Thesis Title: Characterization of Libyan Desert in Support of Vicarious Calibration

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CHARACTERIZATION OF LIBYAN DESERT IN SUPPORT OF VICARIOUS CALIBRATION

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Abstract

Thorough calibration of electro-optical sensors being designed for today’s space-based applications is essential to utilize remotely sensed imagery products. A complete sensor calibration provides in-depth understanding of operation and performance, while verifying that the system meets mission standards. Accurate calibration is crucial in order to give the data physical meaning and allow the imagery to be used and compared for a variety of applications. The use of invariant sites for vicarious calibration has become a valuable tool for the changing design and demands of new instruments. Pseudo-invariant calibration sites provide the opportunity to utilize a much larger site to accommodate the full sensor footprint. Characterizing and understanding these sites is key to successful vicarious calibration.

This study focuses on the common pseudo-invariant test site, Libya 4, located in the Saharan desert and two essential atmospheric parameters necessary for characterizing the surface reflectance: column water vapor and aerosol optical depth. These radiometric effects are explored by using a radiative transfer code (e.g., MODTRAN®) to simulate atmospheric changes within realistic environmental ranges and create look up tables to match real world data. We first estimate the water vapor amount in selected data sets using the Continuum Band Interpolated Ratio technique. The aerosol optical depth is then determined using a look up table scheme, with the first
estimations of the water vapor amount as inputs to MODTRAN®. Finally, with the atmospheric parameters determined by this iterative approach, we study the surface reflectance of the test site to be utilized in future calibration.
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Chapter 1

Introduction

The data obtained from hyperspectral imaging contains a wealth of information that must be analyzed and interpreted in order to understand the properties of the ground materials we try to measure and how they relate to the actual measurements produced by the sensor. The fundamental property of characterizing ground surface materials is their reflectance spectra.

In order to correctly calibrate a hyperspectral instrument and ensure data quality, we must understand how the at-aperture radiance spectra measured by the sensor are related to the reflectance spectra of the imaged surface and the effects of atmospheric propagation, solar illumination and sensor structure on this relationship. Characterizing and understanding this relationship using invariant test sites is key to successful calibration when ground truth data are not available. This thesis focuses on a common desert site in Libya with the ultimate goal of retrieving a surface reflectance spectrum by understanding how the radiometric effects relate to variability in the atmosphere.
1.1 Hyperspectral Imaging

The “hyper” in hyperspectral means “beyond,” implying excess and refers to the several hundred narrow and contiguous wavelength bands that a hyperspectral image contains. Because these images are spectrally overdetermined, they produce a substantial amount of spectral information to identify and distinguish spectrally unique materials. Hyperspectral imagery provides the potential for more accurate and detailed information extraction than possible with any other type of remotely sensed data. This information is characterized by a material’s reflectance spectrum, which describes the proportion of reflected ratio to incident radiation and solar illumination at each wavelength.

The collection of spectral reflectance information in hundreds of spectral bands for each pixel requires the design of hyperspectral imaging sensors that consist of an imaging system and an imaging spectrometer. The imaging system performs spatial sampling by collecting the radiant flux from an area of the earth’s surface, while the spectrometer measures the radiance at a number of spectral bands with a certain accuracy. An example of this type of hyperspectral imaging system is shown in Figure 1.1. Solar radiation is emitted by the sun, attenuated by the atmosphere and reflected and/or absorbed by the surface of interest before propagating back through the atmosphere to be measured by the hyperspectral sensor. The at-sensor radiance is indicative of the actual surface reflectance but the information in certain bands, such as those corresponding to water, oxygen and carbon dioxide absorption bands, is degraded by the atmosphere. These effects must be accounted for in any attempt to extract the material properties of the surface of the Libyan desert.
1.2 Hyperspectral Imaging Sensors

Most multispectral imagers measure radiation reflected from a surface at a few widely, separated wavelength bands. Hyperspectral sensors, on the other hand, collect simultaneously digital images at a series of narrow and contiguous wavelength bands of the ultraviolet, visible, and infrared regions of the electromagnetic spectrum.

This type of detailed spectrum can provide much more information about the surface than a multispectral spectrum, as seen in Figure 1.2 where data from the hyperspectral imager Hyperion is compared with the multispectral Landsat imager. Hyperspectral imagers split the spectrum into many separate, narrow channels on a pixel-by-pixel basis, which provides the ability to understand a material or area’s composition through spectral signature discrimination more effectively than is possible.
Figure 1.2: Hyperion (green line) provides a more accurate depiction than the discrete bands of Landsat (blue dots). Adapted from [21].

Two common approaches to hyperspectral data collection are illustrated in Figure 1.3. In the push-broom design, an entire line of data is imaged onto the focal plane and sampled simultaneously, where the reflected light is spectrally dispersed perpendicular to the long axis of the slit and imaged onto a two dimensional array. The first dimension provides the spatial sampling and the second provides the spectral sampling [25]. The widely used whisk-broom sensors use a method of data collection that is analogous to using a broom to sweep dust (data) into a dust pan (data stream). The sensor employs a rotating mirror to scan the terrain across the satellite’s path, reflecting light into a single detector which collects data one pixel at a time. Each ground resolution element is sensed in as many spectral bands as there are detector elements in the linear array.

Hyperspectral imaging sensors, have a sufficient number of spectral bands to allow
1.3 HSI System Calibration

In order to obtain the maximum amount of information from a hyperspectral imaging system, the imager needs to be very accurately calibrated. A key to the continuation of quantitative data from hyperspectral imaging systems is the radiometric understanding of the sensors being used. An accurate calibration provides the ability to derive reflectance signatures using model based inversions of the atmosphere. The illustration in Figure 1.4 highlights the progression of data processing. The major drive of this thesis is to convert raw hyperspectral at-sensor radiance to apparent
surface reflectance and ultimately to surface reflectance by removing the atmospheric effects and any sensor system-induced electronic anomalies. The retrieved surface reflectance can then be utilized to build an accurate at-sensor radiance model of the site of interest.

Figure 1.4: The processing steps taken to convert the digital number data stored by the sensor to surface reflectance. The DNs must first be calibrated to calculate at-sensor radiance and then corrected for atmospheric effects.

1.4 Thesis Outline

Chapter 2 introduces in detail the hyperspectral imaging sensor, Hyperion. Data products from hyperspectral sensors warrant a high degree of calibration, not only over the lifetime of a particular sensor but over several generations of the sensor to allow for comparison of results. The general calibration concept is explained and
several methods of sensor calibration are emphasized. This chapter also provides the background to atmospheric correction/compensation which is critical for accurate calibration.

Chapter 3 presents an in-depth look at the vicarious calibration method of radiometric calibration as well as develops the techniques and algorithms used to analyze instrument performance. In particular, the reflectance-based approach of vicarious calibration is considered.

Chapter 4 examines the first step of atmospheric compensation and introduces the theory behind column water vapor retrieval and its implementation for hyperspectral instruments. There are several techniques used today to estimate the amount of water present in the atmosphere. Chapter 4 focuses on a specific differential absorption technique and discusses the results obtained by this water retrieval approach.

