The Characterization of Earth Sediments using Radiative Transfer Models from Directional Hyperspectral Reflectance

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The Characterization of Earth Sediments using Radiative Transfer Models from Directional Hyperspectral Reflectance

by

Rehman S. Eon

B.S. Viterbo University, 2015

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Chester F. Carlson Center for Imaging Science
College of Science
Rochester Institute of Technology

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The Characterization of Earth Sediments using Radiative Transfer Models from Directional Hyperspectral Reflectance

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Submitted to the
Chester F. Carlson Center for Imaging Science
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for the Doctor of Philosophy Degree
at the Rochester Institute of Technology

Abstract

Remote sensing techniques are continuously being developed to extract physical information about the Earth’s surface. Over the years, space-borne and airborne sensors have been used for the characterization of surface sediments. Geophysical properties of a sediment surface such as its density, grain size, surface roughness, and moisture content can influence the angular dependence of spectral signatures, specifically the Bidirectional Reflectance Distribution Function (BRDF). Models based on radiative transfer equations can relate the angular dependence of the reflectance to these geophysical variables. Extraction of these parameters can provide a better understanding of the Earth’s surface, and play a vital role in various environmental modeling processes. In this work, we focused on retrieving two of these geophysical properties of earth sediments, the bulk density and the soil moisture content (SMC), using directional hyperspectral reflectance. We proposed a modification to the radiative transfer model developed by Hapke to retrieve sediment bulk density. The model was verified under controlled experiments within a laboratory setting, followed by retrieval of the sediment density from different remote sensing platforms: airborne, space-borne and a ground-based imaging sensor. The SMC was characterized using the physics based multilayer radiative transfer model of soil reflectance or MARMIT. The MARMIT model was again validated from experiments performed in our controlled laboratory setting using several different soil samples across the United States; followed by applying the model in mapping SMC from imagery data collected by an Unmanned Aerial System (UAS) based hyperspectral sensor.
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This work is dedicated to my parents
“I’m just here so I won’t get fined” – Marshawn Lynch
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Chapter 1

Introduction

1.1 Context

Remote sensing techniques are continuously being developed to extract physical information about the Earth’s surface. Over the years, space-borne and airborne sensors have been used for the characterization of surface sediments [1, 2, 3]. Spectral observations of sediments can be used to effectively identify the physical characteristics of the surface. Geophysical properties of a sediment surface such as its density, grain size, surface roughness, and moisture content can influence the angular dependence of spectral signatures, specifically the Bidirectional Reflectance Distribution Function (BRDF) [3, 4, 5, 6, 7, 8]. Models based on radiative transfer equations can relate the angular dependence of the reflectance to these geophysical variables. Extraction of these parameters can provide a better understanding of the Earth’s surface, and play a vital role in various environmental modeling processes [9, 10].

1.2 Objectives

This dissertation addresses three main objectives related to the characterization of earth sediments using radiative transfer models from hyperspectral imagery. The main objectives of our work include:
1. Develop an inversion methodology to retrieve fill factor and single scattering albedo (SSA) of earth sediments from inversion of the Hapke model

   (a) Develop a modified version of Hapke’s isotropic multiple scattering approximation (IMSA) model to account for multiple scattering

   (b) Validate the inversion methodology with controlled laboratory experiments

   (c) Demonstrate that we can retrieve these geophysical properties of earth sediments from data across different imaging platforms

2. Evaluate the soil moisture content (SMC) using a physics based model

   (a) Demonstrate the ability of the multilayer radiative transfer model of soil reflectance (MARMIT) model in retrieving the SMC for sediment samples of varying physical properties

   (b) Demonstrate that these physics based models can be used to map SMC of the coastal zone from remote sensing imaging platforms

3. Evaluate key parameters that impact the inter-calibration process

   (a) Develop a simulation environment using DIRSIG to support the primary mission of the Algodones Dunes campaign

   (b) Verify the ability of DIRSIG to simulate space-borne instruments

   (c) Evaluate the potential in using International Space Station (ISS)-based imaging platforms for inter-calibration

   (d) Assess the impact of differing view-geometries and time-of-collect on the inter-calibration process

1.3 Dissertation Layout

This dissertation contains seven chapters. The Introduction is the first chapter.
1.3.1 Chapter 2: Background

Chapter 2 provides a comprehensive background on the context for this work. We provide a brief introduction to what is remote sensing, and delve into the scientific principles of electromagnetic wave propagation fundamental in remote sensing. We discuss some fundamental definitions and concepts in radiometry, which are essential in topics of ray tracing and radiative transfer. Our research objectives focus on the development of formalism to estimate physical properties of a medium by the analysis of how electromagnetic radiation is scattered or emitted by a surface, as a result, we define some commonly used terminology in describing how light is scattered by semi-infinite mediums.

1.3.2 Chapter 3: Design and Instrumentation

Chapter 3 provides details of the different instruments that we use in our experiments. Hyperspectral BRDF data in both field and laboratory settings were collected using a goniometer system developed here at RIT. In our various experiments, we collected imagery using a ground-based hyperspectral imaging (HSI) system mounted on a telescopic mast, which was radiometrically calibrated using a LabSphere integrating sphere. These spectral measurements, in both field and laboratory settings, were accompanied by a set of geotechnical measurements, which included sediment density, grain size distribution, and moisture content, as well as mechanical properties of the sediment, such as shear strength and the dynamic deflection modulus.

1.3.3 Chapter 4: Sediment Fill Factor Retrieval I

Among the many geophysical parameters describing Earth sediment, the porosity (bulk density) has a significant influence on its spectral properties [4, 5, 11, 12, 13, 14, 3]. Radiative transfer models, such as the one developed by Hapke, typically predict a correlation between reflectance and density of the material [5, 12]. This phenomena has been demonstrated repeatedly in various laboratory studies [3, 4,
15, 16, 17, 18, 19]. Chapter 4 focused on the retrieval of the fill factor from the inversion of the Hapke model and variants. The retrieval models are validated from experiments performed in our controlled laboratory settings. We then take a practical approach to the retrieval of geophysical properties of Earth sediments. We demonstrate that fill factor can also be retrieved from airborne imagery from NASA Goddard’s LiDAR, Hyperspectral, and Thermal (G-LiHT) system collected during the 2015 campaign at the Algodones Dunes in southern California and from imagery collected by the Advanced Baseline Imager (ABI) on the Geostationary Operational Environmental Satellite (GOES) series.

1.3.4 Chapter 5: Inter-calibration Studies

The ability of sensors to detect changes in the Earth’s environment is dependent on retrieving radiometrically consistent and calibrated measurements from its surface. Inter-calibration provides consistency between satellite instruments and ensures fidelity of scientific information. Inter-calibration is especially important for space-borne satellites without any on-board calibration, as accuracy of instruments are significantly affected by changes that occur post-launch. To better understand the key parameters that impact the inter-calibration process, chapter 5 describes a simulation environment that was developed to support the primary mission of the Algodones Dunes campaign. Specifically, measurements obtained from the campaign were utilized to create a synthetic landscape to assess the feasibility of using the Algodones Dunes System as an inter-calibration site for space-borne instruments.

1.3.5 Chapter 6: Soil Moisture Characterization

Another key geophysical parameters describing Earth sediment is the soil moisture content (SMC). In agriculture, SMC can be used as an indicator of the sensitivity of soil to wind erosion. We can also use the SMC to gain knowledge about water infiltration and runoff as well as monitor/manage irrigation processes, which is critical in crop yield estimation. In defense, the determination of SMC
is also important for estimating trafficability. In our research work, we will try to characterize the SMC using a physics based model, the multilayer radiative transfer model of soil reflectance (MARMIT), which is a recent improvement to the works by Bach and Mauser [20] in modeling reflectance of wet soil. This model will again be validated through experiments performed in our controlled laboratory settings, followed by its application in mapping SMC from imagery data collected by an Unmanned Aerial System (UAS) based HSI sensor.

1.3.6 Chapter 7: Sediment Fill Factor Retrieval II

Chapter 7 will be a continuation of the sediment fill factor and single scattering albedo retrieval by inversion of the modified Hapke model that we detailed in chapter 4. In our upcoming experiments, we will apply our retrieval methodology of the sediment fill factor to a completely different physical environment - a salt marsh ecosystem, where imagery data was collected using a ground-based HSI system.

1.4 Related Publications

Portions of this dissertation have been published in the following outlets:


Chapter 2

Background

2.1 What is Remote Sensing?

Remote sensing involves the characterization of an object or scene without any physical contact [21]. This is usually accomplished by considering the characteristic of the material being measured, such as its shape, molecular composition, density, etc. These unique features of materials allow them to absorb, reflect, and emit electromagnetic radiation that is characteristic of their molecular composition [22]. In that regard, we use remote sensors mounted on satellite- or air-borne platforms to capture specific information about the Earth’s surface. These sensors can either be passive or active. Passive sensing systems rely on external sources, such as the moon and sun. They detect the natural electromagnetic radiation that is reflected or emitted by the surface of the Earth, while, active sensors incorporate internal sources, such as a laser, often used in LiDAR systems.

Remote sensing generally combines two different sensing modalities: imaging and spectrometry. The imaging system conveys information in the form of a visual perception related to the spatial distribution of the power from the variable attenuation of light waves or other electromagnetic radiation integrated over some spectral bands. Spectrometry, on the other hand, measures the distribution of light over a specific portion of the electromagnetic spectrum, acquiring information related to
the chemical composition of the material [23].

In remote sensing imaging, we mostly focus on the electro-optical and infrared (EO/IR) portion of the electromagnetic spectrum, the wavelength range being 0.4-14 µm. EO/IR imaging mostly involves measurements from passive sensors; with the two primary sources being reflection from sunlight and thermal emission. Figure 2.1 [23] illustrates the typical information captured by an EO/IR imaging sensor as a function of wavelength. The optical power received in the direction of the sensor is represented as radiance in this figure, where radiance is the radiant flux energy per unit solid angle and per unit projected area of the surface. The spectral range is divided into five different regions: visible (VIS, 0.4-0.7 µm), near infrared (NIR, 0.7-1.1 µm), shortwave infrared (SWIR, 1.1-3.0 µm), midwave infrared (MWIR, 3-5 µm), and longwave infrared (LWIR, 5-14 µm).

