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Eq.</th>
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<td>$L_S(\lambda_k)$</td>
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<tr>
<td>$L_U(\lambda_k)$</td>
<td>Atmospheric Upwelling Radiance</td>
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<tr>
<td>$L_D(\lambda_k)$</td>
<td>Atmospheric Downwelling Radiance</td>
<td></td>
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<tr>
<td>$\tau(\lambda_k)$</td>
<td>Atmospheric Transmission</td>
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<td>$L_G(\lambda_k)$</td>
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<td>$T_G$</td>
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<tr>
<td>$\hat{T}_G$</td>
<td>Ground Temperature Estimate</td>
<td>4.1, 4.20b</td>
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<td>Smoothed Ground Emissivity</td>
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<td>$\epsilon_G(\lambda_k)$</td>
<td>Ground Emissivity Estimate Smoothing Error</td>
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Table 4.1: Key TES Variable List and Equation Numbers
Chapter 5

In-Scene LWIR Downwelling Radiance Estimation

The accuracy of AC and TES is determined by the quality of the atmospheric parameters. While the atmospheric transmission and upwelling radiance can be estimated from the scene using ISAC and in-scene blackbody-like reference pixels, the downwelling radiance is more difficult to estimate due to lack of an in-scene reference. The downwelling radiance consists of the entire atmosphere, including the unmeasured portion above the sensor. In-scene evidence of the downwelling radiance comes only from the upwelling radiance and reflective pixels present in the scene [7]. The upwelling and downwelling radiance are related over the portion of atmosphere that they overlap. The relationship between the two strengthens as the altitude of the sensor increases. Evidence of the downwelling radiance for the entire atmosphere is only provided by the large reflected components of pixels with low and unknown emissivities when they are available. Due to this lack of in-scene evidence, a LUT of atmospheric models is used to provide possible estimates.

Since the downwelling radiance has varying independence from the other atmospheric parameters, an atmospheric model may fit the transmission and upwelling radiance below the sensor without fitting the downwelling radiance. To limit the challenges of estimating the downwelling radiance, ground radiance spectra unaffected by the transmission and upwelling radiance were used to test a downwelling radiance estimation algorithm that uses only a downwelling radiance LUT. The downwelling radiance estimation algorithm is judged by its ability to determine the correct model in the LUT under three conditions: ideal (noiseless), noisy, and affected by wavelength calibration mismatch. Removing the effects of AC errors allows for a more in-depth analysis of
CHAPTER 5. IN-SCENE LWIR DOWNWELLING RADIANCE ESTIMATION

using a LUT to determine an atmospheric parameter.

5.1 Downwelling Radiance Estimation

Combined AC and TES requires the estimation of at least $4K + 1$ parameters where $K$ is the number of spectral bands of the sensor [6]. Due to the large dimensionality of the problem, attempting to estimate all the parameters at once may lead to a non-unique solution that provides believable smooth but incorrect emissivity spectra. To limit the dimensionality of the problem, we assume that AC is done perfectly and use only the ground radiance. Using the ground radiance reduces the number of atmospheric unknowns to the $K$ unknowns of the downwelling radiance spectrum. The downwelling radiance is then estimated from just the ground radiance of reflective pixels using the algorithm shown in Figure 5.1.

Reflective pixels contain low emissivity materials and contain a reflected downwelling component in their ground radiance spectra. Examples of low emissivity spectra and simulated ground radiance spectra are shown in Figure 5.4. Reflective pixels can be found by calculating the brightness temperatures of the ground radiance spectra in a scene, and finding the pixels with the largest brightness temperature variance. The brightness temperature variability will be affected by the variance of the emissivity and its magnitude, along with the features of the downwelling radiance.

The downwelling radiance cannot be directly estimated from a scene because the emissivity is unknown for all the pixels. Due to the lack of in-scene evidence, an accurate atmospheric model is needed to determine the downwelling radiance. The atmospheric model should contain atmospheric temperature and gas profiles that closely match those of the scene for the entire atmosphere.

Atmospheric models for the downwelling radiance were generated using MODTRAN, which was discussed in Section 2.6. MODTRAN was run with permutations of the atmospheric parameters to generate a high resolution LUT of downwelling radiance spectra. Using the wavelength centers and FWHM of the SEBASS sensor, the high resolution MODTRAN models were downsampled to the sensor resolution. Figure 5.2 shows a LUT consisting of 265 downwelling radiance models that were downsampled to the 128 band SEBASS sensor resolution.

Each of the downwelling radiance models in the LUT is used for TES on the reflective pixel spectra. The $L_D(\lambda_k)$ model that provides the emissivity spectra with the lowest TES radiance smoothing error in Eq. (4.12) is chosen as the downwelling radiance of the scene. It was shown
in Section 4.6 that TES is extremely susceptible to small mismatch errors between the estimated downwelling radiance and the true downwelling radiance caused by sensor calibration errors. Any shifting of the wavelength centers and broadening of the bands will cause a slight discrepancy from the MODTRAN downwelling radiance downsampled with the documented calibration parameters. Calibration correction algorithms are required to determine the correct calibration parameters for downsampling each $L_D(\lambda_k)$ model and minimize the mismatch [7].

### 5.1.1 Reduction of Possible Downwelling Radiance Models

The downwelling radiance models present in the LUT are not necessarily all valid models for the available reflective ground radiance spectra. Some models will provide TES results with physically unrealistic emissivities. Several techniques are used to remove the obviously invalid downwelling radiance models from the LUT. One technique to filter out invalid models compares
the height of a large feature in the downwelling radiance model to the largest feature found in the reflective ground radiance spectra. The feature heights are measured using the technique described in Section 4.1.1 to find the improved ground temperature estimate. The downwelling radiance model feature height is the maximum feature height that is reached when a ground radiance spectrum has an emissivity of 0. Invalid downwelling radiance models have feature heights that are less than the largest feature found in the reflective ground radiance spectra, and would require a negative emissivity to create the observed feature. Such models that require non-physical emissivities are removed from the LUT.

The downwelling radiance models in the LUT consist of the entire height of the atmosphere. The upwelling radiance consists of the portion of atmosphere below the sensor. Since the downwelling radiance is modeled just above the ground where the atmosphere is thickest, and can consist of significantly more atmosphere, it should have a higher radiance. Any downwelling radiance model that has radiances less than the upwelling radiance are removed from the LUT.

The downwelling radiance LUT shown in Figure 5.2 includes the true $L_D(\lambda_k)$ in red and its corresponding $L_U(\lambda_k)$ at a sensor altitude of 1.5 km in magenta. Using the simulated ground radiance spectra in Figure 5.4, it was possible to reduce the 265 models in the LUT to the 64 green models using the two methods discussed above.

5.1.2 Sensor Calibration Correction

For the true model to provide smooth emissivity estimates, the wavelength calibration errors that cause a mismatch between the downwelling radiance in the LUT and the reflected downwelling radiance in the ground radiance spectra need to be corrected. The sensor calibration algorithm used to find an accurate estimate of the calibration parameters $\hat{C} = (\lambda_k + \Delta, s \times \text{FWHM})$ is shown in Figure 5.3. Using low emissivity pixel spectra, the current $L_D(\lambda_k)$, and the documented $C$ as an initial estimate of the calibration, the goal is to find the spectral shift $\Delta$ and broadening factor $s$ that provides the smoothest emissivity spectra and removes the sharp gas features. This process is similar to the technique discussed in [12] that uses reflectance smoothness. Emissivity smoothness is the optimization parameter for TES, so TES is utilized to measure the quality of each $\hat{C}$ iteration. In order to reduce the optimization parameters to just the calibration parameters, TES is done for only one iteration with the feature based temperature estimates. The feature based temperature estimates are close enough to the truth to provide emissivities that are relatively free of reflected atmospheric features when the correct $C$ is found. The temperature estimates are updated
CHAPTER 5. IN-SCENE LWIR DOWNWELLING RADIANCE ESTIMATION

Figure 5.3: Sensor Calibration Correction Pipeline

each iteration to account for feature changes from the new downsampling. The \( \hat{C} \) that provides the lowest overall TES error for all the reflective pixels is chosen as the correct calibration.