Chapter 5 describes the concept of aerosol retrieval to be used as the second step to atmospheric compensation. A look-up table approach for the retrieval of aerosol properties, specifically aerosol optical depth/visibility, is discussed and results of the algorithm are presented.

Chapter 6 considers the approach taken to retrieve the surface reflectance of the pseudo-invariant test site from the estimated atmospheric parameters. The results of the retrieval from Hyperion data are presented and discussed.

Finally, Chapter 7 offers conclusions about the atmospheric compensation and surface reflectance characterization and presents suggestions for future work.
Chapter 2

Background

We begin our study by first discussing the fundamentals of hyperspectral instrument calibration and data analysis. We introduce the hyperspectral instrument Hyperion that will provide the data used throughout this analysis. Next we address the concept of calibration as it relates to hyperspectral imagers and the test site that becomes the focus of this study. The basics of atmospheric compensation are examined from a hyperspectral perspective and the radiative transfer code used to determine at-sensor radiance is explained.

2.1 Hyperion

The Hyperion Imaging Spectrometer is one of three principal instruments aboard the EO-1 spacecraft. It provides high quality calibrated data that can support evaluation of hyperspectral technology for Earth observing missions [22]. The instrument images a 7.5 km by 100 km surface with a nadir resolution of 30 m. There are two focal plane arrays (FPAs), the first covering the visible and near infrared (VNIR) while the second covers the short wave infrared (SWIR) bands. The optical path is split using a dichroic
**Table 2.1: The specifications and imagery features of Hyperion.**

<table>
<thead>
<tr>
<th>Specification</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spatial Resolution</td>
<td>30 m</td>
</tr>
<tr>
<td>Swath Width</td>
<td>7.75 km</td>
</tr>
<tr>
<td>Image Format</td>
<td>20 x 7.5 km</td>
</tr>
<tr>
<td>FOV</td>
<td>0.624°</td>
</tr>
<tr>
<td>Return Period</td>
<td>16 days</td>
</tr>
<tr>
<td>Spectral Channels</td>
<td>220 channels (70 VNIR channels from 356 to 1058 nm; 172 SWIR channels from 852 to 2577 nm)</td>
</tr>
<tr>
<td>Spectral Interval</td>
<td>10 nm (nominal)</td>
</tr>
<tr>
<td>Quantization</td>
<td>12 bits</td>
</tr>
</tbody>
</table>

Beam splitter, where the 0.4 to 1.0 µm range is reflected to the VNIR spectrometer and the 0.9 to 2.5 µm range is transmitted to the SWIR spectrometer. The overlap in the spectral range allows for intercomparison of the separate spectrometers [16].

Hyperion has 220 spectral bands (from 0.4 to 2.5 µm) with bandwidths and band separations of about 10 nm [20]. Figure 2.1 illustrates the collection of a Hyperion data cube, where each pushbroom image frame captures the entire swath width.

![Image of Hyperion data cube](image)

**Figure 2.1: The collection of a Hyperion data cube [4].**

The forward motion of the satellite creates a sequence of frames that are combined
into a 2-D spatial image with a third dimension of spectral information. As described earlier in Section 1.2, the push-broom data acquisition introduces new operations and performance characteristics in comparison to the traditional scanner sensors. The challenges of push-broom configurations are that they have a multitude of pixels that need to be calibrated and that the natural calibration process in the scanning system is not readily available [23].

2.2 Calibration

In general terms, the calibration of a scientific instrument can be thought of as the comparison of its accuracy against a known value. It is crucial that measurements be anchored to some standard to which the community has universal access and agreement. The calibration of hyperspectral systems looks to analyze the geometric, spectral and radiometric characteristics of the sensor. Geometric calibration measures the spatial resolution, spatial/spectral alignment or co-registration and the pointing accuracy of the system. Spectral calibration is typically a measurement of the spectral transmission of each band of the system. The out-of-band response is equally important since any light not taken into account will produce incorrect radiometric results. Hyperspectral sensors are particularly sensitive to spectral calibration [26].

Radiometric calibration attempts to characterize the relationship between the amount of light detected by the system and the electrical output. This includes relative responses between detectors, as well as the conversion from digital output to absolute at-sensor radiance units.

The importance of calibrating remote sensing instruments becomes evident when trying to compare results from different system, as well as within individual systems.
themselves. Most systems have different spatial and spectral resolutions and therefore must be brought to a common denominator so that their measurements can be compared. The most important unit in remote sensing is spectral radiance, $L(\lambda)$, and is typically described in units of power per unit area per unit solid angle per unit wavelength (Wm$^{-2}$sr$^{-1}$nm$^{-1}$). This parameter accounts for both the differing spatial and spectral characteristics of individual systems.

### 2.2.1 Geometric Calibration

The correct geometric reconstruction of hyperspectral imagery is only possible with knowledge of the geometric relation of the used sensors and other influencing parameters. This includes the resolving power and geolocation of the system, as well as the co-registration of the spectral bands [20]. The analysis of the performance of individual optical elements and the entire optical system as a whole ensures sensor performance, including its ability to resolve features of expected size and contrast and that images correspond to known physical locations. The spectral bands of the system can be temporally or spatially displaced from one another. In order to perform any spectral analysis of image features, it is necessary that the spectral band images are co-aligned.

Georectification is another important facet to geometric calibration. It refers to the transformation of spatial image data to a standard geographic reference and will result in each pixel having specific coordinate data, usually latitude and longitude [13]. It takes into account spacecraft and imager parameters, making the accuracy of this calibration directly dependent on how well these measurements are made by instruments installed on the sensor. For any hyperspectral imager the spatial registration of the data is important to creating accurate data products.
2.2.2 Spectral Calibration

Spectral calibration of the system concerns the accuracy of the relative spectral response (RSR), or spectral response function (SRF) and involves measuring the sensitivity of an optical system which includes the collection optics, detectors and dispersion elements. The SRF describes the quantum efficiency of a sensor at specific wavelengths over the range of a spectral band. Precise knowledge of the SRF is crucial, especially near spectral absorption features. It is measured over the entire bandwidth of the sensor, which allows the center wavelength to be calculated, usually as a weighted mean value.

For imaging spectrometers, the SRF can often be approximated by fitting a Gaussian curve to the spectral samples. Use of a Gaussian fit can help in defining both the bandwidth and the band center, as seen in Figure 2.2. Hyperion spectral properties were characterized by measuring the spectral shape of 25 pixels systematically distributed in a 5x5 grid on each of the focal planes [23]. The SRF of Hyperion is peak normalized and therefore well represented by a Gaussian profile.

Equations (2.1) and (2.2), seen below, describe this profile

\[
\text{SRF}_i = \frac{1}{\sigma_i \sqrt{2\pi}} e^{-\frac{(\lambda - \lambda_i)^2}{2\sigma_i^2}} \quad (2.1)
\]

\[
\sigma_i = \frac{\text{FWHM}_i}{2\sqrt{2\ln(2)}} \quad (2.2)
\]

where FWHM$_i$ is the distance between the points where the response falls to half of its maximum value. The center wavelength and bandwidth data from the measured pixels is modeled over the remainder of the pixels.