Figure 2.1: Information captured by a EO/IR imaging sensor across specific spectral regions. Credit for this figure belongs to [23].
2.2 Electromagnetic Wave Propagation

In this section, we will delve into the scientific principles in electromagnetic wave propagation fundamental in remote sensing. The analysis of remote sensing imagery and data requires an understanding of interactions between electromagnetic energy with the atmosphere and Earth’s surface. The surface of Earth can absorb, transmit and reflect electromagnetic radiation, and we will review some of the basic physics of how these phenomena takes place. The relationships in electromagnetic wave propagation are depicted in Figure 2.2. These interactions will be further described below.

![Figure 2.2: Electromagnetic wave propagation](image)

2.2.1 Maxwell’s Equation

The principles of electromagnetic propagation are defined by Maxwell’s equations:

\[
\nabla \cdot \mathbf{D}_e = \rho_e \tag{2.1}
\]

\[
\nabla \cdot \mathbf{B}_m = 0 \tag{2.2}
\]
\[\nabla \times \mathbf{E}_e = -\frac{\partial \mathbf{B}_m}{\partial t}\]  
(2.3)

\[\nabla \times \mathbf{H}_m = \mathbf{j}_e + \frac{\partial \mathbf{D}_e}{\partial t}\]  
(2.4)

where \(\mathbf{D}_e\) is the electric displacement, \(\mathbf{B}_m\) is the magentic-induction field, \(\mathbf{E}_e\) is the electric field, \(\rho_e\) is the electric-charge density, \(\mathbf{j}_e\) is the electric current density, and \(t\) represents the time. While, "\(\nabla\cdot\)" and "\(\nabla \times\)" represents the divergence and curl vector operators respectively.

Equation 2.1 states that the source charge density is the source of the electric field (the electric field diverges from the source charge distribution). According to Equation 2.2, the magnetic field does not diverge from a source and the magnetic flux through the surface is equal to zero, i.e. there are no magnetic poles or monopoles in the universe. Equation 2.3 states that changes in the magnetic flux with time generates voltage around the flux perimeter. Lastly, equation 2.4 states that magnetic field is generated by the changing electric flux density with time and the presence of electric current.

**2.2.2 The Wave Equation**

The Maxwell’s equations defined in section 2.2.1 form the fundamental basis for producing the wave equation in either electric or magnetic fields.

\[\nabla^2 \mathbf{E}_e - \mu_0 \epsilon_0 \frac{\partial^2 \mathbf{E}_e}{\partial t^2} = 0\]  
(2.5)

\[\nabla^2 \mathbf{B}_m - \mu_0 \epsilon_0 \frac{\partial^2 \mathbf{B}_m}{\partial t^2} = 0\]  
(2.6)

where \(\epsilon_0\) is the permittivity and \(\mu_0\) is the permeability of free space, while "\(\nabla^2\)" represents the Laplacian operator. The speed of light in vacuum is related to the physical quantities \(\epsilon_0\) and \(\mu_0\).
\[ c = \frac{1}{\sqrt{\epsilon_0 \mu_0}} = c = 2.998 \times 10^8 \text{m/s} \] (2.7)

There are different forms of the solution shown in equations 2.5 and 2.6, with one of the simpler representations being the propagation of a plane wave in a straight line,

\[ \mathbf{E}(r, t) = E_0 e^{-i(k \cdot r - \omega t)} \] (2.8)

where \( E_0 \) is the amplitude and polarization direction of the electric field, \( r \) is the spatial position vector, \( t \) is the time, \( k \) is the wavenumber (\( k = 2\pi/\lambda \), where \( \lambda \) is the wavelength), and \( \omega \) is the angular frequency (\( \omega = 2\pi f \), where \( f \) is the frequency). From the relationship between angular frequency and the wave vector, we get a relationship between the temporal frequency of oscillation and the spatial wavelength, \( c = \lambda f \). The frequency/wavelength of an electromagnetic wave can take on a range of values, and this range of frequencies/wavelength is referred to as the electromagnetic spectrum. A schematic of the electromagnetic spectrum, typical in remote sensing, is shown in Figure 2.1.

\section*{2.3 Radiometry: Background Fundamentals}

Radiometry is defined as the “science of characterizing or measuring how much electromagnetic energy is present at, or associated with, some location or direction in space” [21]. This section will review some fundamental definitions and concepts in radiometry, which are essential in topics of ray tracing and radiative transfer.

In quantum physics, the energy of an electromagnetic wave exists only in discrete amounts, i.e. it is quantized. The basic unit of energy for electromagnetic radiation is called a photon, and energy carried by the photon is expressed as:

\[ q = hf = \frac{hc}{\lambda} \text{ [joules]} \] (2.9)

where \( h \) is Planck’s constant \( (h = 6.63 \times 10^{-34} \text{ [joules \cdot sec]}) \), and energy has SI
CHAPTER 2. BACKGROUND

Figure 2.3: Geometry for writing the elemental area \((dA)\) and solid angle \((d\Omega)\).

units of \textit{joules} \([\text{J}]\).

We often refer to the propagation of energy towards or from a surface as the \textbf{radiant flux} or power \((\Phi)\) in terms of the first derivative of the total energy \((Q)\) with respect to time \((t)\),

\[
\Phi = \frac{dQ}{dt} \ [\text{Watts}] \tag{2.10}
\]

The radiant flux has SI units of Watts \([\text{W}]\), and \(Q\) is a summation of the total energy from the source of the electromagnetic radiation.

From our definition of radiant flux, we can estimate the rate at which power is delivered to a surface per unit area,

\[
E(x, y) = \frac{d\Phi}{dA} \ [\text{Wm}^{-2}] \tag{2.11}
\]

This term in radiometry is known as \textbf{irradiance} \((E)\), with SI units of \(W/m^2\). The quantity \(dA \ [m^2]\) represents the area element on a surface, the geometry of the elemental area in spherical coordinates is shown in Figure 2.3, and \((x, y)\) represents the spatial coordinates.

In radiometry, a term nearly identical to irradiance is \textbf{exitance} \((M)\), with the difference between these radiometric terms being the direction of propagation of
energy. Irradiance is described as the flux per unit area onto a surface, while exitance is the flux per unit area away from a surface. Exitance has the same equation as irradiance (Eq: 2.11), and SI units \([W/m^2]\).

The next radiometric term we will consider is **intensity** \((I)\). Both irradiance and exitance only provide us with spatial information, while the angular variation of the propagation of light or flux is represented by the radiant intensity,

\[
I(\theta, \phi) = \frac{d\Phi}{d\Omega} \text{[Wsr}^{-1}] \tag{2.12}
\]

where \((\theta, \phi)\) are generic orientation angles. Intensity has units of \(W/sr\). The term \(d\Omega\) is the solid angle of the surface element,

\[
d\Omega = \frac{dA}{r^2} \text{[sr]} \tag{2.13}
\]

The concept of solid angle is also illustrated in Figure 2.3, and has units of steradian [sr].

In radiometry, the most useful term is **radiance** \((L)\), which is defined as the radiant flux emitted/ reflected/ transmitted per solid angle per projected area. Radiance combines the spatial information of irradiance/exitance with the angular component of intensity, and is defined as,

\[
L(x, y, \theta, \phi) = \frac{d^2\Phi}{dA \cos(\theta)d\Omega} = \frac{dE}{d\Omega \cos(\theta)} = \frac{dI}{dA \cos(\theta)} \text{[Wm}^{-2}\text{sr}^{-1}\text{]} \tag{2.14}
\]

The SI units of radiance is \(Wm^{-2}sr^{-1}\). All the radiometric terms defined in this section are described in extensive detail by Schott [21].

### 2.4 Bidirectional Reflectance

Our research objectives focus on the development of formalism to estimate physical properties of a medium by the analysis of how electromagnetic radiation is scattered or emitted by a surface. In this section, we will examine some commonly used
terminology in describing how light is scattered by semi-infinite media. The term reflectance refers to the portion of light or other electromagnetic radiation scattered or reflected by a medium. Reflectance has various mathematical definitions depending on directionality of the scattered light by the geometry of the medium. The various geometrical considerations and nomenclature for reflectance are described in detail by Nicodemus [24].

2.4.1 Lambertian Reflectance

An ideal surface is often described as a Lambertian surface, and the scattered light off the surface is perfectly uniform with no angular dependency. An ideal or Lambertian surface has the important property that the radiance leaving the surface is the same in all directions regardless of the source angular geometry. In reality, no Lambertian surfaces are completely perfect, while there are commercially available products that come close such as Spectralon® [25, 26].

Mathematically, the radiance and exitance from a Lambertian surface is related by a factor of $\pi$,

$$L_{Lam} = \frac{E}{\pi}$$

(2.15)

2.4.2 Bidirectional Reflectance Distribution Function (BRDF)

The bidirectional reflectance distribution function (BRDF) of a medium is described as the ratio of scattered radiance to the incident irradiance [24, 27]. It is defined according to the following equation,

$$\rho_{BRDF}(\theta_i; \phi_i; \theta_r; \phi_r; \lambda) = \frac{L(\theta_i; \phi_i; \theta_r; \phi_r; \lambda)}{E(\theta_i; \phi_i; \lambda)} \ [sr^{-1}]$$

(2.16)

where $\theta$ and $\phi$ are the zenith and azimuth angles respectively of the incoming (subscript $i$) and reflected (subscript $r$) flux. The angular dependence of reflectance or BRDF is also a function of wavelength ($\lambda$). It has units of $sr^{-1}$. For a perfect Lambertian surface, the BRDF is $1/\pi$. 
The reflectance properties of a surface are typically defined by the term reflectance factor. From our definition of BRDF, we obtain the concept of the bidirectional reflectance factor (BRF), which is the ratio of the radiant flux reflected by the medium to the radiance flux reflected by an ideal lossless Lambertian surface (e.g. Spectralon) under identical illumination conditions [24, 27]. It is defined in the following equation:

$$\rho_{\text{BRF}}(\theta_i, \phi_i; \theta_r, \phi_r; \lambda) = \frac{L(\theta_i, \phi_i; \theta_r, \phi_r; \lambda)}{E(\theta_i, \phi_i; \lambda)} \times \frac{E(\theta_i, \phi_i; \lambda)}{L_{\text{Lam}}(\theta_i, \phi_i; \theta_r, \phi_r; \lambda)} \quad (2.17)$$

The BRF is a unitless quantity. A truly ideal Lambertian surface has BRDF of $1/\pi$, in that case, we can express BRF as,

$$\rho_{\text{BRF}}(\theta_i, \phi_i; \theta_r, \phi_r; \lambda) = \rho_{\text{BRDF}}(\theta_i, \phi_i; \theta_r, \phi_r; \lambda) \cdot \pi \quad (2.18)$$

Both BRDF and BRF are only theoretical terms, and in practice, due to the finite nature of the sensor and the source, the terms “conical” or “hemispherical” typically describe reflectance factors [24, 27, 28, 14]. Hemispherical conical reflectance factor (HCRF) measurements refer to directional reflectance measurements conducted in outdoor settings. The “conical” term refers to the finite nature of the sensor aperture, while the “hemispherical” term reflects the fact that illumination conditions stem from both direct and diffuse sources [24, 27, 14]. In laboratory settings, the term biconical reflectance factor (BCRF) describes directional reflectance measurements due to the finite nature of both the sensor and directional illumination source [24, 27, 28, 14]. These two reflectance factors, BCRF and HCRF, are typically what we observe in our experimental settings, however, there are numerous other reflectance factor geometries as illustrated in Figure 2.4.
### Figure 2.4: The various nomenclature and definitions of BRDF as described by [24, 27]. The “cases” highlighted in gray are measurable quantities, with BCRF (CASE 5) and HCRF (CASE 6) usually what we observe in our experimental settings. Credit for this figure belongs to [27].