A single correction is accomplished for the entire scene, so it is important for the sensor to be of high enough quality for the calibration to remain consistent across-track. Determining a sensor calibration correction for each along-track sample would require several low emissivity pixels in each of the samples [12]. Depending on the scene, there is no guarantee that each sample will contain low emissivity pixels.

5.2 Downwelling Radiance Estimation Simulation

The proposed techniques used to determine the in-scene downwelling radiance were tested on simulated reflective ground radiance spectra. Simulated spectra were utilized due to the lack of scenes with accurate ground and atmospheric truth. Ground radiance spectra were simulated to exclude any effects caused by AC error, and allow for a more precise study of how the downwelling radiance estimate affects TES.

The simulation was done following the flowchart in Figure 5.5. A downwelling radiance was chosen from the LUT and downsampled to the 128 band SEBASS sensor calibration \( C \) [25]. The downsampled downwelling radiance \( \hat{L}_D(\lambda_k) \) that was used is the red spectrum in Figure 5.2. Three low emissivity spectra were also downsampled to \( C \), and are shown in 5.4a. Five ground radiance spectra were then simulated for each emissivity spectrum. The five spectra for each emissivity were simulated at 5 ground temperatures \( T_G \) from 285 K - 305 K in 5 K steps using Eq. (2.10). The 15 simulated ground radiance spectra are shown in Figure 5.4b along with the corresponding black-body spectra in blue. Sensor noise could then be added to the simulated ground radiance spectra by adding white gaussian noise to each spectral band. Calibration error, \( C_e \), could be added to the true calibration to create an initial calibration estimate \( \hat{C} = \left( \lambda_k + \Delta, s \times \text{FWHM} \right) \) with a specific
offset. The simulated ground radiances, the high resolution \( L_D(\lambda_k) \) LUT, and \( \hat{C} \) are fed into the downwelling radiance estimation algorithm. The downwelling radiance estimation algorithm supplies an estimate of the downwelling radiances \( \hat{L}_D(\lambda_k) \) from the LUT, that is downsampled to a new corrected sensor calibration \( \hat{C} \). For each of the supplied \( L_G(\lambda_k) \) spectra there are corresponding ground temperature \( \hat{T}_G \) and emissivity spectrum \( \hat{\epsilon}_G(\lambda_k) \) estimates. These estimates are compared to the supplied parameters to determine their quality.

The testing was done in three stages. The first stage used noiseless ground radiance spectra and included no calibration error so that \( C = \hat{C} \). The purpose of this stage was to study how the different \( L_D(\lambda_k) \) models effect TES, and whether or not the correct \( L_D(\lambda_k) \) model could be found with no sources of error. Since the two calibrations perfectly matched up, the sensor calibration correction algorithm was removed from the downwelling radiance estimation algorithm, and the hires downwelling radiance models were simply downsampled to \( C \). The noiseless ground radiance spectra in Figure 5.4 were then processed using the simplified downwelling radiance estimation algorithm that ran TES on each of the signatures using each downsampled \( L_D(\lambda_k) \) in the LUT. The \( L_D(\lambda_k) \) model that provided the lowest overall TES error for the signatures was then chosen.

Errors were added incrementally, to understand how individual errors affected the downwelling estimation process. The second stage was identical to the first except that calibration error was added, and the hires downwelling radiance models were downsampled to \( \hat{C} \). The calibration...
error consisted of a spectral shift of $0.25 \times$ the minimum distance between band centers and a band broadening of $1.1 \times$. The effects of calibration error and $L_D(\lambda_k)$ mismatch on TES and determining the correct model were studied. The next stage re-inserted the sensor calibration correction algorithm into the downwelling estimation algorithm to correct the mismatch that was added by $C_e$. The quality of the sensor calibration correction to minimize the $L_D(\lambda_k)$ mismatch and improve the downwelling radiance estimation and TES was studied. The last stage added sensor noise with a noise equivalent spectral radiance (NESR) of $1 \mu$-flick to each band of the ground radiance spectra to determine how noise affected the entire process.

5.3 Results

The four incremental simulation stages were as follows:

- Matched - the $L_D(\lambda_k)$ used to simulate the ground radiance spectra and the $L_D(\lambda_k)$ in the LUT were downsampled using the same $C$ so that $C = \hat{C}$.

- Mismatched Calibration - the $L_D(\lambda_k)$ used to simulate the ground radiance spectra was downsampled at $C$, and the $L_D(\lambda_k)$ in the LUT were downsampled at $\hat{C} = (\lambda_k + \Delta, s \times \text{FWHM})$. $\Delta$ was $0.25 \times$ the minimum distance between band centers and the band broadening of $s$ was 1.1.

- Corrected Calibration - the sensor calibration correction algorithm was used to correct the mismatched $\hat{C}$ used to downsample the $L_D(\lambda_k)$ LUT.

- Ground Radiance Noise - NESR of $1 \mu$-flick was added to each band of the simulated ground radiance spectra.
CHAPTER 5. IN-SCENE LWIR DOWNWELLING RADIANCE ESTIMATION

The results of each stage were compared to each other and the truth using three methods. The true $L_D(\lambda_k)$ model spectrum and the best model spectra with lower TES errors are compared in Section 5.3.1. The TES results using the corresponding low TES error $L_D(\lambda_k)$ models are studied in the next two sections. The temperature estimates are discussed in section 5.3.2 and the corresponding emissivity estimates are discussed in section 5.3.3.

5.3.1 Downwelling Radiance Estimates

For each of the stages the best $L_D(\lambda_k)$ model found in the LUT with the lowest overall TES radiance smoothing error was not the true model used to simulate the ground radiance spectra. Table 5.1 shows the number of models found that had TES errors less than or equal to the true model. It can be seen that as the stages progressed the number of models decreased. The TES errors for the best and true models of each stage are shown in Table 5.2. As expected, the TES error was lowest when the downsampling of the LUT matched the ground radiance spectra. The TES error increased when calibration error was included, and was decreased when the sensor calibration was corrected. The sensor calibration compensated for approximately 2/3 of the error caused by the calibration error. When noise was added to the ground radiance spectra, the TES radiance smoothing error increased by approximately 800 for the best and true models.

<table>
<thead>
<tr>
<th></th>
<th>Matched</th>
<th>Mismatched</th>
<th>Corrected</th>
<th>Noise</th>
</tr>
</thead>
<tbody>
<tr>
<td># of Models</td>
<td>14</td>
<td>8</td>
<td>6</td>
<td>7</td>
</tr>
</tbody>
</table>

Table 5.1: Number of $L_D(\lambda_k)$ models better than true model for each stage.

<table>
<thead>
<tr>
<th></th>
<th>Matched</th>
<th>Mismatched</th>
<th>Corrected</th>
<th>Noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best</td>
<td>8008.2</td>
<td>11560</td>
<td>9219.7</td>
<td>10040</td>
</tr>
<tr>
<td>True</td>
<td>8020.6</td>
<td>11669</td>
<td>9261.6</td>
<td>10079</td>
</tr>
<tr>
<td>Range</td>
<td>12.4</td>
<td>109</td>
<td>41.9</td>
<td>39</td>
</tr>
</tbody>
</table>

Table 5.2: TES error for the estimated best and true $L_D(\lambda_k)$ models for each stage.

The best $\hat{L}_D(\lambda_k)$ model spectra for each of the stages are shown in Figure 5.6. The best $\hat{L}_D(\lambda_k)$ spectra are green and the true $\hat{L}_D(\lambda_k)$ spectra corresponding to the true $L_D(\lambda_k)$ model in the LUT are red. The rest of the models better than the true $\hat{L}_D(\lambda_k)$ are blue. The $L_D(\lambda_k)$ spectra in Figure 5.6a for the matching calibration case are quite similar, which explains the small range of TES errors. Table 5.3 and 5.4 show the angular and distance error between the $\hat{L}_D(\lambda_k)$ spectra and
the true $L_D(\lambda_k)$ for each of the stages. Both errors are zero for the true $\hat{L}_D(\lambda_k)$ because they are identical with the matching calibration. The max angle and distance errors are quite low.