Degradation within the system is expected after launch and will cause spectral shifts and changes to the transmittance, ultimately affecting the SRF. It is common
for hyperspectral systems to utilize a dispersive optical element to achieve spectral selection. Hyperion utilizes vicarious methods of on-orbit spectral calibration to mitigate these degradation issues. This is accomplished by using a solar diffuser while the sun is rising through the atmosphere [4]. The sensor can take measurements of the solar irradiance filtered by the atmosphere as well as the exo-atmospheric solar spectrum. From those measurements atmospheric absorption lines, solar spectral features and spectral features of the solar diffuser can be used to map wavelength data to the focal plane.

2.2.3 Absolute Radiometric Calibration

The goal of radiometric calibration is to convert the data from a sensor stored as digital numbers (DN) to absolute units. This is crucial in order to give the DNs physical meaning and allow them to be compared to other instruments and models. Each sensor has its own gain and offsets applied to the recorded signals to create
the DNs [26]. The methods to radiometrically calibrate satellite and airborne sensors include preflight, on-board and vicarious calibration. Preflight calibration is the most accurate and as the name suggests it is performed in controlled conditions prior to launch. This method provides a system-wide test to ensure proper function and expected output before sensor integration with the spacecraft. On-board calibrators are used after launch to ensure that the preflight calibration stays intact and to characterize any change caused by launch or other degradations. These changes to the system must be understood, making frequent on-board calibration data most useful when observed over the sensor’s lifetime for the detect of possible degradation. Vicarious methods of calibration provide additional and independent validation and will be discussed further in Chapter 3.

2.3 Invariant Test Sites

The ideal test site for calibration has many characteristics. These include being spectrally and spatially homogeneous, temporally invariant, near-lambertian and having relatively high surface reflectance. Stable desert invariant test sites are commonly used for calibration of satellite sensors. Certain test sites - White Sands, New Mexico; Rogers dry lake at Edward’s Air Force Base, California; Lunar Lake and Railroad Valley, Nevada; and La Crau, southern France - are frequently used to perform the absolute calibration of remote sensing instruments [14]. These sites are large, homogeneous and cloud-free to allow good ground characterization to be used as radiance- or reflectance-reference targets. A high altitude site is preferred to reduce the atmospheric aerosols and the errors associated with characterizing their constituents.
Ground reflectance and atmospheric measurements are performed simultaneously with the satellite overpass. Characterizing the test site relies on in situ measurements and predicting at-sensor radiance using the characterization as input to a radiative transfer model.

2.3.1 Ivanpah Playa

For calibration purposes, we are interested in sites that exhibit reasonable spatial, spectral and temporal uniformity. The Ivanpah Playa calibration site, shown in Figure 2.3, is a dry lakebed centered at +35.57° latitude, –115.39° longitude on the border between California and Nevada [31]. This site has been found to satisfy many of the above criteria; it offers a relatively high reflectance across the visible and short wave infrared spectrum, short-term stability, frequently cloud-free skies and is easily locatable in imagery. It also has the advantage of being extensively used for many
years of calibration studies. As seen below in Figure 2.4, the site has a high reflectance, greater than 0.3 for wavelengths greater than 544 nm and is spectrally flat from 800 nm to 2150 nm. It also is highly spatially uniform, with less than 5% variation from 560 nm to 2450 nm.

![Figure 2.4: A typical reflectance spectrum from the Ivanpah Playa calibration site.](image)

2.3.2 Libya 4

Work has shown that portions of the Saharan desert are suitable invariant sites and also meet many of the characteristics listed for an ideal site [12]. For this thesis, a Saharan test site offers the opportunity to utilize a site much larger than Ivanpah Playa to accommodate the entire sensor footprint. This means understanding how to characterize a site for which ground-based data are not available.

A common site for vicarious radiometric calibration is in the Libyan Desert in
Africa, referred to as Libya 4 (WRS-2 path/row 181/40) and shown in Figure 2.5. It is centered at +28.55° latitude, +23.39° longitude [31]. The site is textured with sand dunes at multiple scales but has well established spatial uniformity and temporal stability through long term trending and analysis of large areas. Libya 4 is 118 m above sea level and it is generally acceptable that the site has no vegetation, reasonable spatial, spectral and temporal uniformity and minimal cloud cover [31].

Figure 2.5: Libya 4 desert site to be used for vicarious calibration. Adapted from [11],[31].

### 2.4 Atmospheric Compensation

Hyperspectral data contain a substantial amount of information about atmospheric characteristics at the time of image acquisition. The “raw” radiance values recorded by the sensor must first be calibrated, as described in Section 2.2, for comparison
to laboratory spectra or other remotely sensed hyperspectral imagery. Before such comparisons can be performed, an analysis of the atmospheric composition and a correction process must be used to compensate for the transient effects of atmospheric absorption and scattering. Regardless of the source, all radiation detected by hyperspectral sensors passes through some portion of atmosphere. The net effect of the atmosphere varies with the magnitude of energy being sensed, the atmospheric conditions present and the wavelengths involved.

Figure 2.6: Sources of solar illumination and their paths from the sun to the surface and into the sensor. The total surface-reflected radiance arriving at the sensor consists of direct and diffuse components. The total path-scattered radiance arriving at the sensor consists of adjacent and path components. Adapted from [17].

The atmosphere affects the signal recorded by the sensor over any given point on the ground, as illustrated in Figure 2.6. It attenuates the energy illuminating the surface (and being reflected from the surface) at particular wavelengths thus
decreasing the radiance that can be measured by the sensor and acts as a reflector itself, adding a scattered, extraneous path radiance to the signal detected by the sensor which is unrelated to the properties of the surface. Because hyperspectral data cover a whole spectral range from 0.4 to 2.5 µm at high spectral resolution, which includes water absorption features, a systematic process is generally required for compensation of these atmospheric effects.

2.4.1 Atmospheric Composition

Earth’s atmosphere, primarily composed of nitrogen and oxygen, is a mixture of various gases and suspended liquid and solid impurities. Excluding carbon dioxide and water vapor, other compositions of these gases are stable and therefore have predictable effects on solar transmission. The large numbers of solid and liquid particles suspended in the atmosphere are called aerosols and are mainly produced by volcanic eruptions, ground dust, sandstorms, forest fires, industry and other production and living activities. The magnitude of absorption and scattering varies depending on the concentrations and particle sizes of the various atmospheric constituents.

2.4.2 Absorption and Scattering

When electromagnetic radiation travels through the atmosphere, it may be absorbed or scattered by the constituent particles. Molecular absorption converts the radiation energy into excitation energy of the molecules. Scattering redistributes the radiation energy to all directions. The overall effect of absorption and scattering is the removal of energy from the initial amount of radiation. Atmospheric absorption results in the effect loss of energy to atmospheric constituents [10]. This normally involves absorption at specific wavelengths corresponding to atmospheric absorbers. The most
efficient absorbers of solar radiation in this regard are water vapor, carbon dioxide and ozone, as illustrated in Figure 2.7.