#### 2.5 The Hapke Photometric Scattering Model

Physical properties of the soil surface such as its density, grain size, surface roughness, and moisture content can influence angular dependence of spectral signatures, specifically the Bidirectional Reflectance Distribution Function (BRDF) [3, 4, 5, 29, 6, 30, 31, 32, 7, 33, 34, 35, 36, 37, 38]. Models based on radiative transfer equations (RTE) can relate the angular dependence of the reflectance to these geophysical variables [5, 13, 3, 6, 30, 31, 32, 39]. Extraction of these parameters can provide a better understanding of the Earth’s surface, and play a vital role in various environmental modeling processes [9, 10]. Radiative transfer models, such as the one developed by Hapke, have been widely used in both astronomy and Earth remote sensing applications for the retrieval of physical characteristics of a medium. In this section, we will discuss briefly the fundamental physics of the radiative transfer equa-
2.5.1 Radiative Transfer

Radiative transfer describes the physical phenomenon of energy transfer of electromagnetic radiation. The mathematical interactions commonly used in describing the processes of emission, absorption, and scattering of an electromagnetic wave within a medium are referred to as the equations of radiative transfer. RTE are based on the fundamental assumption that the medium is treated as a continuous medium, and all interactions within the medium happen via the processes of emission, absorption, and scattering. A schematic diagram showing these interactions is
illustrated in Figure 2.5. A differential form of the RTE can be written as [5],

\[
\frac{\partial I(s, \Omega)}{\partial s} = \Delta I_E + \Delta I_s + \Delta I_F \\
= -E(s, \Omega)I(s, \Omega) + \frac{S(s, \Omega)}{4\pi} \int_{4\pi} I(s, \Omega')p(s, \Omega, \Omega') + F(s, \Omega) \quad (2.19)
\]

The equation of transfer states as light particle move through a medium, it can lose energy by absorption, gain energy through emission, and change direction via scattering. In Equation 2.19, we have radiance \( I(s, \Omega) \) at position \( s \) and propagating in the direction of \( \Omega \) within the medium. \( \Delta I_E \) is the extinction through the medium via absorption and scattering, \( \Delta I_F \) is the emission, \( \Delta I_S \) represents the increase in scattering caused by the light of intensity \( I(s, \Omega') \) propagating in the direction of \( \Omega' \). \( E(s, \Omega) \) is the volume averaged extinction coefficient, \( F(s, \Omega) \) is the volume emission coefficient, \( S(s, \Omega) \) is the volume averaged scattering coefficient, and \( p(s, \Omega, \Omega') \) is the volume averaged single-particle phase function.

### 2.5.2 Hapke IMSA Model

Hapke’s isotropic multiple scattering approximation (IMSA) model is based on the method of invariance and considers five orders of scattering [5, 40]. The IMSA model includes terms for single scattering, multiple scattering, the shadow hiding opposition effect (SHOE), and coherent backscatter opposition effect (CBOE) to describe how light scatters from granular materials [5, 41, 40, 42, 43]. The solution takes the following form:

\[
r(\theta_i, \theta_e, g) = K \frac{w(\lambda)}{4} \frac{1}{\mu_i + \mu_e} \left\{ p(g)\left[1 + B_{s0}B_s(g, K, \lambda)\right] + \left[H\left(\frac{\mu_i}{K}\right)H\left(\frac{\mu_e}{K}\right) - 1\right]\right\} \times \left[1 + B_{c0}B_c(g, K, \lambda)\right] \quad (2.20)
\]

where \( \mu_i \) & \( \mu_e \) are the cosines of the incident (\( \theta_i \)) and scattered zenith angles.
(θe), g is the phase angle\(^1\), \(p(g)\) is the single particle scattering phase function, \(B_s(g, K, \lambda)\) models the SHOE with \(B_{S0}\) being an accompanying scaling constant, while \(B_c(g, K, \lambda)\) represents the angular dependence of the CBOE with \(B_{C0}\) a scaling constant, \(H\left(\frac{\mu_i}{K}\right)\) and \(H\left(\frac{\mu_e}{K}\right)\) are the Chandrasekhar-Ambartsumian H-functions describing the multiple scattering, \(w(\lambda)\) is the single scattering albedo as a function of wavelength, and \(K\) is the porosity coefficient.

The CBOE dominates at very small phase angles (< 2 deg), where scattering within and between particles produces coherent amplification of observed reflectance \([42, 44, 45]\). In our experiments we ignored the effect of CBOE, since the BCRF and HCRF measurements described in this thesis do not include sufficiently small phase angles. The IMSA model in Eq. 2.20 also excludes factors of \(1/\pi & \mu_i\) as the measurements described are typically BCRF and HCRF.

2.5.2.1 Single-Scattering Phase Function

The phase function defines the angular distribution of the scattered energy by a particle at a given wavelength. In RTE, nearly all single-scattering phase functions for irregular particles are based on empirical expressions and easily quantifiable normalized functions. The commonly used phase functions are the Legendre polynomials and the Henyey-Greenstein (HG) phase function.

The Legendre polynomial phase function is,

\[
p(cos \Theta) = \sum_{l=0}^{N} \omega_l P_l(cos \Theta) \tag{2.21}\]

where \(\Theta\) is the scattering angle, \(P_l\) is the Legendre function, and \(\omega_l\) represent the moments of the Legendre polynomials, while the HG phase function is defined as,

\[
\Pi_{HG1}(g) = \frac{1 - \xi^2}{(1 - 2\xi \cos g + \xi^2)^{3/2}} \tag{2.22}\]

where \(\xi\) is the Henyey-Greenstein parameter representing the cosine asymmetry

\[\cos(g) = \cos(\theta_i) \cos(\theta_e) + \sin(\theta_i) \sin(\theta_e) \cos(\Delta \phi), \text{ where } \Delta \phi = |\phi_i - \phi_e| \text{ is the relative azimuth angle}\]

\(^1\)cos(g) = cos(\theta_i) cos(\theta_e) + sin(\theta_i) sin(\theta_e) cos(\Delta \phi), \text{ where } \Delta \phi = |\phi_i - \phi_e| \text{ is the relative azimuth angle}
factor, $\xi = \langle -\cos g \rangle$. If we consider the particle to be completely isotropic, the HG phase function is equal to 1 when $\xi = 0$. We can also write the Henyey-Greenstein function in terms of Legendre polynomials according to the following equation,

$$\Pi_{HG1}(g) = \sum_{l=0}^{N} (2l + 1)(-\xi)^{l}P_{l}(g)$$  \hspace{1cm} (2.23)

The equation shown in 2.22 is the one parameter HG phase function having only one lobe. However, most particles are double-lobed representing both forward and backward scattering of the particle. The double-lobed HG phase functions can be represented using a two-parameter HG function [5],

$$\Pi_{HG2}(g) = \frac{1 + c}{2} \left( \frac{1 - b^2}{1 - 2b \cos g + b^2} \right)^{3/2} + \frac{1 - c}{2} \left( \frac{1 - b^2}{1 + 2b \cos g + b^2} \right)^{3/2},$$  \hspace{1cm} (2.24)

and the three-parameter HG function,

$$\Pi_{HG3}(g) = \frac{1 + c}{2} \left( \frac{1 - b_1^2}{1 - 2b_1 \cos g + b_1^2} \right)^{3/2} + \frac{1 - c}{2} \left( \frac{1 - b_2^2}{1 + 2b_2 \cos g + b_2^2} \right)^{3/2}$$  \hspace{1cm} (2.25)

In equations 2.24 & 2.25, the first and second term describes the forward and backward lobe respectively. The shape of the lobes is determined by the parameters $b$, $b_1$ and $b_2$, and they are constrained between the range $0 \leq b, b_1, b_2 \leq 1$. The magnitude or relative strength of the lobes is determined by $c$, which does not have any constraint. Figure 2.6 illustrates the two-parameter HG phase functions for several different values of $b$ & $c$.