When calibration error was added, $\hat{L}_D(\lambda_k)$ spectra significantly different from $L_D(\lambda_k)$ were found. The best mis-calibrated downsampled $\hat{L}_D(\lambda_k)$ spectra are shown in Figure 5.6b. The number of models decreased to 8. Of the 8 models, only the last two models were consistent between the matching and mismatched calibration models. The angular and distance errors between $\hat{L}_D(\lambda_k)$ and $L_D(\lambda_k)$ increased significantly. Sensor calibration correction removed the two highest radiance models from the mis-calibration models. The remaining $\hat{L}_D(\lambda_k)$ models can be seen in Figure 5.6c.

The angular and distance errors between $\hat{L}_D(\lambda_k)$ and $L_D(\lambda_k)$ decreased close to their original values. Adding sensor noise to the ground radiances had little effect on the $\hat{L}_D(\lambda_k)$ spectra as shown in Figure 5.6d.

<table>
<thead>
<tr>
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<th>Mismatched</th>
<th>Corrected</th>
<th>Noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best</td>
<td>0.86</td>
<td>4.58</td>
<td>2.74</td>
<td>2.74</td>
</tr>
<tr>
<td>True</td>
<td>0</td>
<td>1.37</td>
<td>0.17</td>
<td>0.14</td>
</tr>
<tr>
<td>Max</td>
<td>1.27</td>
<td>5.76</td>
<td>2.74</td>
<td>4.21</td>
</tr>
</tbody>
</table>

Table 5.3: Angular Error (Degrees) between the true $L_D(\lambda_k)$ model and the estimated best and true models for each stage.

<table>
<thead>
<tr>
<th></th>
<th>Matched</th>
<th>Mismatched</th>
<th>Corrected</th>
<th>Noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best</td>
<td>193.05</td>
<td>762.93</td>
<td>467.87</td>
<td>467.93</td>
</tr>
<tr>
<td>True</td>
<td>0</td>
<td>76.76</td>
<td>9.60</td>
<td>7.70</td>
</tr>
<tr>
<td>Max</td>
<td>217.25</td>
<td>1034.2</td>
<td>467.87</td>
<td>754.23</td>
</tr>
</tbody>
</table>

Table 5.4: Distance Error between the true $L_D(\lambda_k)$ model and the estimated best and true models for each stage.

5.3.2 Ground Temperature Estimates

The temperature estimate errors for each of the stages are shown in Figure 5.7. Each of the figures shows the temperature estimate errors for the $\hat{L}_D(\lambda_k)$ models corresponding to each stage and all the ground radiance spectra. The ground radiance spectra are grouped into 3 sets of 5 by their emissivities, where each set has temperatures 285 K - 305 K in 5 K steps. Similar to the $\hat{L}_D(\lambda_k)$ model spectra, the temperature errors corresponding to the best $\hat{L}_D(\lambda_k)$ spectra are green and red for those corresponding to the true $\hat{L}_D(\lambda_k)$. The rest of the models in-between are blue. The magenta
CHAPTER 5. IN-SCENE LWIR DOWNWELLING RADIANCE ESTIMATION

Figure 5.6: Best $L_D(\lambda_k)$ models.

The black lines are the initial ground temperature estimates using the maximum brightness temperature of the ground radiance. The black lines are the initial temperature estimates for the true $L_D(\lambda_k)$ model using the method discussed in Section 4.1.1 that compares the height of reflected gas features to the feature in the $\hat{L}_D(\lambda_k)$ model. The average temperature errors of the 5 spectra for each emissivity spectrum are shown in Table 5.5 for the best and true $\hat{L}_D(\lambda_k)$ models.

For all the stages there was a pattern where the temperature error increased with the true temperature of the ground radiance spectrum. The temperature errors for the matching calibration case are shown in Figure 5.7a. Due to the similarity of the $\hat{L}_D(\lambda_k)$ spectra, the temperature errors for each $\hat{L}_D(\lambda_k)$ model were nearly identical. The temperature errors were always under 1.5 K
with averages less than 0.5 K. Ground radiance spectra simulated with Sig 2, the highest emissivity spectrum, had the lowest error. The feature based initial temperature estimates remained below 2 K and were significantly better than the estimates using the maximum brightness temperature. The temperature error increased significantly when calibration error was added, as shown in Figure 5.7b. The average errors in Table 5.5 increased by over an order of magnitude for the true model. The feature based initial temperature estimates still remained below 2 K, and were better than the final estimates. The sensor calibration correction was able to correct the temperature estimates with errors within -0.5 K for the true model, where all the estimates were too low. The feature based initial temperature estimates were nearly identical to the initial estimates for the matching calibration. Sensor noise had little effect on the temperature error other than adding a slight randomness.

<table>
<thead>
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<th>Corrected</th>
<th>Noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sig 1</td>
<td>Sig 2</td>
<td>Sig 3</td>
<td></td>
</tr>
<tr>
<td>Best</td>
<td>0.37</td>
<td>0.11</td>
<td>0.43</td>
</tr>
<tr>
<td>True</td>
<td>0.35</td>
<td>0.10</td>
<td>0.41</td>
</tr>
<tr>
<td>Sig 1</td>
<td>Sig 2</td>
<td>Sig 3</td>
<td></td>
</tr>
<tr>
<td>Sig 1</td>
<td>1.25</td>
<td>0.56</td>
<td>3.11</td>
</tr>
<tr>
<td>Sig 2</td>
<td>-1.52</td>
<td>-0.98</td>
<td>-1.66</td>
</tr>
<tr>
<td>Sig 3</td>
<td>-1.53</td>
<td>-0.82</td>
<td>-1.47</td>
</tr>
<tr>
<td>Sig 1</td>
<td>Sig 2</td>
<td>Sig 3</td>
<td></td>
</tr>
<tr>
<td>Sig 3</td>
<td>3.67</td>
<td>1.95</td>
<td>5.91</td>
</tr>
<tr>
<td>Sig 2</td>
<td>-0.46</td>
<td>-0.36</td>
<td>-0.34</td>
</tr>
<tr>
<td>Sig 3</td>
<td>-0.34</td>
<td>-0.12</td>
<td>-0.01</td>
</tr>
</tbody>
</table>

Table 5.5: Average Temperature Error (K)

5.3.3 Emissivity Estimates

The emissivity estimates with the best $\hat{L}_D(\lambda_k)$ for each of the stages are shown in Figure 5.8. The three truth emissivity spectra are red, and the estimates are blue. The average angular and distance emissivity errors of the 5 spectra for each emissivity spectrum are shown in Tables 5.6 and 5.7 for the best and true $\hat{L}_D(\lambda_k)$ models. The emissivity estimates for the matching calibration in Figure 5.8a are below the truth. The temperatures were as close to the truth as the true $\hat{L}_D(\lambda_k)$, so the difference in emissivity is caused by the slight shape and height difference between the best $\hat{L}_D(\lambda_k)$ and $L_D(\lambda_k)$. The effects of mismatched calibration are evident in Figure 5.8b from the roughness of the emissivity spectra. The temperature estimates and $\hat{L}_D(\lambda_k)$ were above the truth lowering the emissivity estimates. The sensor calibration correction was able to correct the $L_D(\lambda_k)$ mismatch and give the emissivity estimates in Figure 5.8c that were close to the matching calibration estimates. The sensor noise added to the ground radiance spectra was transferred to the emissivity estimates in Figure 5.8d but the overall shapes remained the same.

The emissivity estimates with the true $\hat{L}_D(\lambda_k)$ for each of the stages are shown in Figure 5.9. With the true $\hat{L}_D(\lambda_k)$, the emissivity estimates are significantly closer to the truth. Mismatched calibration added roughness to the emissivity estimates shown in Figure 5.9b. TES failed giving
temperature estimates several degrees above the truth which lowered the emissivity estimates. The sensor calibration correction was able to correct the $L_D(\lambda_k)$ mismatch and give the emissivity estimates in Figure 5.9c that were close to the matching calibration estimates. The estimates were slightly above the truth due to the temperature estimates being slightly below the truth. The sensor noise added to the ground radiance spectra was transferred to the emissivity estimates in Figure 5.9d, but the overall shapes remained the same.