![Radiation Transmitted by the Atmosphere](image)

**Figure 2.7:** Absorption by atmospheric constituents on a scale from 0 to 1 as a function of wavelength.

Atmospheric scattering is caused by both the gaseous and aerosol components of the atmosphere. The net effect of scattering by atmospheric constituents is the degradation of the hyperspectral imagery. Scattering of radiation energy is mainly divided into two categories: selective scattering, which is further divided into Rayleigh
scattering and Mie scattering, and non-selective scattering [26].

Rayleigh scattering disperses radiation when the particles responsible for the scattering event are much smaller than the wavelength of the radiation. The Rayleigh scattering effect is inversely proportional to the fourth power of wavelength. Which means that there is a much greater tendency for the shorter wavelengths to be scattered in this manner. Scattering by aerosol particles depends on the size, shape and material. If the size of the particle is similar to or larger than the radiation wavelength, then Mie scattering occurs [25]. Dust and smoke are major causes of Mie scatter. Although, Rayleigh scatter tends to dominate under most atmospheric conditions, Mie is significant in slightly overcast ones. Non-selective scattering comes about when the diameters of the particles are much larger than the wavelengths being sensed. This type of scattering is not relevant to this study.

2.4.3 Correction of Atmospheric Effects

Atmospheric correction consists of two parts: the estimation of atmospheric parameters and the retrieval of surface reflectance. One option is to derive information about atmospheric conditions directly from the image itself, thus circumventing the need for on-site measurements of atmospheric and site conditions. Image-based approaches to atmospheric correction generally use scene-derived information about the atmosphere, in combination with a radiative transfer (RT) code to retrieve surface reflectance factors.

The interaction of electromagnetic radiation with the earth’s atmosphere is complex. We limit this discussion to simple interactions within the atmospheric windows, ignoring atmospheric refraction, turbulence and polarization. Furthermore, the sky is assumed to be a uniform Lambertian scatterer and the surface is assumed to be a flat,
Lambertian reflector. The assumptions of isotropic sky irradiance and Lambertian surface reflectance are used extensively in remote sensing analysis.

At-sensor radiance is a sum of different sources, as seen in Figure 2.6. It is directly affected by the surface reflected radiance and atmospherically scattered radiance. Surface reflected radiance is further specified as a sum of light directly transmitted to and from the surface and reflected downwelling diffuse light scattered by the atmosphere. The atmospherically scattered radiance includes both the upwelling light scattered by the atmosphere and the adjacency scattered light. This sum is described as

\[ L_{\text{total}} = L_{\text{diffuse}} + L_{\text{direct}} + L_{\text{adjacent}} + L_{\text{path}} \] (2.3)

where \( L_{\text{total}} \) is at-sensor radiance, \( L_{\text{direct}} \) is the surface component of the radiance, \( L_{\text{diffuse}} \) is the diffuse atmospheric reflected radiance, \( L_{\text{path}} \) is the upwelling atmospherically scattered radiance and \( L_{\text{adjacent}} \) is the adjacency scattered radiance.

If the surface is Lambertian and all of the atmospheric parameters are known, then the surface reflectance can be directly retrieved. Based on radiative transfer theory and assuming that the target is a uniform Lambertian surface, the radiance received by the sensor can be expressed in a simplified form as

\[ L_{\text{total}} = \frac{\rho E_{\text{SUN}} T}{\pi} + L_{\text{path}} \] (2.4)

where \( L_{\text{total}} \) is the total spectral radiance measured by the sensor, \( L_{\text{direct}} \) can be described further using the surface reflectance \( \rho \), the exo-atmospheric solar irradiance \( E_{\text{SUN}} \) and the transmission of the atmosphere \( T \), and \( L_{\text{path}} \) is the sum of the atmospheric scattered radiance and the adjacency scattered radiance, which describe the radiance from the atmosphere to the surface. According to the equation, the at-sensor
radiance can be calculated by the radiative transfer model and used to calculate the surface reflectance. The total radiance is modeled with these components because they are readily available from a radiative transfer code.

Other than particle scattering, the main atmospheric absorbers include water vapor, ozone, oxygen and aerosols. Molecular scattering and absorption by ozone, oxygen and other gases are relatively easy to correct because the concentrations of these elements are relatively stable in time and space. However, estimating the aerosol and water vapor parameters is rather difficult. Therefore, removal of the impacts of aerosols and water vapor is the main component of atmospheric correction.

### 2.5 Radiative Transfer Code

Characterizing the test sites used for calibration relies on derived atmospheric components and prediction of at-sensor radiance using this characterization as input to a RT model. RT codes simulating the propagation of radiation through the atmosphere serve as cornerstones for satellite remote sensing. They are mostly used for the calculation of look-up tables (LUTs) or pre-computed sets of values, such as reflectance, for data processing algorithms. Created LUTs are then applied to solve both direct and inverse problems. The atmospheric radiative transfer model is a critical link that connects the surface characteristic parameters with the signals received by the sensor.

The Moderate Resolution Atmospheric Transmittance and Radiance Code (MODTRAN®) is utilized in this thesis. MODTRAN® is a scalar RT code developed by the Air Force Research Laboratory in collaboration with Spectral Science, Inc. [6]. Like its name suggests, the code calculates atmospheric transmittance and radiance and efficiently simulates molecular and cloud-aerosol emission. It assumes a stratified
atmosphere and an spherical earth surface [1]. Different atmospheric characteristics, such as temperature, pressure and atmospheric species concentrations need to be specified at the boundaries of each layer. In the approximation, each layer has its own transmission and scattering contributions to the total radiance [2]. The transmittance calculations performed are based on band models of molecular line absorption, continuous molecular absorption and extinction coefficients of aerosols.

An important output of MODTRAN® is the at-sensor radiance. The radiance can be averaged with the relative spectral responses of the sensor of interest to find the band-averaged radiance values, providing valuable information for effective calibration as well as surface reflectance characterization purposes. This means that MODTRAN® provides a useful tool to aid in the characterization of calibration test sites. Modeling the at-sensor radiance is an integral step for in-flight calibration efforts. Vicarious calibration makes use of a characterized test site and modeled radiance to update the calibration of sensors derived in the lab. This type of calibration is described in the proceeding chapter.
Chapter 3

Vicarious Calibration

Vicarious calibration refers to techniques that make use of natural or artificial sites on the surface of the Earth for the post-launch radiometric calibration of sensors. It is an important supplement to the on-orbit radiometric calibration of remote sensing systems and the techniques have become widely adopted as the means to provide independent assurance of the quality of remotely sensed data. Vicarious calibration using pseudo-invariant sites has become increasingly accepted as a fundamental post-launch calibration method to monitor long term performance of satellite sensors.