2.5.2.2 Isotropic Multiple Scattering Approximation

In the original Hapke IMSA model (eq. 2.20), the single-scattering term for the BRDF is calculated exactly,
Figure 2.6: The two parameter Henyey-Greenstein parameter for several values of the parameters b & c

\[ r_{SS} = \frac{w}{4\pi} \frac{\mu_0}{\mu_0 + \mu} p(g), \quad (2.26) \]

while the multiple-scattering term is approximated by considering isotropic scattering, \( p(g) = 1 \), and is given by,

\[ r_{MS} = \frac{w(\lambda)}{4\pi} \frac{\mu_0}{\mu_0 + \mu} [H(\mu_0)H(\mu) - 1] \quad (2.27) \]

The method of invariance combined with the assumption of isotropic phase function for multiple scattering was used to obtain the approximation of eq. 2.27. The method of invariance states that the reflectance of a semi-infinite, particulate medium does not change in the presence of an optically thin layer of identical particles placed on top. The method was derived for the first five order of scattering, with the net effect of the radiance due to the presence of additional layer being
The five different orders of scattering are shown in Figure 2.7. The method of invariance leads to the following nonlinear equation for reflectance:

$$
\left( \frac{1}{\mu_0} + \frac{1}{\mu} \right) r(\Omega_0, \Omega) = \frac{w}{4\pi} \left[ \frac{1}{\pi} p(\Omega_0, \Omega) + \int_{\Omega_0} p(\Omega_0, \Omega_0') \frac{r(\Omega_0', \Omega)}{\mu_0'} d\Omega_0' + \int_{\Omega} \frac{r(\Omega_0, \Omega')}{\mu} p(\Omega', \Omega) d\Omega' 
\right. 
+ \left. \int_{\Omega} \int_{\Omega_0} r(\Omega_0, \Omega') p(\Omega', \Omega_0') \frac{r(\Omega_0', \Omega)}{\mu_0} d\Omega_0' d\Omega' \right], \quad (2.28)
$$

if we let,

$$
L(\Omega_0, \Omega) = \frac{4\pi \mu_0 + \mu}{w} r(\Omega_0, \Omega) \quad (2.29)
$$

Substituting this in equation 2.28 leads to,

$$
L(\Omega_0, \Omega) = p(\Omega_0, \Omega) + \frac{w}{4\pi} \mu \int_{\Omega_0} p(\Omega_0, \Omega_0') \frac{L(\Omega_0', \Omega)}{\mu_0' + \mu} d\Omega_0' 
+ \frac{w}{4\pi} \mu_0 \int_{\Omega} \frac{L(\Omega_0, \Omega')}{\mu_0 + \mu'} p(\Omega', \Omega) d\Omega' 
+ \left( \frac{w}{4\pi} \right)^2 \mu_0 \mu \int_{\Omega} \int_{\Omega_0} \frac{L(\Omega_0, \Omega', \Omega_0')}{\mu_0 + \mu'} p(\Omega', \Omega_0') \frac{L(\Omega_0', \Omega)}{\mu_0'} d\Omega_0' d\Omega' \quad (2.30)
$$

where \( r(\Omega_0, \Omega) \) is our bidirectional reflectance, \( \Omega \) \& \( \Omega_0 \) are directions of the incident and exiting light.

If we consider the scattering to be isotropic, the phase function can be set to 1. As a result, the \( L\)-function in equation 2.29 becomes independent of sensor and solar azimuth, and only a function of \( \mu \) \& \( \mu_0 \) . We can then solve equation 2.30 as a product of the Ambartsumian-Chandresekhar H-Function,

$$
L(\mu_0, \mu) = H(\mu_0)H(\mu), \quad (2.31)
$$
where, the Ambartsumian-Chandresekhar H-Function is

\[
H(x) = 1 + \frac{w}{2} x H(x) \int_0^1 \frac{H(x')}{x + x'} dx'
\]  (2.32)

In this dissertation, the H-function that we used in the IMSA model (eq. 2.20) is an analytical approximation to exact solution in equation 2.32,

\[
H(x) \approx \left\{ 1 - wx \left[ r_0 + \frac{1 - 2r_0x}{2} \ln \left( \frac{1 + x}{x} \right) \right] \right\}^{-1},
\]  (2.33)

where \( r_0 \) is the diffusive reflectance,

\[
r_0 = \frac{1 - \gamma}{1 + \gamma},
\]  (2.34)

and,

\[
\gamma = \sqrt{1 - w}
\]  (2.35)

The approximate solution to the H-function in equation 2.33 has a relative error of less than 1% when compared to the exact solution in equation 2.32 [5].

2.5.2.3 Shadow Hiding Opposition Effect (SHOE)

The surge in brightness observed at small phase angles is represented by the shadow hiding opposition effect (SHOE) in Hapke’s radiative transfer equation [5, 43, 19]. It should be noted that the SHOE along with the CBOE are not based on the exact derivation of the radiative transfer equation, and were added to the Hapke model in an \textit{ad hoc} manner. The SHOE is explicitly dependent on the fill factor, but implicitly dependent on grain size distribution [5, 43]. Hapke’s model of the SHOE takes the following form:

\[
B_{SH}(g) \approx 1 + \frac{B_{S0}}{1 + \frac{1}{h_s} \tan \left( \frac{g}{2} \right)}
\]  (2.36)

\( B_{S0} \) is an empirical scaling factor constrained between 0 \( \leq B_{C0} \leq 1 \). \( h_s \) is the
Figure 2.7: A schematic diagram showing the first five-orders of scatterings used in the method of invariance to derive the expression for the bi-directional reflectance described by Hapke. The scattering changes are caused by the addition of an optically thin layer on top of an infinitely thick medium.

angular width parameter, which depends on both the grain-size distribution and the porosity of the medium. Hapke evaluates the parameter for various different particle size distributions [5]. In a unimodal case, the distribution takes the form:

\[ h_s = \left( \frac{3}{8} \right)^{\frac{3}{2}} K(\phi) \phi \]  

(2.37)

However, sediment grain size distributions can be quite complicated, with the distribution often consisting of more than one mode. An example of the grain-size distribution for a sediment sample from one of our experiment is shown in Figure 4.4. The smaller peaks of the secondary modes are due to the presence of finer sand and silts within the mixture. As a result, we modified the width parameter to account for multimodal particle distributions [3]:

\[ h_s = \epsilon k(\phi) \phi \]  

(2.38)

where \( \epsilon \) is a scaling constant, with \( 0 \leq \epsilon \leq 1 \). We chose this form to retain the
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functional dependence on \( \phi \) found in the simple distributions modeled by Hapke [5], which differed only by an overall scaling factor.

2.5.2.4 Coherent backscatter opposition effect (CBOE)

The coherent backscatter opposition effect is another \textit{ad hoc} addition to the Hapke IMSA model. The CBOE also measures the surge in brightness observed at very small phase angles (\(< 2 \text{ deg}\)), which arises from the multiple-scattering of particles. It is defined as,

\[
B_{CB}(g) = 1 + B_{C0} B_C(g)
\]

(2.39)

where \( B_{C0} \) is an amplitude factor, and an empirical approximation of \( B_C(g) \) is,

\[
B_C(g) \approx \left\{1 + \left[1.3 + K \left( \frac{1}{h_C} \tan \left( \frac{g}{2} \right) + \left( \frac{1}{h_C} \tan \left( \frac{g}{2} \right) \right)^2 \right] \right\}^{-1},
\]

(2.40)

where

\[
h_C = \frac{\lambda}{4\pi \Lambda_T}
\]

(2.41)

\( \Lambda_T \) is the mean free path in the medium, which is defined as the mean distance traveled by the photon within a medium before its direction changes [5].

The models in our research ignore the CBOE, since our BCRF and HCRF measurements do not include sufficiently small phase angles.

2.5.2.5 Single Scattering Albedo

The single scattering albedo (SSA), \( w(\lambda) \), at a given wavelength is the ratio of the total amount of light scattered to the total amount of light scattered and absorbed by the particle [5]:
\[ w(\lambda) = \frac{S}{S + A} \tag{2.42} \]

where \( S \) and \( A \) are the fraction of light scattered and absorbed by the particle respectively. SSA ranging in values from 0 to 1 is assumed to be an average property of the particles. It depends on the optical properties of the medium, determined by factors such as composition, grain-size distribution, shape and structure [19, 41, 40]. Non-absorbing media normally have high SSA, while media with large particles and high index of refraction generally have smaller SSA [19]. Irregularly shaped particles also have a higher SSA compared to spherical particles of the same size, since the path of a photon traveling through the particle is shorter for an irregularly shaped particle. For materials such as sediment, where particles are closely packed and large, SSA increases with decrease in particle size [19].

2.5.2.6 Fill Factor

The most recent addition to the Hapke radiative transfer model is the effect of porosity or soil compaction [12] on the angular reflectance of regoliths. The effect of porosity is described using a nonlinear function [5, 12]:

\[ K \approx -\frac{\ln (1 - 1.209\phi^{\frac{2}{3}})}{1.209\phi^{\frac{2}{3}}} \tag{2.43} \]

where \( \phi \) is the fill factor, and is defined as \( 1 - \text{porosity} \).

Studies have shown the inherent dependence of reflectance on the fill factor (decreasing porosity) of the medium, when the particles are significantly larger than the wavelength [12]. Hapke’s model predicts that the reflectance of the medium typically increases with increasing fill factor. As the fill factor increases and the medium becomes more opaque to the light passing in between the particles [12], eventually a threshold is reached where the particles are sufficiently closely packed that the scattering is more like that observed from larger single particles, with light reflecting off the surface less efficiently [12]. Hence, at high fill factors a noticeable decrease in reflectance can be observed [5].
2.5.2.7 Modified Hapke IMSA Model

The Hapke IMSA model calculates single-scattering contributions exactly, however, multiple scattering calculations include the approximation of an isotropic phase function [5]. In recent work, we modified the Hapke IMSA model to include anisotropic scattering of particles by introducing directional dependence into the multiple scattering term [3]. The modification includes an extra factor which depends on the phase function and a scaling parameter \( \eta \):

\[
r(\theta_i, \theta_e, g) = K \frac{w(\lambda)}{4} \frac{1}{\mu_i + \mu_e} \times \left( p(g) [1 + B_s B_s(g, K, \lambda)] + \eta p(g) \left[ H \left( \frac{\mu_i}{K} \right) H \left( \frac{\mu_e}{K} \right) - 1 \right] \right) \times [1 + B_c B_c(g, K, \lambda)]
\]

(2.44)

2.6 Soil Moisture Characterization

The change in spectral reflectance with varying moisture content of the soil is generally based on two different processes: (1) the internal reflection of the incident photons between the water and soil layer, resulting in the darkening of the soil, and (2) the absorption of the incoming photon by the water layer [20]. In this section, we introduce a physics based model that takes into account these two phenomena in expressing the effect of soil moisture content. This model, detailed in section 2.6.1, is the multilayer radiative transfer model of soil reflectance (MARMIT), which is a recent improvement to the works by Bach and Mauser [20] in modeling reflectance of soils under varying moisture conditions.

2.6.1 MARMIT: A Multilayer Radiative Transfer Model

MARMIT models wet soil by considering a rough dry soil surface covered by a thin layer of water [46]. Figure 2.8 shows the path of an incident light beam and the various parameters associated with each phase of the light ray. The surface of the
Figure 2.8: The MARMIT assumes a rough dry surface covered with a thin layer of water. The surface of the soil is assumed to consist of randomly oriented facets that reflect specularly. The reflectivity and transmissivity between the media are given by $r_{ij}$ and $t_{ij}$ respectively. $T_w$ is the transmittance of the water layer and $R_d$ is the reflectance of the dry soil [46].

soil is assumed to consist of randomly oriented facets that reflect specularly [47]. The arbitrary ray of light gets transmitted from the air (medium 1) to the water layer (medium 2) with a transmission coefficient $t_{12}$. A fraction of the incident beam is also reflected by the air-liquid interface, and the reflection coefficient is given by $r_{12} = 1 - t_{12}$. The beam of light undergoes multiple scattering events between the liquid-soil interface, $R_d$, and the liquid-air interface, $r_{21}$. The multiple scattering events between these interfaces increase the probability of the incident photon being absorbed by the soil particles. This results in the common visual observation that surfaces appear darker as they become wet. The fraction of the light that is not reflected back to the surface is transmitted from the water to the air with the transmission coefficient $t_{21}$.