The optimum emissivity estimates with the true $\hat{L}_D(\lambda_k)$ models of each stage were determined by calculating the emissivities with the correct temperatures of each ground radiance spectrum and the true $\hat{L}_D(\lambda_k)$ model. By calculating the emissivities with the correct temperature, the emissivity estimates are free of TES errors. The calculated emissivities for all the stages excluding the matching calibration are shown in Figure 5.10. Figure 5.10a show the true $\hat{L}_D(\lambda_k)$ models for each of the stages. Except for the mismatched calibration case in Figure 5.10b where TES failed, the estimated and calculated emissivities are close to each other. The average angular and distance emissivity errors of the 5 calculated emissivity spectra for the 5 ground radiance spectra made for each emissivity signature are shown in Tables 5.6 and 5.7.

<table>
<thead>
<tr>
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<th>Mismatched</th>
<th>Corrected</th>
<th>Noise</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sig 1</td>
<td>Sig 2</td>
<td>Sig 3</td>
</tr>
<tr>
<td>Best</td>
<td>0.89</td>
<td>0.47</td>
<td>1.23</td>
</tr>
<tr>
<td>True</td>
<td>0.11</td>
<td>0.03</td>
<td>0.14</td>
</tr>
<tr>
<td>Correct Temp</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

Table 5.6: Average Angular Emissivity Error (Degrees)

<table>
<thead>
<tr>
<th>Matched</th>
<th>Mismatched</th>
<th>Corrected</th>
<th>Noise</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Sig 1</td>
<td>Sig 2</td>
<td>Sig 3</td>
</tr>
<tr>
<td>Best</td>
<td>0.25</td>
<td>0.15</td>
<td>0.28</td>
</tr>
<tr>
<td>True</td>
<td>0.06</td>
<td>0.02</td>
<td>0.07</td>
</tr>
<tr>
<td>Correct Temp</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

Table 5.7: Average Distance Emissivity Error

5.4 Best Model Errors for Individual Spectra

The correct model was not found when the overall smoothing error was minimized for all the spectra. The best model was determined for each individual signature to determine if specific characteristics of the ground radiance spectra caused an incorrect model to provide a minimum error.
CHAPTER 5. IN-SCENE LWIR DOWNWELLING RADIANCE ESTIMATION

Figures 5.11 and 5.12 show the angle and distance errors of the best models for each individual spectrum respectively. Signatures 1 and 2 found the same model except for their ground spectra at the coldest temperature. The correct model was only found with the coldest ground spectrum made with signature 2. Ground Spectra made with signature 3, the roughest emissivity spectrum, found models with the largest errors. The large smoothing errors of the signature 3 spectra caused the best overall model to have a higher error. When using in-scene spectra to determine the downwelling radiance, it is important that only spectra with smooth emissivities are used. The large smoothing errors from rough spectra will cause an error in determining the correct model.

5.5 Summary

The LUT based method of finding the atmospheric parameters of a scene was tested. The test was accomplished with ground radiance spectra, to remove the extra unknowns added from atmospheric compensation. The goal was to find the correct downwelling radiance model used to simulate ground radiance spectra from a LUT of downwelling radiance models. It was found that the true $\hat{L}_D(\lambda_k)$ model did not provide emissivity estimates with the minimum TES error. However, the best $\hat{L}_D(\lambda_k)$ model was still within $3^\circ$ of the $L_D(\lambda_k)$, and provided temperature estimates within 2 K and emissivity estimates within $3^\circ$ of the truth. It was shown how wavelength calibration error could cause TES to fail, but that a majority of the mismatch could be removed with a sensor calibration correction algorithm returning the results close to the originals. It was found that ground radiance spectra built with the roughest emissivity spectrum had the most difficulty determining the correct downwelling model, meaning that ground radiance spectra should be tested before being used to determine the correct model.
CHAPTER 5. IN-SCENE LWIR DOWNWELLING RADIANCE ESTIMATION

Figure 5.7: Ground temperature estimates of ground radiance spectra with corresponding best $L_D(\lambda_k)$ models.
CHAPTER 5. IN-SCENE LWIR DOWNWELLING RADIANCE ESTIMATION

Figure 5.8: Emissivity estimates from ground radiance spectra with best $L_D(\lambda_k)$ models.
CHAPTER 5. IN-SCENE LWIR DOWNWELLING RADIANCE ESTIMATION

Figure 5.9: Emissivity estimates from ground radiance spectra with true $L_D(\lambda_k)$ models.
CHAPTER 5. IN-SCENE LWIR DOWNWELLING RADIANCE ESTIMATION

Figure 5.10: Calculated Emissivities using the true ground temperatures and true $L_D(\lambda_k)$ model of each stage
FIGURE 5.11: Angle error for best model for each individual signature.

FIGURE 5.12: Distance error for best model for each individual signature.
Chapter 6

Atmospheric Mismatch Effects on Temperature Emissivity Separation

The goal of any atmospheric compensation and temperature emissivity separation system is to first find the correct atmospheric parameters, and then use them to find the emissivity of each pixel in the scene. The atmospheric parameters are found by determining the atmospheric model that provides the smoothest emissivity spectra for a set of reflective pixels.

To understand this process it is important to know how sensitive the system is to errors in the atmospheric parameters. All three atmospheric parameters have to work together to provide believable TES results. Even if an atmospheric model provides accurate atmospheric compensation for the atmosphere below the sensor, the same model may not contain the correct downwelling radiance for the entire atmosphere.

There may not necessarily be a single unique atmospheric model that provides believable TES results. Understanding the atmospheric parameter space that provides believable TES results will provide a way to model the range of temperature and emissivity errors that can be expected.

The chapter is organized as follows. In Section 6.1 a study of atmospheric parameter mismatch on temperature and emissivity results is accomplished with the purpose of understanding the sensitivity of the system. Section 6.2 uses the atmospheric compensation model with ISAC to understand the atmospheric parameter space that provides believable temperature and emissivity results.
6.1 TES Atmospheric Model Mismatch Effects

In this section we study how atmospheric model mismatch affects the results for the TES algorithm that uses boxcar averaging and minimizes the radiance smoothing error. At-aperture radiance spectra were simulated with constant emissivity spectra of \( \epsilon_G(\lambda_k) \) of 1, 0.8, and 0.6 at ground temperatures of 282.94 K to 302.94 K in 5 K increments. The TUD model in Figure 2.5 generated with MODTRAN using the Mid-Latitude Summer atmospheric profiles with a water multiplier of 0.75, an ozone multiplier of 1, and at an altitude of 0.5 km was used to add atmospheric effects. TES was applied to the spectra using atmospheric models with water multipliers of 0.625 to 0.875 in 0.025 increments, with the goal of observing how small water multiplier mismatch affected the temperature and emissivity results. Figure 6.1 shows the transmissions of the TUD models with varying water multipliers.

![Figure 6.1: Transmissions for atmospheric models with water multipliers from 0.625 to 0.875 in 0.025 increments.](image)

Figure 6.1: Transmissions for atmospheric models with water multipliers from 0.625 to 0.875 in 0.025 increments.

Figure 6.2 shows the temperature errors versus temperature for the various at-aperture radiance spectra with the three \( \epsilon_G(\lambda_k) \) using the different atmospheric models. For the at-aperture radiance spectra with blackbodies, all the atmospheric models have a minimum temperature error at 292.94 K near the apparent atmospheric temperature. As the emissivity decreases, the temperature at which the minimum occurs increases. The temperature errors increase with increasing water multiplier mismatch and decreasing emissivity.