There are three different approaches to vicarious calibration:

- Reflectance based
- Radiance based
- Irradiance based

Both reflectance-based and radiance-based techniques rely upon test sites, as described in Section 2.3, with high spatial and spectral uniformity. The reflectance-based method requires ground reflectance and atmospheric measurements coincident
with the sensor overflight while the radiance-based approach relies on placing a nadir-viewing, well-calibrated radiometer above most of the scattering and absorbing elements in the atmosphere, which requires use of an airborne platform. This method has been used successfully but is limited by cost and aircraft ability. The irradiance-based method is similar to the reflectance-based method but requires a diffuse-to-global irradiance radiometer in addition to the typical instrumentation. There is thorough discussion of radiance-based and irradiance-based approaches in the literature [28, 30]; this work presents results of vicarious calibration of Hyperion utilizing the reflectance-based approach.

It should be noted that a vicarious calibration is critical for even the most robustly laboratory characterized sensors as on-orbit performance can be impacted by launch trauma and optics can degrade over time requiring periodic calibration monitoring and updates [14].

### 3.1 Reflectance-Based Approach

In general, the reflectance-based method involves characterizing the surface reflectance and atmospheric properties of a test site during sensor overpass. These data are then used as input to a RT code that predicts the band-averaged top-of-atmosphere radiance for each spectral band. A comparison is then made with the sensor under test by obtaining the corresponding test site imagery and extracting the DNs. This requires little information from the instrument but in-depth knowledge of the test site. Figure 3.1 shows the procedure that is needed to characterize the atmosphere and reflectance of a test site to build an at sensor radiance model.

However, collecting in situ measurements can be difficult, labor intensive and
Figure 3.1: Steps necessary for characterizing a calibration site to be used in the reflectance-based approach.

costly. Pseudo-invariant test sites eliminate the need for simultaneous ground measurements because their rate of change is slow enough that their characteristics can be known within an acceptable uncertainty. The Libyan desert site is the ideal site with respect to desirable physical traits and can be utilized with this methodology because we assume stability.

From the description of the reflectance-based method, it can be seen that there are three basic areas of uncertainty in the method: (1) surface characterization, (2) atmospheric characterization and (3) radiative transfer code [29]. Thus, the challenge of this thesis is predicting a continuous spectrum of at-sensor radiance when ground truth measurements of the physical properties of the surface and atmospheric components of the Libya 4 test site are unknown. Figure 3.2 displays the approach that
will be taken in this work to ultimately characterize the test site.

Figure 3.2: Procedure for surface reflectance retrieval using atmospheric compensation techniques.

3.1.1 Calibration Coefficients

Vicarious calibration provides a useful and necessary way to generate, monitor and verify the calibration coefficients for airborne hyperspectral data. Calibration coefficients are generated by averaging the radiance within a particular spectral response function (SRF) and dividing by the dark subtracted signal recorded by the FPA electronics in DNs. The band-averaged radiance is obtained using the following equation:

\[ \bar{L}(\lambda') = \frac{\int L(\lambda) SRF(\lambda' - \lambda) d\lambda}{\int SRF(\lambda' - \lambda) d\lambda} \]  \hspace{1cm} (3.1)
where $\bar{L}(\lambda')$ is the band-averaged radiance, $L(\lambda)$ is the source radiance and $\text{SRF}(\lambda' - \lambda)$ is the spectral response function for the $\lambda'$ spectral channel. This is combined with the dark subtracted signal to produce the radiometric calibration coefficients for a particular spectral channel with the final form given by

$$\text{Cal Coef}(\lambda') = \frac{L(\lambda')}{\text{DN}_{\text{Source}} - \text{DN}_{\text{Dark}}}$$

(3.2)

where $\text{Cal Coef}(\lambda')$ is the calibration coefficient corresponding to the $\lambda'$ spectral channel, $\text{DN}_{\text{Source}}$ is the signal from the corresponding detector element in digital number and $\text{DN}_{\text{Dark}}$ is the signal in digital number for the detector element when it is not illuminated. These calibration coefficients are insensitive to the exact shape of the SRF if the in-band radiance $L(\lambda)$ has little variation within the spectral channel of interest. It is obvious that if $L(\lambda)$ is a constant the numerator reduces to $L$ and the calibration coefficient is just the radiance divided by the dark subtracted signal.

Converting from digital number to radiance relies on the already established calibration coefficients of the instrument. The Hyperion imagery used in this work was obtained in digital number format and needed to be converted to radiance. This conversion for Hyperion is a simple scale factor. Due to the fact that Hyperion is composed of two overlapping FPAs, each array has a different scale factor which makes the calibration for Hyperion wavelength dependent. The VNIR array has a scale factor of 40 and SWIR array has a scale factor of 80, which are described in the following radiance equations

$$L(\lambda) = \frac{\text{DN}}{40} (\text{VNIR})$$

(3.3)

$$L(\lambda) = \frac{\text{DN}}{80} (\text{SWIR})$$

(3.4)
where $L(\lambda)$ is the at-aperture radiance and DN is the digital number[23].

The conversion of a hyperspectral image cube from DNs to radiance must take place before further analysis can be performed. Figure 3.3 shows the portion of Libya 4 imagery acquired by Hyperion that is used for this work. The data set is calibrated and filtered for cloud content contamination. The radiance conversion is then carried out using the scale factors described above. An average radiance spectrum from the data is shown in Figure 3.4. The near zero signal in the spectral regions near 940 nm, 1130 nm, 1350 nm and 1800 nm are due to atmospheric water vapor absorption. Additional atmospheric absorbers as well as the inherent solar irradiance cause other sharply varying features in the radiance spectrum.

The radiance data provides a starting point for characterization of the atmospheric and surface parameters of the test site. The data used is key to the validity and ability to perform this study. This initial preprocessing is an important step in order to assure image quality and only after this can the first investigation, exploring column water vapor retrieval, be outlined. The next chapter examines the scene derived radiance cube to calculate the amount of water vapor present in Libya 4.
Figure 3.3: Hyperion scene of the Libyan test site.
Figure 3.4: Average radiance of the Libya site on 12 Sept 2011.
Chapter 4

Water Vapor Retrieval

Determination of column water vapor is a fundamental problem in remote sensing and is important both for understanding atmospheric variability and also for removing atmospheric effects from remotely sensed data. In this work, determination of column water vapor abundance is needed in order to compensate for water vapor absorption in the derivation of surface reflectance from Hyperion data. The atmospheric column water vapor content is generally obtained through an absorption channel, centered at either 940 or 1130 nm. The dependence of column water vapor amount on these absorption channels is illustrated in Figure 4.1.

At present, the two leading methods for determining water vapor column abundance are the Continuum Interpolated Band Ratio (CIBR) and the Atmospheric Precorrected Differential Absorption (APDA) [24]. The ADPA method performs better in the low-to medium reflectance interval but because the invariant test sites chosen are known to have high reflectance, the CIBR method is sufficient in this analysis.
Figure 4.1: The 940 nm and 1130 nm absorption features show the dependence of the band-averaged radiance on column water vapor amount.

### 4.1 Derivation of CIBR Method

Measurements of water vapor can be performed using sensor channels located in bands of the water vapor absorption spectrum. The CIBR method uses two reference bands instead of a single band. The advantage of the method over a simple band ratio is that the unequal influence of scattering by other water constituents on the reference and the absorption band is eliminated [8].