Ångström was the first to model the “darkness” of wet soil in 1925 [48]. Ångström explained this phenomena using a first order approach, where the diffuse reflection from a rough surface results in total internal reflection at the liquid-air interface
of the water layer covering the surface. The total internal reflection increases the absorption of light by the particles, which describes the darkening effect of wet soil [48, 20]. This is expressed as,

\[ \rho = \frac{\rho_0}{n^2(1 - \rho_0) + \rho_0} \quad \text{(2.45)} \]

where \( \rho \) is the reflectance of a wet surface, \( \rho_0 \) is the reflectance of a dry surface and \( n \) is the refractive index of liquid.

This approach of modeling wet surfaces by Ångstrom was further improved by Lekner and Dorf (L&D) in 1988 [49]. The initial Ångström model was intended for the total albedo of the soil, and L&D incorporated the effects of spectral reflectance and the influence of the wavelength dependency of the refraction–index of water [20, 49, 46]. L&D assumed water absorption is negligible in the VIS-NIR, and the total absorptance for a wet soil is given by,

\[ A_{wsL} = \frac{t_{12}A_d}{1 - r_{21}R_d} \quad \text{(2.46)} \]

where \( A_d = 1 - R_d \) is the absorptance of the dry soil. The reflection and transmission coefficients between the interface are calculated based on Fresnel equation for unpolarized light [46]. They are dependent on the relative refractive index, \( n \), given by the ratio of the refractive index of pure water (\( n_w \)) to the refractive index of air (\( n_a \approx 1 \)): \( n \approx n_w / n_a \approx n_w \). The reflectivity at the air-liquid interface, \( r_{12} \), then can be calculated by,

\[ r_{12} = \frac{1}{2}(r_{12,s} + r_{12,p}) \quad \text{(2.47)} \]

where, \( r_{12,s} \) represents the s-polarized light,

\[ r_{12,s} = \left| \frac{n \cos \theta_i - \cos \theta_t}{n \cos \theta_i + \cos \theta_t} \right|^2 = \left| \frac{n \cos \theta_i - \sqrt{1 - (n \sin \theta_i)^2}}{n \cos \theta_i + \sqrt{1 - (n \sin \theta_i)^2}} \right|^2 \quad \text{(2.48)} \]

and \( r_{12,p} \) represents the p-polarized light,
\[ r_{12,p} = \left| \frac{n \cos \theta_i - \cos \theta_i}{n \cos \theta_i + \cos \theta_i} \right|^2 = \left| \frac{n \sqrt{1 - (n \sin \theta_i)^2} - \cos \theta_i}{n \sqrt{1 - (n \sin \theta_i)^2} + \cos \theta_i} \right|^2 \]  

(2.49)

where \( \theta_i \) is the incident angle formed between the normal and incident ray, and \( \theta_t \) is the refraction angle formed between the normal and transmitted ray.

L&D computed the reflectivity at the liquid-air interface, \( r_{21} \), by integrating it over the entire hemisphere [49, 46, 47]. Thus, we can define \( r_{21} \) in terms of the refractive index of pure water and the average reflectance of an isotropically illuminated surface (\( r_{12}' \)) [49, 50],

\[ r_{21} = 1 - \frac{1}{n^2} (1 - r_{12}') \]  

(2.50)

where,

\[ r_{21}' = \frac{3n^2 + 2n + 1}{3(n + 1)^2} - \frac{2n^3(n^2 + 2n - 1)}{(n^2 + 1)^2(n^2 - 1)} + \frac{n^2(n^2 + 1)}{(n^2 - 1)^2} \log n \]

\[ - \frac{n^2(n^2 - 1)^2}{(n^2 + 1)^2} \log \frac{n(n + 1)}{n - 1} \]  

(2.51)

As we have mentioned above the model proposed by L&D is only expressed in the VIS-NIR, where water absorption is assumed negligible. However, the model becomes invalid in the SWIR, where we have strong absorptions bands for water. Bach & Mauser in 1994 [20] introduced absorption features into the reflectance model. They calculated the transmittance of the light ray using the Beer-Lambert law,

\[ T_w = \exp(-\alpha_B L) \]  

(2.52)

where \( \alpha_B \ [m^{-1}] \) is the specific absorption coefficient of water and \( L \ [m] \) is the thickness of the water layer. The reflectance of wet soil now can be written as,
\[ R_{wsB} = (1 - A_{wsL}) \exp(-2\alpha_B L) \quad (2.53) \]

\( A_{wsL} \) is the total absorption of wet soil (equation 2.46). The factor of 2 in the transmittance function represents the light beam traveling twice through the water layer. The soil surface is considered to be a combination of wet and dry areas, which Bach [51] modeled by introducing an efficiency parameter \( \epsilon \),

\[ R_{modB} = \epsilon R_{wsB} + (1 - \epsilon) R_d \quad (2.54) \]

When the soil is dry, \( \epsilon = 0 \), and when soil is completely saturated with water, \( \epsilon = 1 \).

The MARMIT model introduced in [46] is a recent improvement to the Bach model which takes into account the transmittance of light across the liquid-air layer (see Figure 2.8). The total reflectance of the wet soil is expressed as a summation of the successive reflections and refractions at the surface,

\[ R_{ws} = r_{12} + t_{12} T_w^2 R_d t_{21} + t_{12} T_w^4 R_d^2 t_{21} r_{21} + \ldots \quad , \quad (2.55) \]

which when factorized,

\[ R_{ws} = r_{12} + t_{12} t_{21} R_d T_w^2 (1 + r_{21} R_d T_w^2 + r_{21}^2 R_d^2 T_w^4 + \ldots) \quad , \quad (2.56) \]

the form within the bracket can be expressed as a geometric series that converges to

\[ \frac{1}{1 - x} \quad \text{if} \quad |x| < 1 \quad \text{with} \quad x = r_{21} R_d T_w^2 \quad (2.57) \]

Thus, our new expression for the total reflectance is:

\[ R_{ws} = r_{12} + \frac{t_{12} t_{21} R_d T_w^2}{1 - r_{21} R_d T_w^2} \quad (2.58) \]

When the soil is completely dry, the parameters \( t_{12}, t_{21} \) and \( T_w \) are 1. While, \( r_{12} \& r_{21} \) are equal to 0, and \( R_{ws} = R_d \). Similar to equation 2.54, MARMIT also has an efficiency term,
$R_{mod} = \epsilon R_{ws} + (1 - \epsilon) R_d$ (2.59)
Chapter 3

Design and Instrumentation

In this chapter we will briefly discuss the instrumentation that we use in our various experiments. Hyperspectral BRDF data in both field and laboratory settings were collected using a goniometer system developed here at RIT (section 3.1). We also collected imagery using a hyperspectral imaging sensor (HSI) mounted on a telescopic mast (section 3.2), which was radiometrically calibrated using a LabSphere integrating sphere (section 3.3). These spectral measurements, in both field and laboratory settings, were accompanied by a set of geotechnical measurements, which included sediment density, grain size distribution, and moisture content, as well as mechanical properties of the sediment, such as shear strength and the dynamic deflection modulus (section 3.4). In our various studies, we have also utilized commercially available imaging systems, both space- and air-borne sensors, as well as imagery collected from an Unmanned Aerial System (UAS). These different payloads will be discussed further in following chapters.

3.1 Goniometer System

In the remote sensing community, goniometers are instruments that measure the reflected light from surfaces/materials as a function of varying view and illumination geometries. BRDF of a surface/target can be determined using these instruments...
Figure 3.1: (left) The GRIT during measurements at the Algodones Dunes experiment, and (right) GRIT being used in a laboratory setting.

due to their ability in precisely measure reflectance at different angular orientations over a hemisphere. In other words, we can use a goniometer to validate the models/theories described in sections 2.4 & 2.5. The sensor attached to a goniometer is dependent on the scientific requirements of the user. In our specific case, it is a spectrometer-based system capable of measuring electromagnetic radiation over a large range of wavelengths. Our lab at RIT has used two generations of this instrument over the past few years: (1) goniometer of the Rochester Institute of Technology (GRIT) and (2) a second generation system called GRIT-two (GRIT-T) [3].

The first generation of the instrument, GRIT, was designed and developed by Charles Bachmann and his research group at RIT, which was a successor to the goniometer for outdoor portable hyperspectral earth reflectance (GOPHER) used by Bachmann at the Naval Research Lab (NRL) [14]. GRIT was operational from 2013-2015 performing experiments in both field and laboratory settings. It took part in several different field campaigns such as the Algodones Dunes of California and the Nevada Automotive Test Center (NATC) in 2015. The system being operated in field and lab settings is shown in Figure 3.1. GRIT had several limitations, which prompted the design and development of a second-generation of the instrument.
Figure 3.2: (a) The main components of the goniometer system, GRIT-T. The two ASD spectrometers simultaneously measures the radiance of the target plane and the downwelling radiance from the sky. After postprocessing, they provide spectral reflectance measurements from 350nm to 2500nm at a resolution of 1-nm. The C-shaped design of the base ring along with the rotating arm allows measurements of the surface over the complete hemisphere. (b), (c), & (d) Illustrates the versatility of GRIT-T being deployed in various field and laboratory settings. Figure from [52].

GRIT was extremely heavy, weighing in at approximately 230 lbs, which made it difficult to use in field experiments, especially in the rough terrain of our various field sites. The closed ring design of the instrument introduced a significant amount of self-shading onto our surface/target of interest. This resulted in an azimuth range of ±15 degrees in the backscatter direction being completely shadowed due to the instrument. The system was also designed to operate manually with two users controlling softwares for the spectral measurements and movement of GRIT. This caused measurements to take approximately 2.5 hours, which is not ideal for outdoor remote sensing measurements.