Figure 6.3 shows the SSE of the emissivity estimates versus temperature for various at-aperture radiance spectra. As expected the emissivity errors increase with increasing water multi-
CHAPTER 6. ATMOSPHERIC MISMATCH EFFECTS ON TES

Figure 6.2: Temperature errors for at-aperture radiance spectra of varying temperatures and emissivities using atmospheric models of different water multipliers.

Figure 6.3: Emissivity SSE for at-aperture radiance spectra of varying temperatures and emissivities using atmospheric models of different water multipliers.

plier mismatch and decreasing emissivity. The emissivity errors tend to be lower for atmospheric models that have water multipliers less than the truth. In addition, the temperature at which the minimum temperature error occurs does not match with the temperature with the minimum emissivity error.

Figures 6.4 and 6.5 show the estimated emissivity spectra for the at-aperture radiance spectra at different temperatures using the atmospheric models with water multipliers of 0.625 and 0.875 respectively. The mismatched water multipliers cause a shifting of the emissivity spectra and an increase in the apparent atmospheric features. These errors increase with decreasing emissivity,
and appear to be greater for the colder at-aperture radiance spectra. The direction of the spectral error depends on whether the model multiplier is greater or less than the truth.

Figures 6.6 and 6.7 show the estimated emissivity spectra for the at-aperture radiance spectra at ground temperatures of 282.94 K and 302.94 K respectively using the atmospheric models with water multipliers between 0.625 and 0.875. The shifting of the mismatched water multipliers increases with decreasing emissivity. There are larger residual atmospheric features for the lower temperature emissivity spectra in Figure 6.6.

It was shown that even small mismatches in the shape and magnitude of atmospheric
parameters caused by a water multiplier error can cause large temperature and emissivity errors. Even when the temperature that provides the smoothest emissivity spectrum is found, the resulting emissivity spectrum will have prominent residual atmospheric features. This means that there are a very small number of models that will provide believable emissivity spectra.


6.2 TES Atmospheric Parameter Space

When studying the TES atmospheric parameter space, it is easier to separate the atmospheric compensation and TES processes. For high emissivity pixels, the downwelling radiance is insignificant, and one is trying to find atmospheric parameters that provide a smooth blackbody like spectrum. TES is merely finding the temperature that provides the observed blackbody like spectrum. Using ISAC, atmospheric parameters can be found that provide smooth blackbody like spectra. In Section 3.10 it was shown that realistic ground radiance spectra could be obtained with multiple ISAC atmospheric parameters. ISAC parameters with magnitude alterations, and alterations in shape from the shape of the ground emissivity reference both provided realistic ground radiances. This shows the span of possible atmospheric parameters that provide realistic ground radiances after atmospheric compensation.

For TES to work on low emissivity pixels with the ISAC atmospheric parameters, a corresponding downwelling radiance is required. The required corresponding downwelling radiance was determined by running AC on the at-aperture radiance of a perfect reflector. The downwelling radiance for the assumed ISAC atmosphere can be modeled by substituting $\epsilon_G(\lambda_k) = 0$ into Eq. (3.30a) so that

$$L_D(\lambda_k) = \left[ \frac{L_{Dr}(\lambda_k)\tau(\lambda_R)}{\tau(\lambda_k)} + C_E(\lambda_k) \right] \frac{\epsilon_R(\lambda_R)B_{\Delta x}(\lambda_k)}{\epsilon_R(\lambda_k)\tau_M(\lambda_R)} + \frac{L_{\Delta y}(\lambda_k)}{\tau_S(\lambda_k)} - L_{\Delta x}(\lambda_k)$$

TES can then be done on the estimated ground radiance using the modeled downwelling radiance. The estimated emissivities are then

$$\hat{\epsilon}_G(\lambda_k) = \frac{\hat{L}_G(\lambda_k) - \hat{L}_D(\lambda_k)}{B(\lambda_k, \hat{T}_G) - L_D(\lambda_k)}$$

$$= \epsilon_G(\lambda_k) \frac{\tau(\lambda_R)}{\tau_M(\lambda_R)} \frac{\epsilon_R(\lambda_R)B_{\Delta x}(\lambda_k)}{\epsilon_R(\lambda_R)} \hat{\epsilon}_{AC}(\lambda_k, \hat{T}_G)$$  \hspace{1cm} (6.2a)

$$\hat{\epsilon}_{AC}(\lambda_k, \hat{T}_G) = \frac{B(\lambda_k, \hat{T}_G) - \frac{L_{Dr}(\lambda_k)}{\tau(\lambda_k)}}{B(\lambda_k, \hat{T}_G) - L_D(\lambda_k)}$$

$$= \frac{B(\lambda_k, \hat{T}_G) - \frac{L_{Dr}(\lambda_k)}{\tau(\lambda_k)}}{B(\lambda_k, \hat{T}_G) - L_D(\lambda_k)} + \frac{B(\lambda, \hat{T}_G) - B(\lambda, \hat{T}_G)}{B(\lambda_k, \hat{T}_G) - L_D(\lambda_k)}$$  \hspace{1cm} (6.2b)

There is a mismatch between the downwelling radiance in the numerator and the denominator. Similar to the TES performance prediction model the emissivity calculation can be separated into two parts. If the correlation between these parts are high, a temperature error will compensate for the mismatch error and result in a smooth realistic result.

117
To determine how well a temperature estimation error could compensate for the downwelling radiance mismatch, the temperature estimate which provided the smoothest $\hat{\epsilon}_{AC}(\lambda_k, \hat{T}_G)$ was found. Figure 6.8 shows the smoothing $\hat{\epsilon}_{AC}(\lambda_k, \hat{T}_G)$ results for several cases. The first column corresponds to the results in Figure 3.29 where the ISAC parameters were determined from blackbodies. The ISAC parameters were unscaled, scaled with the true atmospheric model with a water multiplier of 0.75, and scaled with a water multiplier of 1.0. The $\hat{L}_D(\lambda_k)$ correspond to the spectra for $\epsilon_G(\lambda_k) = 0$ in the third column of Figure 3.29. The third column corresponds to the results in Figure 3.30 where ISAC parameters were determined using grass. The middle column is for ISAC parameters found with an $\epsilon_R(\lambda_k) = 0.95$. The first row shows $\hat{\epsilon}_{AC}(\lambda_k, T_G)$ using the true ground radiance for the 5 corrected ground radiances with the different ground temperatures processed using the ISAC parameters for each scaling. The downwelling mismatch is evident by the noticeable atmospheric features that are present. The second row shows the $\hat{\epsilon}_{AC}(\lambda_k, \hat{T}_G)$ for the $\hat{T}_G$ that provided the smoothest estimates. It can be observed that all the $\hat{\epsilon}_{AC}(\lambda_k, \hat{T}_G)$ are smooth, and that the estimates remain consistent despite the ground temperature of the spectrum. The third column shows the ground temperature estimation error using ISAC parameters with different water multiplier scaling factors. A water multiplier of 0 corresponds to the unscaled ISAC parameters.

Figure 6.9 shows the ground temperature estimation errors for corrected ground radiance spectra of varying temperatures and emissivities using ISAC parameters derived from blackbodies and scaled using atmospheric models with varying water multipliers. As expected, the temperature errors for the scaling with the true atmospheric model are 0. The unscaled and water multiplier of 1 have temperature errors between 0.5 and -0.5, have opposite signs, and switch sign at the apparent atmospheric temperature. Interestingly, the ground temperature errors remain consistent despite the $\epsilon_G(\lambda_k)$ of the spectrum.

Figure 6.10 shows the estimated emissivity spectra for corrected ground radiance spectra of varying temperatures and emissivities using unscaled ISAC parameters derived from blackbodies. The estimated emissivity spectra show nearly 0 error, and change very little despite the ground temperature. The downwelling radiance mismatch error was compensated by the ground temperature error. The estimated emissivities were nearly identical using the scaled ISAC parameters. The temperature errors for the different cases compensate for the scaling errors to retrieve the same emissivity spectra.