As described in Section 2.4.3, the radiance measured in a single channel $i$ of a
sensor can be expressed as

\[ L_i = \frac{\rho_i E_i T_i}{\pi} + L_{\text{path},i} = L_{g,i} T_{0,i} T_{w,i}(WV) + L_{\text{path},i} \] (4.1)

where \( \rho_i \) is the ground reflectance, \( E_i \) is the solar irradiance, \( T_i = T_{0,i} T_{w,i} \) is the total transmission. The atmospheric transmission due to water vapor is \( T_{w,i} \) and the transmission without water vapor is \( T_{0,i} \) and depends on aerosols and absorptions.

To simplify notation we define \( L_{g,i} = \frac{\rho_i E_i}{\pi} \). Again, the path radiance \( L_{\text{path},i} \) is the sum of the atmospheric and adjacency scattered radiances. The CIBR method uses a simulated radiance at the top of the atmosphere for comparison with the measured radiance, therefore the influence of the atmospheric scattering effects on the ratio is neglected. In the proceeding steps, the scattering terms will be ignored [7].

Using Equation (4.1) we first write the radiances in three channels \( i = m, r_1, r_2 \), where \( m \) is a measurement channel in an the 940 nm absorption region and \( r_1, r_2 \) are two reference channels. The transmission \( T_{w,i} \) is a function of water vapor for the measurement channel but not for the reference channels. Assuming a small difference between the central wavelengths \( \lambda_{r_1}, \lambda_{r_2} \) of the reference channels and \( \lambda_{r_1} < \lambda_m < \lambda_{r_2} \), the radiance of the measurement channel \( L_m(WV) \) can be approximated by a linear interpolation as

\[ L_m = [\omega_1 L_{g,i} T_{0,r_1} + \omega_2 L_{g,i} T_{0,r_2}] T_m(WV) \] (4.2)

where

\[ \omega_1 = \frac{\lambda_{r_2} - \lambda_m}{\lambda_{r_2} - \lambda_{r_1}}, \omega_2 = \frac{\lambda_m - \lambda_{r_1}}{\lambda_{r_2} - \lambda_{r_1}} \] (4.3)

We assume that the reference channels have no water vapor absorption, or \( T_{r_1} = T_{r_2} = 1 \). Using Equation (4.2) for the transmission in the water vapor channel
\[ T_m(WV) \text{ and substituting } L_{g,r_1} \text{ and } L_{g,r_2} \text{ from Equation (4.1) we find} \]

\[ T_m(WV) = \frac{L_m}{\omega_1 L_{r_1} + \omega_2 L_{r_2}} \tag{4.4} \]

Through this linear interpolation between the two reference bands at each side of the absorption band, a reference value with normalized influence of scattering is simulated on the absorption band. The absorption value is then divided by a reference value similarly affected by scattering, diminishing the influence on the ratio [8]. The CIBR equation is given by

\[ \text{CIBR} = \frac{L_m}{\omega_1 L_{r_1} + \omega_2 L_{r_2}} \tag{4.5} \]

\[ L_i = \frac{\int L(\lambda) \text{SRF}(\lambda) d\lambda}{\int \text{SRF}_i(\lambda) d\lambda} \tag{4.6} \]

where \( L_i \) is the band-averaged radiance at a given wavelength \( \lambda \).

### 4.2 Water Vapor Estimation Using CIBR

The CIBR method was based on three Hyperion bands, Bands 52, 80, and 86 with center wavelengths 874.53, 942.73 and 1003.3 nm respectively. We assume that the Hyperion measurement channel at 942.73 nm accurately represents the 940 nm absorption band within reason.

\[ \text{CIBR}_{\text{Hyperion}} = \frac{L(80)}{0.4704 \times L(52) + 0.5296 \times L(86)} \tag{4.7} \]

The lookup table is generated using MODTRAN® with the correct Hyperion parameters including location, viewing geometry and solar illumination. The water
vapor profile was scaled using the MODTRAN® parameter H2OSTR for 30 water vapor amounts from 0.05 - 5.0 g/cm².

For each pixel, the CIBR data was calculated from sensor data and measured radiances $L_m$, $L_{r1}$ and $L_{r2}$. A one-dimensional lookup scheme was performed in MATLAB to determine the approximate water vapor amount for that pixel from the LUT. If the CIBR data falls between two values in the LUT, the water vapor amount is the result of a cubic spline interpolation between corresponding LUT values. From the calculated water vapor amounts a watermap across the entire scene is created to be used in the atmospheric correction described in the proceeding chapters.
4.3 Results of Water Vapor Retrieval

The three-channel CIBR technique is used to derive atmospheric radiances of the absorption channels and subsequently the column water vapor amounts over the Libyan desert site. Figure 4.4 shows the continuum relative to the two reference channels that were used.

The original Libya 4 radiance cube was preprocessed to eliminate bad bands before it was input into the retrieval code in MATLAB. VNIR bands 8-57 and SWIR bands 79-224 were retained. From this radiance subset, a watermap was created that shows the total column water vapor varying between 1.5 - 2.0 g/cm² with an average value
of 1.7931 g/cm². These results are shown in Figure 4.5. This scene-averaged value falls into the expected range of water vapor amount of an arid, desert region.

This calculation provides a necessary input to the next step of atmospheric compensation, making it crucial to have a high level of confidence in the calculated value. For validation, MODTRAN® is run using the average column water vapor for this scene and compared with the sensor data. The agreement between these two curves can be seen in Figure 4.6.
Figure 4.5: CIBR radiance based retrieved water vapor image in g/cm² for Libya 4. The measured water vapor amount was 1.7931 g/cm².
Figure 4.6: Hyperion scene averaged radiance (black) compared with retrieved MODTRAN® radiance (red) using measured water vapor amount.
Chapter 5

Aerosol Retrieval

Approximately 30% of the land surface is arid, having desert or semi-desert conditions. Aerosol originating from these regions plays a significant role in climate and atmospheric chemistry of the atmosphere, as well as atmospheric radiative forcing by scattering and absorbing radiation [5]. Retrieving aerosol properties from spaceborne sensors above desert conditions, where the surface is usually very bright, is a challenging problem. The proportion of the surface to top of atmosphere (TOA) reflectance can reach values over 90%, especially for wavelengths above 500 nm [15]. For these reasons detailed knowledge of aerosol properties from these regions is required to separate atmosphere from intrinsically bright surfaces.

Retrieval of data pertaining to aerosol distribution and properties over land with the help of the “dark object” atmospheric correction algorithm have yielded valuable results. However, the use of this algorithm is restricted to land surface with low reflectance (e.g., water and dense vegetation), while over bright surfaces it often fails to estimate the aerosol information accurately. This work looks for an alternative to determine the visibility and aerosol properties using lookup tables to match
the satellite observed spectral TOA reflectance to MODTRAN® generated values. Figure 5.1 portrays the dependence of the scene TOA reflectance on varying aerosol distributions.

![Dependence of TOA Reflectance on AOD](image)

Figure 5.1: Dependence of TOA reflectance values on aerosol optical depth/visibility.