The goniometer of the Rochester Institute of Technology-Two (GRIT-T) is a second-generation system designed to obtain BRDF measurements in both labora-
CHAPTER 3. DESIGN AND INSTRUMENTATION

GRIT-T has been operational from 2015-present, and has also taken part in several field campaigns across the United States. The studies performed in my research focused mostly on data collected using this second-generation instrument. Figure 3.2 illustrates the different components of the GRIT-T system, deployed in various experimental settings. This second-generation instrument improved upon many of the limitations and flaws of GRIT. The instrument consists of two Analytical Spectral Devices (ASD) FR4 spectro-radiometers to simultaneously provide directional radiance measurements from the target plane while recording the directional downwelling radiance from the sky. The ASD spectrometers provide spectral measurements from the visible through the short-wave infrared (350-2500 nm). The design of GRIT-T ensures positioning of the fore-optic over an azimuthal range of 0 deg to 180 deg, and -70 deg to +70 deg in zenith. This allows sampling of the target surface over the complete hemisphere. The target-plane tracking of the instrument minimizes any variations in the field of view. As a result, it has an angular position accuracy of ±0.2 deg in both azimuthal and zenith sensor positions. The small form of the sensor head assembly also minimizes self-shading. GRIT-T is capable of producing digital elevation models using two different methods: (1) from an onboard laser measurement unit [53] and (2) at higher resolution from an on-board field-of-view camera, which provides stereo views of the measurement location as input to a structure-from-motion algorithm [54].

3.2 Hyperspectral Imaging Sensor

A major part of our field campaigns were imaging salt marsh vegetations and sediment structure using a very fine hyperspectral imaging system. The hyperspectral camera, Headwall VNIR Micro-hyperspec High Efficiency E-series, is a pushbroom system providing spectral measurements from 400 to 1000 nm with 371 spectral bands and 1600 across-track spatial pixels. Figure 3.3 illustrates the different components and imagery collected by the system.

The HSI sensor resides within a maritime-rated General Dynamics Vector 20
pan-tilt unit. The pan-tilt unit scan range is -34° to 34° in pitch, and -175° to 175° in yaw. The imaging system also hosts a Vectornav VN-300 IMU-GPS to provide pointing information and GPS time-stamps. In the field, the HSI system is placed on-top of a telescopic mast, which is designed to be raised 1-15 m above the ground.

The pan-tilt unit alongside the telescopic mast is capable of imaging a scene at multiple view-geometries, which allows us to perform hyperspectral Bidirectional Reflectance Distribution Function (BRDF) measurements from the imaging sensor. The ability to perform measurements at different heights, using the telescopic mast, also allows us to observe the effect spatial resolution has on hyperspectral imagery.

Figure 3.3: (a) The HSI system being deployed in the field on-top of a telescopic mast. (b) The different components of the HSI system. (c) A typical hyperspectral image obtained by the system. Figure from [55].
The sensor can also be used as a low-rate video system, providing hyperpsectral measurements at frame-rates up-to 250 Hz [56].

![LabSphere Helios integrating sphere.](image)

**Figure 3.4: LabSphere Helios integrating sphere.**

### 3.3 Integrating Sphere

The Headwall VNIR system detailed in section 3.2 was calibrated and characterized in-house using a 0.5 m LabSphere Helios integrating sphere paired with a calibrated spectrometer. The Helios system consists of an ocean-optics VNIR spectrometer, a quartz tungsten halogen bulb, two xenon plasma arc lamps, a silicon broadband detector measuring in the VNIR, and an Indium Gallium Arsenide (InGaAs) detector measuring radiance in the shortwave infrared. The light sources output constant uniform illumination through an 8” exit port of the integrating sphere onto a target/surface; capable of reaching full day light down to night vision radiances. The
system, combination of the high intensity plasma lamps and VNIR spectrometer, are utilized to radiometrically calibrate our Headwall imaging sensor from raw digital number (DN) to radiance ($W m^{-2} sr^{-1} \mu m^{-1}$).

Figure 3.5: The various geotechnical instruments we used in our studies in both field and laboratory settings: (a) pluvation apparatus, (b) dynamic cone penetrometer (DCP), (c) mechanical sieve shaker, (d) sprinkle Infiltrometer, (e) static cone penetrometer (SCP), (f) Humboldt drying oven, (g) sand cone density apparatus, (h) light weight deflectometer (LWD).
3.4 Geo-technical Instrumentation

The lab and field spectral measurements are accompanied by a set of geotechnical measurements, which included sediment density, grain size distribution, and moisture content, as well as mechanical properties of the sediment, such as shear strength.

Sediment density was measured with a sand cone density apparatus (Fig 3.5g). Samples collected were also analyzed to determine moisture content and grain size distributions using, respectively, a drying oven (Fig 3.5f) and a mechanical sieve shaker (Fig 3.5c). To achieve samples of varying sediment density, they were pluviated using an apparatus (Fig 3.5a) in our laboratory following an ASTM standard [57]. The light weight deflectometer (LWD) along with the static cone penetrometer (SCP) and dynamic cone penetrometer (DCP) were used to evaluate the consistency of soils, their load-bearing capacity and level of compaction in our various field experiments; the instruments are shown in Figures 3.5h, 3.5b and 3.5e respectively. In our laboratory studies, to evaluate the effect of moisture content, a sprinkle Infiltrometer (Fig 3.5d), which is a portable rainfall simulator, was used to introduce moisture into the sediment samples over a range of predetermined rates.
Chapter 4

Sediment Fill Factor Retrieval I

4.1 Introduction

This chapter focuses on the retrieval of the fill factor from the inversion of the Hapke model and variants (increasing fill factor corresponds to decreasing porosity). Modifications were made to the Hapke isotropic multiple scattering approximation (IMSA) model to account for directional dependence in the multiple scattering term [3, 58].

Located in Southern California, our area of study is the Algodones Dunes, a potentially desirable site for the vicarious calibration of space-borne imaging sensors [59]. A major field campaign was conducted in March 2015 to characterize the Dunes. The NASA Goddard LiDAR, hyperspectral, and thermal (G-LiHT) sensor suite [59, 60] collected airborne imagery during the field campaign, and the field team collected sediment samples from various sites across the dune system, capturing the variation in its geophysical properties [3, 59]. During the campaign, Hyperspectral hemispherical conical reflectance factor (HCRF) measurements of sediments were collected on site using the Goniometer of the Rochester Institute of Technology (GRIT), and later from samples returned to RIT in a laboratory setting using GRIT and a second generation instrument, the Goniometer of the Rochester Institute of Technology Two (GRIT-T) [53, 3, 59].
In this study, we retrieve fill factor from GRIT-T BRDF measurements of Algodones sediment samples in the controlled conditions of our laboratory [3]. We also demonstrate that fill factor also can be retrieved from airborne imagery from the NASA G-LiHT system collected during the 2015 campaign and from imagery collected by the the Advanced Baseline Imager (ABI) on the Geostationary Operational Environmental Satellite (GOES) series [61]. Specifically, in this study, we retrieved two geophysical parameters of Earth sediments, fill factor and single scattering albedo, through inversion of a modified version [3] of the radiative transfer model developed by Hapke [5]. The specific objectives of this study were to: 1) validate the inversion methodology by performing controlled experiments within a laboratory setting using a field sediment sample drawn from a different part of the Algodones Dunes system than what was used to develop the original laboratory-based demonstration of the retrieval in [3], 2) apply the inversion methodology to airborne data from NASA G-LiHT, and 3) to space-borne data collected by the NOAA GOES system.

4.2 Study Area

The study area, Algodones Dunes, located in southeastern California (32° 52’ 58.44” N, 115° 1’ 8.4” W), is one of the hottest and driest regions in the United States [62]. The Dunes, which are 64 km in length and 6-10 km wide, have formed and continue to evolve through aeolian deposition and can reach heights up-to 100 m (Figure 4.1) [62, 63]. Prevailing winds and the presence of high mountains located in the west and northwest have led to the formation of larger dunes with coarser sands in the west, and drier dunes with finer sediments in the east [63]. The sediments are typically composed of 70-80% quartz, 10-15% feldspar, 5-15% rock fragments, and an assortment of heavy minerals make up the rest [64].

The Algodones Dunes System has recently been identified as a potential site for the inter-calibration of space-borne sensors. The site has shown promise due to its similarity to the pseudoinvariant calibration site (PICS) Libya-4 [59, 65]. The
2015 field campaign provided the information required to perform absolute radiometric correction using the Algodones site as a PICS [59]. Portable spectrometers and hyperspectral goniometers obtained ground truth data which characterized both spatial and temporal variability’s within the dunes [3, 59, 66]. The imaging platform G-LiHT collected complementary hyperspectral and LiDAR data for the characterization of the terrain [59, 60].

### 4.3 Inversion Methodology

Our inversion of the Hapke model for the retrieval of geophysical properties relies on the key observation that the single scattering phase function is invariant to the illumination geometry [3], with a geometric dependence only on the phase angle $g$. Hence, the Hapke model in Eq. 2.20 can be reorganized in terms of a scaled version of the observed reflectance and the multiple scattering term:
The approach requires the acquisition of BRDF data at different illumination geometries, and minimizes the residual between the single scattering phase function for the two sets of data:

$$\min_{\phi, w(\lambda)} \left[ \{p(g) \left[ 1 + B_{s0} B_s(g, K, \lambda) \right] - p(g) \left[ 1 + B_{s0} B_{s,1}(g, K, \lambda) \right]\}^2 \right]$$  (4.2)

The single phase scattering function and the minimization shown in equations 4.1 & 4.2 respectively are for the original Hapke model (Eq. 2.20), but it can also be applied to the modified Hapke model (Eq. 2.44). The two different methodologies will be discussed in further detail below.

Figure 4.2: Workflow for inversion of the IMSA model. Figure from [3].
4.3.1 Inversion: Original Hapke Model

An overall flow diagram of the processing steps for the inversion [3] of the original Hapke model is shown in Figure 4.2. In the first step of the inversion process, the two sets of BCRF scans (at the two different illuminations) must be interpolated to a common phase angle grid to facilitate the minimization of the single scattering phase function. This was achieved by using the Steffens algorithm, which provided a stable, well-behaved interpolation of the BCRF data [67]. Additional refinements, which decrease the overall residual, include the use of a low-pass filter (Sovitsky-Golay filter) during the interpolation onto the common phase angle grid [68]. The two-parameter search over the single scattering albedo, \( w(\lambda) \), and the fill factor, \( \phi \) uses the gradient-based Nelder-Mead simplex method [69].