Figure 6.11 shows the ground temperature estimation errors for corrected ground radiance spectra of varying temperatures and emissivities using ISAC parameters derived from grass and scaled using atmospheric models with varying water multipliers. The temperature errors range
between -0.2 and -1.4. The temperature errors for the scaling with the true model had temperature errors that changed the least with the ground temperature. The unscaled and water multiplier of 1 where on opposite sides of the true model results, and switched sides near the apparent atmospheric temperature. Despite using a non-blackbody material as the ground reference emissivity the ground temperature errors remained consistent despite the $\epsilon_G(\lambda_k)$ of the spectrum.

Figure 6.12 shows the estimated emissivity spectra for corrected ground radiance spectra of varying ground temperatures and emissivities using unscaled ISAC parameters derived from grass. The emissivity estimates are nearly identical for the 5 ground temperatures between 282.94 K to 302.94 K. For the constant emissivity spectra, the emissivities had errors that matched the shape of $\epsilon_R(\lambda_R)/\epsilon_R(\lambda_k)$ for grass. The emissivity estimates were nearly identical when the scaled ISAC parameters derived form grass were used. The temperature errors for the different scaling cases compensate for the scaling errors to retrieve the same emissivity spectra.

The downwelling radiance is a major component of TES. To determine if the ground temperature error could compensate for further downwelling radiance mismatch, an altered downwelling radiance was created

$$
\hat{L}_{DS}(\lambda_k) = \hat{L}_D(\lambda_k) - \left[ B(\lambda_k, T_1) - B(\lambda_k, T_2) \right], \quad T_1 > T_2
$$

(6.3)

where $T_1$ and $T_2$ are two temperatures that give the desired downward shift of the downwelling radiance. It was hoped that since the temperature induced emissivity component consist of a difference of two blackbodies, it would be able to compensate for an additional blackbody difference shift. With the altered downwelling radiance, Eq. (6.2b) can be written as

$$
\hat{\epsilon}_{GS}(\lambda_k) = \epsilon_G(\lambda_k) - \frac{\tau(\lambda_R)}{\tau_M(\lambda_R)} \left[ \frac{\epsilon_R(\lambda_R)B_{\Delta x}(\lambda_k)}{\epsilon_R(\lambda_k)} \right] \hat{\epsilon}_{AS}(\lambda_k, \hat{T}_G) + \frac{B(\lambda, T_1) - B(\lambda, T_2)}{B(\lambda_k, \hat{T}_G) - \hat{L}_{DS}(\lambda_k)}
$$

(6.4a)

$$
\hat{\epsilon}_{AS}(\lambda_k, \hat{T}_G) = \frac{B(\lambda_k, T_G) - \frac{\hat{L}_{DS}(\lambda_k)}{\tau(\lambda_k)}}{B(\lambda_k, \hat{T}_G) - \hat{L}_{DS}(\lambda_k)}
$$

(6.4b)

where the second component is the emissivity component from the blackbody difference shift. Figure 6.13 shows the $\hat{L}_D(\lambda_k)$ found using the unscaled ISAC parameters derived from blackbodies, and the $\hat{L}_{DS}(\lambda_k)$ found by subtracting the difference between two blackbodies at 290 K and 273 K.

The ability of the temperature induced emissivity error to compensate for the additional downwelling radiance mismatch from the blackbody difference shift was studied by finding the temperature estimate which provided the smoothest $\hat{\epsilon}_{GS}(\lambda_k, \hat{T}_G)$ for the same corrected ground radiance spectra in Figure 6.8. Figure 6.14 show the smoothest emissivity estimates and temperature
errors using the blackbody difference shift of 290 K and 273 K. The columns correspond to the columns in Figure 6.8. Despite the large decrease in the downwelling radiance estimates, the emissivity estimates remained smooth, showing compensation from the temperature induced emissivity error. Additional evidence of compensation for the smaller downwelling radiance in shown by the increased temperature errors.

The atmospheric parameter space that provides smooth realistic emissivity estimates can be explained starting with the atmospheric parameters found with ISAC using blackbodies. The ISAC parameters found with blackbodies have the same shape as the true atmospheric parameters. The transmission and upwelling radiance can be scaled and provide similar ground radiances. Changing the shape of the ground emissivity reference allows for changes in the shape of the transmission and upwelling radiance, and these shape changes are transfered to the ground radiance. When the changes to the ISAC parameters are transfered to the downwelling radiance, TES provides smooth emissivities that are effected by the ground emissivity reference. It was shown that the downwelling radiance could be shifted down resulting in an additional temperature estimation error. All these possible changes in the atmospheric parameters make it possible for atmospheric models other than the truth to provide smooth realistic emissivities. When one uses a LUT of atmospheric parameters, the LUT may not contain the true atmosphere. Depending on the scope of the LUT, it may contain an atmosphere that provides realistic but incorrect results.

6.3 TES with True Downwelling Radiance after Atmospheric Compensation

During a data collect, target emissivity spectra can be calculated from the target’s measured ground radiance and a measured downwelling radiance spectrum. The calculated target emissivity spectra can then be used for ground truth. When TES is done at the ground radiance level after AC, the measured downwelling radiance from the ground can not simply be used. Even when AC is done perfectly and the measured downwelling radiance spectrum has the same sensor calibration as the airborne sensor, the band-averaging error caused by $L_{D_\tau}(\lambda_k)/\tau(\lambda_k) \neq L_{D_\tau}(\lambda_k)$ is significant enough where atmospheric features can not be removed. The measured downwelling radiance can not be used to create a $L_{D_\tau}(\lambda_k)$ to avoid the band-averaging error because a high resolution $\tau(\lambda_k)$ is unavailable. In addition, the measured downwelling radiance will have calibration mismatch with the sensor. Figure 6.15 shows the TES emissivity estimates with the true downwelling radiance after
CHAPTER 6. ATMOSPHERIC MISMATCH EFFECTS ON TES

AC with the true atmospheric parameters. The atmospheric features are visible in the emissivity estimates, and increase in size as the reflected component becomes larger. The measured downwelling radiance is useful to use as a reference. However, using it to evaluate TES would require calibration correction, accurate AC, and high resolution transmission and downwelling radiance spectra. Obtaining all this information is difficult.

6.4 Summary

When TES is done on an at-aperture radiance spectrum, it is important to have accurate atmospheric parameter estimates. The effect of using an atmospheric TUD model with an inaccurate water multiplier on TES was shown. As the water multiplier deviated from the true multiplier, atmospheric compensation was unable to remove atmospheric effects and a temperature could not be found to supply a smooth emissivity without residual atmospheric effects. This showed the sensitivity of TES to having an atmospheric model with accurate shape and magnitude.

The effects of the ISAC error on TES were explained using the numerical model developed in Chapter 3. The ground radiance from a perfect reflector was used as the downwelling radiance. It was shown that the atmospheric shape errors from fitting with a non-blackbody $\epsilon_G(\lambda_k)$ were transferred to the emissivity estimates, and that emissivity estimates were unaffected by scaling errors. The effects of scaling errors on the emissivity estimates were compensated by increased temperature errors. The link between the magnitude of the downwelling radiance and the temperature estimate of TES was shown by the ability of temperature errors to compensate for shifts in the downwelling radiance. The ISAC numerical model shows ways that the true atmospheric parameters can be affected and still supply believable smooth emissivity estimates.
CHAPTER 6. ATMOSPHERIC MISMATCH EFFECTS ON TES

Figure 6.8: Compensation of $\hat{L}_D(\lambda_k)$ mismatch with a ground temperature error, when the reflected ground radiance of a reflector is used.
CHAPTER 6. ATMOSPHERIC MISMATCH EFFECTS ON TES

Figure 6.9: Temperature errors for corrected ground spectra of varying temperatures and emissivities using ISAC parameters derived from blackbodies and scaled using atmospheric models with varying water multipliers.

Figure 6.10: Emissivity spectra for corrected ground spectra of varying temperatures and emissivities using unscaled ISAC parameters derived from blackbodies.
CHAPTER 6. ATMOSPHERIC MISMATCH EFFECTS ON TES

Figure 6.11: Temperature errors for corrected ground spectra of varying temperatures and emissivities using ISAC parameters derived from grass and scaled using atmospheric models with varying water multipliers.