### 5.1 Methodology to Determine Aerosol Properties

First-principles atmospheric compensation that converts spectral imagery to surface reflectance requires an estimate of the scene visibility/aerosol optical depth. This approach relies on the utilization of LUTs or precomputed sets of TOA reflectance values to find a solution to an inverse problem. The inverse problem means retrieval of
surface reflectance properties on the basis of given TOA reflectance values and atmospheric parameters [32], which is contrary to a direct problem, when TOA reflectance values are modeled on the basis of known surface and atmospheric parameters.

Similar to the water vapor retrieval, this inverse problem is solved under a Lambertian surface approximation. In general, the accuracy of the resulting surface reflectance is mainly dependent on the accuracy of sensor calibration, input atmospheric parameters and LUTs [33]. To minimize the number of simulations (i.e., MODTRAN® runs) required to generate the LUTs, a TOA parameterization of the radiance-reflectance relationship is used. This relationship can differ across the scene due to variations in water vapor column density. Therefore, the water vapor amount is first determined for each pixel as described in Chapter 4, then the result is used as an input to estimate the aerosol properties.

The following equation is used to convert the at-sensor spectral radiance to planetary directional TOA reflectance for a Lambertian surface

\[
\rho_{\text{TOA}} = \frac{\pi L(\lambda) d^2}{E_{\text{SUN}} \cos(\theta_{\text{zenith}})} \quad (5.1)
\]

where \(L(\lambda)\) is the spectral radiance, \(d\) is the Earth-Sun distance in astronomical units, \(E_{\text{SUN}}\) is the mean exo-atmospheric solar irradiance and \(\theta_{\text{zenith}}\) is the solar zenith angle in degrees. Figure 5.2 shows the scene averaged TOA reflectance of the Hyperion data set. The TOA reflectance for an underlying Lambertian surface with albedo \(A\) at wavelength \(\lambda\) is presented as

\[
\rho = \rho_a + \frac{AT_1T_2}{1 - Ar} \quad (5.2)
\]

where \(\rho_a\) is the atmospheric reflectance and \(r\) is the spherical albedo of the atmosphere.
for illumination from below.

Figure 5.2: TOA reflectance of Libya 4 on 12 Sept 2011.

All parameters in Equation (5.2), with the exception of A, depend on the aerosol optical depth (AOD) defined as

\[ \tau(\lambda) = \int_0^H k_{\text{ext}}^a(z, \lambda)dz \]  

(5.3)

where H is the TOA height, \( k_{\text{ext}}^a(z, \lambda) \) is the aerosol extinction coefficient at height \( z \) above the ground, for wavelength \( \lambda \). The main task of this aerosol retrieval is to determine the spectral dependence of \( \tau \) from satellite measurements of the spectral reflectance, \( \rho \) [18].
LUTs are calculated using MODTRAN® for different illumination/observation geometries, and aerosol phase functions dependent on the scattering angle, single scattering albedo and AOD. The LUTs describe the relationships between TOA reflectance, visibility and the AOD. Visibility, as defined in MODTRAN®, is related to the aerosol optical depth at 550 nm via the equation

$$\text{VIS} = \frac{\ln(50)}{\tau_{550} + 0.01159}$$  \hspace{1cm} (5.4)

where 0.01159 is the surface Rayleigh scattering coefficient at 550 nm in units of km$^{-1}$.

LUT selection was performed by matching TOA reflectance between observation and calculation from 11 high resolution MODTRAN® runs with visibility values ranging from 5.00 km to 323.58 km. The retrieval procedure involves solving the RT equation for the aerosol bandpass reflectance over a series of trial visibility values that are evenly spaced in optical depth. The scene visibility is then calculated by interpolating between the trial values to yield a minimization of the least squares error between sensor data and MODTRAN® simulated data [27].

5.2 Results of Aerosol Retrieval

The algorithm procedure described above was used to process the TOA reflectance from the Hyperion data set to obtain an optimum visibility value. Figure ?? shows an example of the initial results for visibility over Libya 4. As in the water retrieval, the original Libya 4 radiance cube was preprocessed to eliminate bad bands and retain VNIR bands 8-57 and SWIR bands 79-224 before it was input into the retrieval code.

The dashed blue line is the scene averaged TOA reflectance of the Libyan desert
site, while the solid red line represents the TOA reflectance at the optimal visibility determined by the retrieval algorithm. The optimal visibility obtained from the LUT calculations can be seen in Figure 5.3. The retrieval calculated a visibility of 42.9972 km. As seen from the data, the reflectance spectra were a significant match.

![Optimal Visibility Retrieval](image)

Figure 5.3: Results of visibility value retrieval. Optimal visibility of 42.9772 km.

The optimal visibility coincides with prior knowledge of the Saharan desert from long term trending. The region is expected to have a low aerosol content and only exhibit low visibility in the occasion of a dust storm caused by desert sand [12]. With this in mind, the optimal visibility retrieved from the aerosol algorithm can now be used as an input to the final steps of our characterization described in the proceeding chapter.
Chapter 6

Surface Reflectance Characterization

A key element to the success of the reflectance-based result is the determination of
the surface reflectance at hyperspectral resolution permitting the spectral features of
the surface to be included in the determination of band-averaged, at-sensor radiance.
The goal is to predict the surface reflectance of Libya 4 using radiance values from
Hyperion as values for $L_{\text{total}}$. In desert regions, the spectral surface reflectance is very
high in the red part of the visible spectrum and near infrared, but decreases relatively
fast in the blue for wavelengths shorter than 500 nm. This behavior contrasts to that
of, for example, clouds or snow, which are predominately spectral neutral [15].

Unfortunately, surface reflectance is coupled with all three radiance components
that make up the total at-sensor radiance. Each component has interaction with the
surface, as illustrated in Figure 2.6. $L_{\text{diffuse}}$ is the smallest component of the total
radiance throughout the spectrum. $L_{\text{path}}$ only becomes a significant portion of the
total radiance as the lower wavelength bound is approached. $L_{\text{direct}}$ is the component
that is most heavily dependent on surface reflectance for the spectral region beyond 500 nm. Therefore, an approximation of surface reflectance can be made by modeling $L_{\text{direct}}$ with

$$L_{\text{direct}} = \frac{\rho T_{\text{down}} T_{\text{up}} E_{\text{SUN}} \cos(\theta_{\text{zenith}})}{\pi}$$

(6.1)

where $\rho$ is the surface reflectance, $T_{\text{down}}$ is the atmospheric transmission along the solar-ground path, $T_{\text{up}}$ is the transmission along the ground-sensor path, $E_{\text{SUN}}$ is the exo-atmospheric irradiance and $\theta_{\text{zenith}}$ is the solar zenith angle. This model assumes a Lambertian surface, and can be combined with Equation (2.3) to yield the following equation for surface reflectance

$$\rho = \frac{\pi (L_{\text{total}} - L_{\text{diffuse}} - L_{\text{path}})}{T_{\text{down}} T_{\text{up}} \cos(\theta_{\text{zenith}})}$$

(6.2)

In order to correctly obtain the surface reflectance, an iterative approach must be considered. This is due to the fact that the inputs to the RT code require information about the surface reflectance, the desired product. Atmospheric characterization of the test site is necessary to be able to perform these calculations. The previous chapters discuss the characterization of water vapor and aerosols present in the Libya 4 scene to ultimately be used as inputs to MODTRAN® for surface reflectance retrieval.