We also introduced an additional constraint [3] in our inversion methodology to improve the convergence of the model to a consistent solution. This constraint is motivated by the goal that the resulting fill factor retrieved should be consistent across all wavelengths. This is a physical requirement of our inversion methodology, but without insisting on this constraint, the processing steps described in eqs. 4.1 & 4.2 and illustrated in the flow-chart are essentially wavelength agnostic. The minimization technique can be applied independently to each wavelength, and therefore there is a potential to obtain solutions that do not report a consistent fill factor across all wavelengths. In contrast, we expect to obtain a unique value of \( w(\lambda) \) for each \( \lambda \). As a result, we want to constrain the individual estimates obtained for the fill factor at a particular wavelength (\( \phi_\lambda \)) so that they do not differ from the average,

\[
\bar{\phi} = \frac{1}{N_\lambda} \sum_\lambda \phi_\lambda ,
\]

(4.3)

by more than a specified amount \( \delta \),

\[
|\phi_\lambda - \bar{\phi}| \leq \delta
\]

(4.4)

In the inversion process, we must first run the optimization over all wavelengths (eqs. 4.1 & 4.2) without the constraint introduced in equation 4.4. We then repeat
CHAPTER 4. SEDIMENT FILL FACTOR RETRIEVAL I

the same steps, but this time the NelderMead simplex optimization step enforces the constraint (eq. 4.4). We can reiterate this constraint multiple times if desired, where the size of $\delta$ is given by $\delta = \delta(t)$, and $\delta(t)$ is a decreasing function of the iteration step $t$.

4.3.2 Inversion: Modified Hapke Model

An overall flow diagram of the processing steps for the inversion of the modified Hapke model is shown in Figure 4.3 [3]. The initial steps of this inversion process follow a similar approach outlined in section 4.3.1. This provides us with an initial estimate of the fill factor, $\phi(t = 0)$, and SSA, $w(\lambda, t = 0)$. These values are then passed through equation 4.1 to obtain an initial estimate of the scaled single-scattering phase function ($\{p(g) [1 + B_{s0} B_s(g, K, \lambda)]\}_{est.,1,2}$). These estimates are interpolated onto the common phase angle grid as before. This is followed by the optimization of two sets of the scaled single-scattering phase functions in terms of the free parameters $B_{s0}$ & $\epsilon$ of the SHOE (eqs. 2.36 & 2.38), and the coefficients of the three-parameter HG function (eq. 2.25) $b_1$, $b_2$ and $c$. The goal of this step is ultimately to find an estimate of the phase function, $p(g)$. In this optimization step, we again use the NelderMead simplex method. The residual between the forward-propagated values of the scaled single scattering phase function ($\{p(g) [1 + B_{s0} B_s(g, K, \lambda)]\}_{fwd}$) is compared against the initial estimate of the scaled single scattering phase function, $\{p(g) [1 + B_{s0} B_s(g, K, \lambda)]\}_{est.,1,2}$, for the two illumination conditions at the common phase angle grid obtained in the earlier step. This provides us with values for $b_1$, $b_2$ and $c$ to calculate $p(g)$ required for inversion of the modified Hapke model. We insist at this new step that the minimization be over a common set of coefficients $B_{s0}$, $\epsilon$ $b_1$, $b_2$ and $c$ for both illumination conditions.

$^{1}$The subscripts “1” and “2” refer to the two sets of data used in the optimization process. In the case of the laboratory experiments, they are the two different illumination conditions.
Figure 4.3: Workflow for the modified model incorporating directional dependence in the multiple scattering term in a multi-stage optimization procedure. Figure from [3].
Having now an estimate of the phase function, \( p(g) \), and a free scale parameter \( \eta \) we then calculate the scaled single scattering phase function from our modified Hapke model (see section 2.5.2.7),

\[
\begin{align*}
\min_{B_{s0,c,b1,b2,c}} & \left[ \left( \{ p(g) [1 + B_{s0} B_{s,1}(g, K, \lambda)] \}^{est.,1} - \{ p(g) [1 + B_{s0} B_{s,1}(g, K, \lambda)] \}^{fwd} \right) + \left( \{ p(g) [1 + B_{s0} B_{s,1}(g, K, \lambda)] \}^{est.,2} - \{ p(g) [1 + B_{s0} B_{s,1}(g, K, \lambda)] \}^{fwd} \right) \right]^2 \\
& \quad + \left( \{ p(g) [1 + B_{s0} B_{s,1}(g, K, \lambda)] \}^{est.,2} - \{ p(g) [1 + B_{s0} B_{s,1}(g, K, \lambda)] \}^{fwd} \right)^2 
\end{align*}
\] (4.5)
conditions. This choice leads to an inversion depending only on two parameters, the porosity and single scattering albedo, compared to the original ten free parameters of the Hapke model. Other differences between past approaches and our optimization scheme include the fact that past approaches used least-squares gradient descent and grid search optimization techniques [11, 19], while our approach [3] uses a simplex-based search method, the Nelder-Mead Simplex Method [69]. Additional advantages of using the Nelder-Mead optimization include a decreased computation time and more repeatable retrieval process. We also found that the best optimization results relied on using regularization to achieve numerically stable solutions [3].

Our modified Hapke model, which no longer assumes isotropic multiple scattering, also provided consistently better results compared to the original model when using our inversion methodology. The use of all these techniques within our optimization to invert the Hapke model and our variant of this model has consistently given us a meaningful retrieval of the sediment fill factor and single scattering albedo from both controlled experiments in a laboratory setting as well as from air-/space-borne data.

4.4 Laboratory Studies

Our laboratory studies in this work included BCRF measurements of sediment samples acquired from the Algodones Dunes during the 2015 field campaign. These studies involved manipulating the density of the samples, and examining how this geophysical variable affected the observed BCRF. These data are the basis of the fill factor and single scattering albedo joint retrievals using our original/modified Hapke optimization model in the laboratory portion of the present study. The Algodones sediment sample 1306-M-03 acquired from the northern end of the dunes system (32° 58’ 45.00” N, 115° 7’ 47.00” W) was used for the laboratory analysis. The grain size distribution along with a microscopic images of the sediment sample is shown in Figure 4.4.

After mechanical sieving, we found that the largest grain size fraction was for
Figure 4.4: (a) The grain size distribution of the sediment sample 1306-M-03 acquired from the northern end of the dunes. The sediment consists of fraction up to 450 µm in size (b) The prepared sand sample to perform the laboratory studies using the goniometer. (c) Microscopic image (4× magnification) of the sediment, demonstrating the complexity of the material. Figure from [52].

the 450 µm sieve; particles of this size will result in scattering described by the geometric optics regime. The microscopic image in Figure 4.4 demonstrates the complexity of the material observed in the grain-size distribution and shape as well as its variety in mineral composition. The complexity of the mixture is also reflected in the multi-modal distribution of the particle size. In our work, we introduced a modification to the width parameter of the SHOE (equation 2.38), which depends on the grain size distribution, to allow greater flexibility in representing the possibility of multi-modal distributions [3].

The sample was manipulated via pluviation to achieve a series of different densities [57]. The drop height of the sediment in the apparatus is correlated with the resulting relative density of the sediment, and we use this approach because past analysis indicates that results are more repeatable than an existing ASTM standard [57]. Other approaches to sample preparation, such as the use of a wind
Figure 4.5: The laboratory set-up to perform BCRF measurements using the GRIT-T instrument. The illumination source for the measurements was a 300 Watt Fresnel lamp, mounted on a mechanical arm to steer the source to the desired zenith angles, (a) 20 and (b) 60 deg. (c) The goniometer collecting measurements from a Spectralon® panel, which serves as the reference standard.

tunnel, have also been studied [37, 38]. Such approaches arguably can produce distributions, and in particular gradients, across a larger area that are important in analyzing the details of Aeolian processes, however, our goals here were much simpler, namely the production of a uniform relative density of the sediment that was highly repeatable, both of which result from the use of a pluviation approach [57]. The GRIT-T system measured the BCRF for each sample preparation. The objective of the laboratory measurements was to validate the radiative transfer model and the retrieval process detailed in section 4.3.

The samples were measured at two different illumination geometries (20 deg and 60 deg) for each sediment density preparation. The minimization process described in section 4.3 uses two data sets acquired at the different illuminations as input. The lab set-up for performing the series of BCRF measurements is shown in Figure 4.5. Figures 4.5a & 4.5b shows the set-up with the illumination source at a zenith of 20 and 60 deg respectively. The source is a 300 Watt Fresnel lamp, which provided collimated light onto the target plane. The radiance measurements from the ASD spectrometer were referenced to a Spectralon® panel [70], which approximates a Lambertian surface, shown in Figure 4.5c.
4.4.1 Spectral Analysis and Fill Factor Retrieval

The reflectance spectrum for the sample 1306-M-03 at a density of 1.5252 g/cm$^3$ at two different illumination angles is shown in Figure 4.6. The figure displays the reflectance spectra for sensor positions over the complete hemisphere, with the illumination source at zenith angles of 20 and 60 deg. The colorbar in the figure corresponds to the sensor azimuth. All of the lab measurements in this study followed a similar trend. Several different factors influence the reflectance spectrum of the sediment: the presence of organic matter, mineral composition, roughness, particle size distribution, and density [71]. The reflectance increases with wavelength in the visible part of the spectrum (400-700 nm). There are weak absorptions bands at wavelengths less than 1000 nm due to the presence of iron oxides within the sample [72]. The strong absorption peaks observed at wavelengths 1450 nm and 1950 nm are due to water and hydroxyl bands [71]. The presence of clay materials influences the absorption peaks observed near 2200 nm [72].
Figure 4.7: BCRF measurements for sample 1306-M-03 at density 1.5252 g/cm³. The BCRF measurements are shown at the two different illumination geometries, (a) 20 deg and (b) 60 deg. The BRDF shape depends on both wavelength and illumination geometry. Figure from [52].

Figure 4.7 shows the BCRF plots observed at the two different illumination angles (20 deg and 60 deg) for five different wavelengths from the visible to the short wave infra-red (SWIR). As the Figure shows, the geometry of the source strongly influences the structure of the BCRF. There is a greater amount of diffuse scattering at illumination angles closer to nadir (20 deg). When the illumination angle is closer to nadir, there is more multiple scattering within the medium, resulting in more diffuse reflectance. At large zenith angles (60 deg), there are more prominent backward and forward scattering lobes. Also evident, a “bowl-shape” at off-nadir positions appears due to volumetric scattering. The influence of wavelength on the BCRF plots is also quite apparent, especially for BCRF measurements at a zenith angle of 60 deg. The backscatter lobe becomes more prominent with increasing wavelength as illustrated in Figure 4.7b.