Figure 6.12: Emissivity spectra for corrected ground spectra of varying temperatures and emissivities using unscaled ISAC parameters derived from grass.
Figure 6.13: Downwelling radiance spectrum shifted down by the difference between two black-bodies.

Figure 6.14: Emissivity and temperature estimates using shifted downwelling radiance spectrum.
Figure 6.15: Emissivity estimates using the true downwelling radiance after AC with the true atmospheric parameters.
Chapter 7

Analysis of Results with Real Data

In this chapter we process real data with the AC and TES techniques discussed throughout the thesis. A data set was processed and the results are evaluated using truth for the ground and downwelling radiance. AC is evaluated by comparing the corrected ground radiance of a target to its calculated ground radiance. TES is evaluated by comparing the estimated temperatures and emissivities of targets with their corresponding library emissivities and temperature measurements. The commercially available AC and TES algorithm Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes-InfraRed (FLAASH-IR) is also evaluated using the same truth [2]. The errors in the AC and TES results for both algorithms are explained using the developed AC and TES models. The chapter is organized with Section 7.1 describing the AC and TES method we used to process the data. Section 7.2 describes the FLAASH-IR algorithm, and Section 7.3 describes and analyzes the results for the data set.

7.1 Method Used to Process Real Data

Blackbody like pixels were found in a scene by using the OLSTER algorithm discussed in Section 3.5. The “most hits” method described in Section 3.3.2 was used to find a clear reference band and an initial estimate of blackbody-like pixels in the scene. The initial blackbody-like pixels were then used with ISAC to come up with initial estimates of the transmission and upwelling radiance. If the ISAC transmission had a transmission greater than the reference band, ISAC was repeated with the maximum transmission band as the new reference band.

The ISAC transmission and upwelling radiance were then used for the initial AC step of OLSTER. Blackbody pixels were then found by finding the pixels with the highest negative
concavity. ISAC was then used with the blackbody pixels using the previously determined reference band. If an ISAC transmission was greater than the reference band, ISAC was repeated with that as the new reference band. The final ISAC parameters were scaled by using the average $\tau_M(\lambda_R)$ and $L_U(\lambda_R)$ of the best models determined for each blackbody like pixel using the water feature AC technique in Section 3.8.3. The scene was converted to ground radiance using the scaled ISAC parameters, so that the AC could be evaluated.

The temperature and emissivity of each pixel in the scene were then determined using TES with boxcar averaging smoothing to minimize the smoothing error in the radiance domain. A method was not developed to determine the downwelling radiance of the scene, instead the measured downwelling radiance or calculated ground radiance of a reflector was used. The determined emissivities and temperature were then used to evaluate the entire AC TES process.

### 7.2 Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes-InfraRed (FLAASH-IR)

FLAASH-IR is another emissivity smoothness-based automated atmospheric compensation and TES method. TES is performed by finding the temperature that minimizes

$$\sigma^2 = [\tilde{L}_S(\lambda_k)]^2$$

(7.1) where $\tilde{L}_S(\lambda_k)$ is the error between the at-aperture radiance and the smoothed at-aperture radiance defined in Eq. (4.9) and the underline denotes a running average. When the temperature that provides the minimum $\sigma^2$ is found, the corresponding unsmoothed emissivity is used. Effects of uncertainties in wavelength calibration and the instrument function are minimized by using a wide smoothing window of around $\approx 0.3 \, \mu m$ (typically $\approx 7$ channels), or combining this wide smoothing window with 3-channel averaging that is applied to both the unsmoothed and smoothed emissivities before taking the difference. These steps remove the fine spectral features from wavelength miscalibration, so that $\sigma^2$ consists of the coarser spectral features from temperature errors. When TES is used for determining the emissivity and temperature of a pixel, the spectral region from $\approx 9 - 10.2 \, \mu m$ around the ozone feature is used. The presence of this feature correlates with the reflectance of the pixel [2].

FLAASH-IR determines the atmosphere of the scene by creating a set of trial atmospheric spectra by specifying a three-dimensional grid of atmospheric parameters, such as surface air temperature, water vapor column density, and ozone column density scale factors. These parameters
are used to modify a MODTRAN atmospheric model, which may be selected by latitude and season. A TUD LUT is formed, and polynomial fitting is used to interpolate the spectra between grid points. The best-fitting atmospheric model is determined by selecting around 10-20 pixels of varying brightness temperature and spectral shape, where reflective pixels are included. TES is then run on each of the pixels to determine what temperature provides the minimum $\sigma^2$ for each pixel. A three dimensional atmosphere search is conducted using a downhill simplex method to determine the atmosphere that provides the smallest overall $\sigma^2$ for the whole set of pixels. When determining the correct atmosphere, TES uses the full $\approx 8 - 13 \mu m$ atmospheric window to include the large atmospheric water features [2].

### 7.3 Atmospheric Radiation Measurement (ARM) Collect

The test data was collected at the Atmospheric Radiation Measurement facility near Lamont Oklahoma in June of 1997. The site altitude is 1000 ft above sea level, and the cube was collected at a sensor altitude of 5000 ft. The ARM site surfaces consist of various ground covers (e.g., grass, cut grass, pond water, soil, gravel), building roofs, and a variety of emissivity and reflectance panels. The atmospheric and ground truth was taken within 15 minutes of the flight time. The atmospheric truth consisted of a high resolution measurement of the downwelling radiance. The ground truth consisted of a temperature and emissivity measurement of an emissivity panel [25].

Flaash-IR and OLSTER were run on the data cube to determine the transmission and upwelling radiance. Figure 7.1 shows the OLSTER concavity versus ground temperature estimate scatter plot to find the blackbody-like pixels for the final ISAC atmospheric parameters. The blackbody-like pixels found with OLSTER are in red.

The OLSTER ISAC parameters were scaled using the average scaling factor of the best water atmospheric compensation models found for the determined blackbody pixels. Figure 7.2 shows the TUD parameters found with the OLSTER and FLAASH-IR algorithms. The transmission and upwelling radiance are nearly identical before 11 $\mu m$, but show a large shape difference afterwards. The FLAASH-IR parameters are flat, while the OLSTER parameters are slanted. There is a large variation in magnitude between the downwelling radiance. The OLSTER downwelling radiance is the true ground measurement. The overall slope of the upwelling radiances after 11 $\mu m$ roughly matches the corresponding downwelling radiance.

The scaling factor found using the average of the models found with the water feature AC method for the determined blackbody pixels was the only scaling method that provided a believable
CHAPTER 7. ANALYSIS OF RESULTS WITH REAL DATA

Figure 7.1: OLSTER scatter plot used to find blackbody-like pixels.

Figure 7.2: ARM OLSTER and FLAASH-IR TUD Parameters

scaling factor. The water feature AC method was discussed in Section 3.8.3. Figure 7.3 shows the OLSTER transmission scaled using the three scaling methods in blue. The scaled blue spectra are close to their corresponding model transmissions found with AAC and the closest angle. AAC was discussed in Section 3.8.2. While the angle method found a model close in shape to the ISAC transmission, the model transmission was too low. AAC found a transmission model that had a large shape difference from the ISAC transmission. There was a large difference in \( T_r \) between the model and ISAC transmissions. It appears that an accurate model was not present in the LUT.

The quality of the FLAASH-IR and OLSTER atmospheric compensation were tested by
converting the at-aperture radiance spectra of the emissivity panel to ground radiance. The ground radiance spectra were then compared to a calculated ground radiance of the panel. The ground radiance was calculated using the temperature and emissivity of the panel, and the measured downwelling radiance. Figure 7.4 shows a comparison of the atmospheric compensated ground radiances for each method to the calculated truth. The atmospheric compensated ground radiances will have an error from $L_{D_T}(\lambda_k)/\tau(\lambda_k) \neq L_D(\lambda_k)$. This error is more significant below 9 $\mu$m as shown in Figure 3.29 for the perfect reflectors. The OLSTER ground radiance is close to the calculated truth, but deviates below 9 $\mu$m. The FLAASH-IR has a large deviation after 11 $\mu$m which corresponds to the difference in shape of its transmission and upwelling radiance.