### 6.1 BRDF Effect in Surface Reflectance Retrieval

Our retrieval thus far has only been concerned with the removal of atmospheric attenuation due to molecular, gaseous and aerosol scattering and absorption. However, there is an interaction between the surface and the atmosphere, as a result of multiple
scattering, that is affected by the surface Bidirectional Reflection Distribution Function (BRDF) properties [3]. This could impact the accuracy of the surface reflectance retrievals under certain conditions.

Topographic modeling can be used to correct imagery for these effects based on local solar illumination. The illumination depends not only upon the sun’s position but also upon the slope and aspect of the surface terrain being illuminated. Figure 6.1 shows the angles involved, where $\theta_z$ is the solar zenith angle, $\phi_a$ is the solar azimuth, $\theta_p$ is the slope, $\phi_o$ is the aspect and $\gamma_i$ is the local solar incidence angle.

![Geometry involved in computation of local solar incidence. Adapted from [9].](image)

The quantity to be calculated is the local solar incidence $\gamma_i$ which determines the local irradiance. From trigonometry we can calculate the relation

$$\cos \gamma_i = \cos \theta_p \cos \theta_z + \sin \theta_p \sin \theta_z \cos \phi_a - \phi_o$$  \hspace{1cm} (6.3)
The above equation can be used to determine $\gamma_i$. With $\gamma_i$ known, the standard cosine correction relating the observed radiance to that which would have been observed had the surface been truly Lambertian is

$$L_{\text{Lambertian}} = L_{\text{observed}} \frac{\cos \theta_z}{\cos \gamma_i}$$  \hspace{1cm} (6.4)

The Lambertian approximation can be a poor assumption but provides the ability to perform straightforward retrieval calculations. The actual reflectance determined using a BRDF describes the dependence of reflectance on both solar illumination and viewing geometry as well as wavelength, and must be considered when performing this retrieval.

### 6.2 Hyperion Retrieval Results

As described in Equation 6.2, the majority of the parameters needed to calculate surface reflectance come from MODTRAN®. The RT code is run using the average water vapor amount of 1.7931 g/cm$^2$ and optimal visibility of 31.1448 km.

Outputs from the MODTRAN® iteration include $L_{\text{diffuse}}$, $L_{\text{path}}$, $T_{\text{down}}$ and $T_{\text{up}}$. The diffuse and direct portions of the total at-sensor radiance are shown in Figure 6.2. As seen in Figure 6.2, the proportions of these components vary significantly over the spectral region that we are considering. The rapidly increasing proportions of the diffuse component at shorter wavelengths is something to be noted. We expect this due to atmospheric scattering. These data are averaged with the relative spectral responses of Hyperion to find the band-averaged radiance values.

The MODTRAN® calculations are combined with the scene radiance to arrive at our estimate of surface reflectance. The surface reflectance retrieval was applied
Figure 6.2: The MODTRAN\textsuperscript{®} calculated diffuse and path radiance components.

to the same 196 band subset of Hyperion data used in estimating the atmospheric parameters. The resulting surface reflectance spectrum is shown in Figure 6.3.

Hyperion data contains both striping and spectral smile. A portion of the ringing and non-physical features present in the reflectance spectrum can be attributed to these characteristics of the sensor. We know this because MODTRAN\textsuperscript{®} is a validated code and the reflectance spectrum is a smoothly varying parameter. To provide a more physically meaningful result, the surface reflectance was smoothed using an FFT filter algorithm. The final reflectance product is shown in Figure 6.4 after smoothing is performed to remove sensor artifacts.

The results shown here for Hyperion compare favorably to those derived from other
sensors. Figure 6.5 shows a comparison of the reflectance data to MODIS reflectance statistics of Libya 4 two days after the Hyperion collect. MODIS minimum, maximum and average data is shown at seven discrete spectral locations for September 14, 2011. The agreement between the two sensors gives confidence to the retrieval, as well as the assumption that we expect Libya 4 reflectance to vary minimally between the different dates. This is mostly due to the large size of the test site and its shown uniformity, as well as the low variation in arid climate.
Figure 6.4: Results of smoothing algorithm on surface reflectance spectrum.

Figure 6.5: Surface reflectance retrieval of Libya 4 on 12 Sept 2011, compared with MODIS statistical reflectance data on 14 Sept 2011.
Chapter 7

Summary

The calibration of hyperspectral systems using pseudo-invariant test sites is becoming more prevalent with advancing technology. The fundamental goal of this thesis was to establish surface reflectance characteristics of the Libya 4 pseudo-invariant test site to build an at-aperture radiance model. Libya is a commonly used calibration site and a detailed knowledge of the surface will provide insight for future calibration efforts. The recovery of the reflectance spectrum of each pixel from the observed radiance spectrum was facilitated with the use of sophisticated atmospheric compensation techniques.

To understand hyperspectral imaging data exploitation, it is important to realize how the presence of the atmosphere affects the relationship between the observed radiance spectra and the associate reflectance spectra. Atmospheric correction with RT code is generally influenced by two atmospheric parameters - water vapor amount and visibility. Water vapor amount was estimated from the data on a pixel-by-pixel basis using the CIBR technique at the 940 nm absorption feature. A LUT for retrieving water vapor from the scene radiance was generated using MODTRAN®.
and then fitted against the Hyperion data. One dimension of the table is the CIBR and the other is the water vapor amount. The at sensor radiance is affected by atmospheric aerosol because of the quantity of scattering and the attenuation of the surface-reflected radiance.

Comparisons of the surface reflectance retrieval with MODIS data provided a level of confidence in our results. The reflectance spectrum of Libya 4 coupled with the MODTRAN® data already created, allowed for the modeling of the Libyan site in the absence of in situ measurements. An accurate at-sensor radiance model is imperative to be able to calibrate the entire footprint of various hyperspectral sensors.

7.1 Future Work

This thesis used two-dimensional LUTs to model and remove the effects of atmospheric water vapor and aerosol optical depth on a pixel-by-pixel basis. Further study could include using a higher-dimensional lookup table that will permit pixel-by-pixel correction for all of the local atmospheric and scatter effects, not just the two parameters that were our focus.

The results presented in this thesis illustrate a step-by-step approach to surface reflectance retrieval using multiple techniques to account for atmospheric constituents. This procedure is modeled on other atmospheric compensation algorithms that are available, but required special care for such a bright, homogeneous surface. The reflectance-based approach to vicarious calibration relies on these measurements for effective evaluation and sensor calibration. The modular nature of this retrieval allows for the development of an automated approach to retrieve surface parameters of desert scenes such as Libya.
In order to properly validate the surface characteristics retrieved in this thesis, it would be advantageous to perform this analysis on multiple Hyperion data sets and future work will focus on this. With further analysis on a broader range of data, the end result will be a complete and consistent at-aperture radiance model of Libya 4.
Bibliography