We attempted to estimate a possible $\epsilon_R(\lambda_R)$ that could explain the error between the calculated and estimated ground radiance with ISAC. It was assumed that $\epsilon_R(\lambda_R)$ was close to one, and that there was a constant magnitude error for each band. The magnitude error was determined by taking the difference between the estimated and ground radiances at $\lambda_R$. The magnitude error was subtracted from each band of the estimated ground radiance, and the ratio between the shifted and calculated ground radiance was determined to get the general shape of the possible $\epsilon_R(\lambda_R)$. The ratio was multiplied by a single scaler to be on the same scale as the measured grass spectrum of the scene. Figure 7.5 shows a comparison of the measured grass spectrum and the estimated $\epsilon_R(\lambda_R)$. The two are relatively close above 10.5 $\mu$m. The grass has an upward trend before 10.5 $\mu$m that the estimate does not have till 9.5 $\mu$m. This is the location of the ozone feature and the discrepancy can be accounted for by a calibration error of the measured downwelling radiance used to calculate the ground radiance.
7.4 Summary

The OLSTER ISAC method was compared to the LUT based method of FLAASH-IR on a real data set. For the ARM collect, OLSTER and FLAASH-IR provided transmission and upwelling radiance estimates that differed significantly in shape. AC with OLSTER provided a ground radiance estimate for the panel that was closer to the truth, while the FLAASH-IR ground
Figure 7.6: Comparison of ARM FLAASH-IR and OLSTER panel emissivity estimates.

radiance estimate had a shape error from it’s atmospheric estimate errors. The failure of FLAASH-IR can be attributed to the failure of the LUT not containing an accurate model for the scene.

The blackbody assumption used by ISAC for the grass spectra was more accurate than the assumption used by FLAASH-IR. The ISAC model explained how the errors of the blackbody assumption were transferred to the ground radiances. The effects of AC band-averaging errors were also shown by the effects on the emissivity results from using the measured downwelling radiance with the corrected ground radiance. The AC and TES models also provide an explanation of how the shape errors in the FLAASH-IR atmospheric parameters were transferred to its ground radiance and emissivity estimates, and how the downwelling radiance magnitude error was compensated by an increase in its temperature estimate.
Chapter 8

Conclusion

LWIR hyperspectral imaging is used to detect and identify materials on the ground by their emissivity spectra. The emissivity spectra must be retrieved from the measured at-aperture radiance, and the quality of this retrieval determines the final detection and identification performance. The quality of the emissivity estimates depend on the accuracy of the atmospheric model used for atmospheric compensation (AC) and temperature emissivity separation (TES). Determining the transmission, upwelling radiance, and downwelling radiance of a scene along with the temperature and emissivities of each pixel is an extremely difficult problem. AC and TES algorithms make assumptions to limit the number of unknowns and find estimates for each of the variables. It is important to understand how these assumptions affect the final emissivity estimates used for detection. In this thesis, AC and TES algorithms were analyzed and models were developed to explain how the assumptions made by each algorithm affect their final estimates. Since AC is required for TES, the models for the two algorithms were combined to explain how AC errors are transferred to the final emissivity estimates.

The main difficulty in retrieving accurate emissivity spectra comes from finding an accurate atmospheric model for a scene. Together, the atmospheric transmission, upwelling radiance, and downwelling radiance spectra constitute 3 unknowns per each band. These unknowns need to be estimated from the at-aperture radiances of pixels, which each have an unknown temperature and emissivity spectrum. In-scene Atmospheric Compensation (ISAC) is able to retrieve estimates for the transmission and upwelling radiance whose quality depends on the ability to find the best blackbody-like pixels. We determined that the OLSTER ISAC method was capable of determining the best blackbody-like pixels in a scene with a humid atmosphere, compared to other techniques. The atmospheric transmission and upwelling radiance found with OLSTER were compared
CHAPTER 8. CONCLUSION

to parameters determined using the FLAASH-IR LUT approach for a scene containing high quality blackbody-like vegetation pixels. It was observed that the ISAC estimates were more accurate than the FLAASH-IR LUT estimates. We developed a model that explained the accuracy of the ISAC estimates based on the quality of ground blackbodies. The model showed how the blackbody assumption caused the shape of the atmospheric and ground radiance estimates to change based on the ground reference emissivity. The model also showed how scaling errors in correcting for the clear channel assumption caused a magnitude shift in the ground radiance estimates.

A TES performance model was developed to explain the sensitivity of TES techniques, that use the emissivity smoothness assumption, to multiple factors. We determined that the interaction between the emissivity bias error caused by the roughness of an emissivity spectrum interacted with the emissivity error caused by a temperature error. The ability of the temperature induced emissivity error to compensate for the emissivity bias error had the effect of increasing the final temperature and emissivity errors. Factors such as increasing ground temperature and decreasing emissivity caused increasing temperature errors. We studied the effects of band shifting and broadening wavelength calibration errors on TES. These wavelength calibration errors caused atmospheric mismatch errors. It was shown that the upwelling and transmission atmospheric mismatch errors are negatively correlated, and nearly cancel each other out when the emissivity of a material is close to one. As the emissivity decreases the total atmospheric error increases. The transmission error decreases while the upwelling error remains constant, reducing the amount of cancellation. The downwelling radiance error increases as the reflected component of a pixel increases. When the atmospheric mismatch error increases the emissivity bias error, the temperature induced error compensates for a fraction of it. This compensation further increases the temperature and emissivity errors. The band broadening calibration error had an extremely high correlation between its temperature induced and atmospheric errors. This large correlation allowed for more effective temperature induced compensation, causing increased temperature and emissivity errors.

The downwelling radiance is the most difficult atmospheric component to estimate, where the only evidence of it comes from reflective pixels with unknown emissivity. A downwelling radiance estimation technique should be able to find the most reflective pixels in a scene, and provide valid emissivity estimates for these pixels. We showed how using the LUT based method to find the downwelling radiance is affected by TES sensitivity to spectral roughness, and that pixels with rougher emissivities provide more inaccurate estimates. The ISAC model was extended to the downwelling radiance by using a perfect reflector. The model showed how errors in AC were transferred to the downwelling radiance. The estimates of all three atmospheric parameters interact and need
CHAPTER 8. CONCLUSION

to change together accordingly for the recoverability of smooth realistic emissivity spectra.

Lastly, we showed how the ISAC errors explained by the model were transferred to the emissivity and temperature estimates when the ground radiance of a perfect reflector was used as the downwelling radiance. The shape errors caused by the ISAC blackbody assumption were transferred to the emissivity estimates. The emissivity estimates remained constant despite the scaling error changing. The scaling error was compensated by an increase of the temperature induced emissivity error. The link between the magnitude of the downwelling radiance and the temperature estimate of TES was shown by the ability of temperature errors to compensate for shifts in the downwelling radiance by the difference between two blackbodies. In order for a downwelling radiance estimate to supply smooth emissivity estimates the temperature induced emissivity error needs to be able to compensate for the sharp atmospheric errors. The ability for the temperature induced error to compensate for such atmospheric errors makes it difficult to determine the correct atmospheric estimates.

The developed models describe how AC and TES errors affect the final emissivity spectra. Knowledge of possible errors in emissivity spectra can be used to determine how detection and identification performance can be affected. We found that OLSTER found the best blackbody-like pixels, and gave the best transmission and upwelling estimates. Downwelling radiance estimation with a LUT requires that a model for the scenes atmosphere be present. When the correct model is not present, the best model in the LUT will have a mismatch that will affect the emissivity estimates. The effect of this mismatch will become more apparent as the emissivity decreases. The models describe how AC errors should affect the downwelling radiance estimate, and how some downwelling errors can be compensated by TES temperature errors. Understanding the types of downwelling errors that provide valid emissivity estimates gives insight into potential novel techniques, estimation methods, or metrics for improved emissivity retrieval.
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