The inversion of the radiative transfer model detailed in section 4.3 used the two sets of measurements conducted at different incident illumination geometries. As described in Section 4.3, the original and modified Hapke model was inverted to retrieve the fill factor and SSA. Figures 4.9 and 4.8 shows the retrieved fill factor and
the SSA respectively for ten different densities ranging from $1.4542 \text{ g/cm}^3$-$1.6904 \text{ g/cm}^3$. We report the retrieved parameters from both the original and modified Hapke model. Figure 4.8 displays the averaged SSA for all ten densities, and the corresponding standard deviation over the optimization runs used to invert the radiative transfer model. The SSA provides insight into the optical properties of the medium. For granular materials, the SSA typically increases with a decrease in the particle size [19]. In both cases, the estimates of the single scattering albedo appear consistent with each other for all wavelengths and across all densities. The original method seems to be slightly noisier in the SWIR compared to the modified method. The final fill factor was an average of the fill factors obtained at each wavelength by the inversion process, since the density does not depend on the wavelength. The inversion of both the original and modified Hapke model show moderately good correlation between the retrieved fill factor and the measured density, with a $R^2$ value of 0.76 & 0.72 respectively, as shown in Figure 4.9. The $R^2$ value obtained from both methods are comparable, however, the variation across wavelengths is significantly higher in the original IMSA model. This can be seen in the the range of the standard deviation within the figure. The difference in retrieved fill factor is due to the values varying between the visible near infrared and the short wave

Figure 4.8: The average retrieved SSA for the (right) original and (left) modified Hapke model.
Figure 4.9: The average retrieved fill factor from the inversion of the (right) original and (left) modified Hapke model versus the measured density for the 1306-M-03 sediment sample from the Algodones Dunes (R^2 value of 0.76 & 0.72 respectively).

infrared. The variation seems to have a significant effect in the original IMSA model compared to the modified model. A previous study [3] also showed a similar result. We note that this result, which we have obtained for a sample derived from the northern end of the Algodones Dunes system, achieves a level of accuracy similar to this same approach applied to a sample derived from the western side of the central dune system in our earlier study [3], confirming the validity of the approach.

Having validated the inversion methodology in a set of controlled laboratory experiments, we now turn our attention to the retrieval of the fill factor from data collected by airborne (Section 4.5) and satellite (Section 4.6) systems using our modified Hapke model.
Figure 4.10: NASA Goddard’s G-LiHT system collected airborne data from Monday March 9, 2015, to Friday March 13, 2015. (a) The flight lines (in red) of the airborne system over the 4 day period during the field campaign. (b) G-LiHT provided hyperspectral, thermal and LiDAR data from several different flight lines over the region shown. Figure from [52].

4.5 NASA Goddard’s LiDAR, Hyperspectral, and Thermal (G-LiHT) Airborne Imager

4.5.1 G-LiHT: Design & Instrumentation

An integral part of the 2015 field campaign was obtaining hyperspectral and LiDAR airborne data using NASA Goddard’s G-LiHT system [59, 60]. The hyperspectral imager, designed by Headwall Photonics Inc. (Bolton, MA, USA), is a pushbroom system providing spectral measurements from 400 to 1000 nm at a spectral resolution of 1.5 nm with an FOV of 50 deg [60]. The LiDAR is a VQ-480 airborne laser scanner (Riegl USA, Orlando, FL, USA). The LiDAR [60] provided a detailed digital elevation model of the terrain [59]. The flight line and the spatial coverage of the G-LiHT system over the Algodones Dunes system is shown in Figure 4.10. The
G-LiHT system provided hyperspectral imagery, a LiDAR-derived digital elevation model, as well as thermal imagery at a spatial resolution of 1 m.

Airborne data was collected using the G-LiHT system from Monday 9 March 2015 to Friday 13 March 2015. There were several flight lines (A-, T-, and E-lines) at various different orientations flown over the course of the field campaign. For sets of flightlines flown on the same azimuthal heading, successive lines in the set have significant overlap with neighboring flight-lines. The combination of all these different flights provided hyperspectral imagery obtained from multiple imaging and illumination geometries over the same region on the ground. For one of the typical areas of maximum overlap used in our analysis, G-LiHT obtained hyperspectral
imagery from 16 different view geometries over the same 102 m by 139 m region on
the ground. Figure 4.11 shows a mosaic of the 16 different flight lines along with
the region of interest (ROI) for our study. The multiple view-geometries provided
the necessary range of phase angles to perform the inversion of our modified Hapke
model using the acquired hyperspectral G-LiHT imagery.

Figure 4.11: A mosaic of the 16 different flight lines along with the region of interest (ROI) for our study.

4.5.2 Spectral Analysis & Fill Factor Retrieval

Figure 4.12 illustrates the spectral library and polar plots for a pixel located at
32°54′50.7553″N, 115°6′53.8587″W. The spectral library in Figure 4.12a plots the
reflectance for all 16 view-geometries in the visible and near-infrared (400–1000 nm).
The spectral characteristics are consistent with the observations in the laboratory
studies, mentioned earlier in Section 4.4. The spectral library illustrates the angular
dependence of the reflectance of the target from airborne platforms, with the colorbar
representing the phase angle. It should be noted that the solar/sensor angular
calculations from G-LiHT take into account the slope aspect of the dunes. We
used the accompanying LiDAR data from the flight to correct for the slope of the
dunes in our angle final calculations. The overall intensity of the reflectance is
distinctly dependent on both illumination and view geometry, as shown in the plot. The scattering of the target pixel is strongest in the backscatter direction, with the phase angle varying from typically 20 deg to 80 deg. This range of phase angles was evident for all the pixels within the scene.

Figure 4.13: Image-derived HCRF plots for four individual pixels within the ROI at wavelength 714 nm. The sensor and solar geometries are distinctly different for each individual pixel, leading to unique HCRFs. Figure from [52].

Figure 4.12b,c shows the polar plots at wavelengths 551 nm and 807 nm, respectively. The plots shown are a composite of the 16 different looks from the G-LiHT overpasses for a single pixel within the ROI. The sensor zenith angles are less than 30 deg for the different looks, which is typical of measurements taken from airborne and space-borne platforms. The view geometries, and the consequent HCRF, for each pixel within the ROI are fairly different from each other, as illustrated in Figure 4.13. The figure shows the polar plots at a wavelength of 714 nm for four pixels across the ROI. The reflectance measurements are significantly different for each of the pixels, influenced by the geometries as well as the geophysical properties of the regolith.

In contrast with our lab studies using the goniometer in Section 4.4, the image-derived HCRF from G-LiHT does not provide us with sensor positions over the
Figure 4.14: Retrieved fill factor derived from 102 m by 139 m region of the Algodones Dunes, using G-LiHT hyperspectral imagery from 16 different view and illumination geometries. Figure from [52].

complete hemisphere. However, the imagery set does provide a comparable range of phase angles due to both varying heading of the aircraft overflight as well as the change in solar position throughout the day. Thus, we could perform inversion for a similar range of phase angles to that used in our laboratory study in inverting our model of the G-LiHT imagery data, and we were able to get similar values for the fill factor and SSA. As a result, we believe the range of the phase angle for each pixel in the ROI provided satisfactory information about the scene to perform inversion of the Hapke model to retrieve the fill factor. The range of view-geometries for
each pixel in the ROI provided satisfactory information about the scene to perform inversion of the Hapke model to retrieve the fill factor. In the inversion procedure, we assumed that neighboring/adjacent pixels had the same geophysical properties. Since the G-LiHT system provided imagery at high spatial resolutions (1 m), it was a reasonable assumption for the inversion process. As a result, the spectra from adjacent pixels served as the two input data sets for inversion using Equation (4.2). Figure 4.14 shows the retrieved fill factor for the 102 m by 139 m region. Since the fill factor is proportional to the bulk density of the sample [73, 74], we can see, therefore, that the sediment density varies across the terrain. The primary goal of 2015 campaign was focused on acquiring calibration data in support of inter-satellite calibration across the extensive dune system [59]. Although flights occurred over sites where geotechnical data, such as bulk density, was collected, the flight plans were not specifically designed to maximize the number of views of each calibration site, but rather to ensure that there was G-LiHT data collected across the entire dune system, and at least some coverage of the calibration sites. For the geotechnical calibration sites, there were typically only a few overlapping flight lines, and not the higher degree of overlap that occurred circumstantially near but not at the precise calibration locations. The particular spot chosen for our imagery ROI was located in the zone of highest overlap where inversion of the radiative transfer could be most successfully applied. Thus, we do not have any ground bulk density data from within the 109 m by 139 m ROI. However, we did take bulk density measurements from locations close to our ROI (1 km away), and we used the regression of the fill factor vs. density from lab studies in Section 4.4 (shown in Figure 4.9) to convert the relative fill factor to bulk density for the ROI. We observed that the range of density (based on the regression) varies from 1.1 to 2.15 g/cm$^3$, which is comparable to bulk density measurements obtained during the field campaign (Table 4.1).
Table 4.1: Bulk density measurements conducted during the 2015 Algodones field campaign from sites near our ROI. Table from [52].

<table>
<thead>
<tr>
<th>Sample Name</th>
<th>GPS Location</th>
<th>Bulk Density (g/cm³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BC01-01</td>
<td>32° 55’ 8.25” N, 115° 7’ 2.42” W</td>
<td>1.96</td>
</tr>
<tr>
<td>BC01-02</td>
<td>32° 55’ 9.47” N, 115° 7’ 0.06” W</td>
<td>2.25</td>
</tr>
<tr>
<td>BC02-01</td>
<td>32° 54’ 54.77” N, 115° 6’ 33.03” W</td>
<td>2.18</td>
</tr>
<tr>
<td>BC02-02</td>
<td>32° 54’ 55.35” N, 115° 6’ 33.91” W</td>
<td>2.08</td>
</tr>
<tr>
<td>BC03-01</td>
<td>32° 54’ 55.07” N, 115° 6’ 34.76” W</td>
<td>2.02</td>
</tr>
<tr>
<td>BC03-02</td>
<td>32° 54’ 53.98” N, 115° 6’ 34.26” W</td>
<td>2.19</td>
</tr>
</tbody>
</table>

The retrieved single scattering albedo is plotted in Figure 4.15. The figure shows the average retrieved SSA from all pixels over the ROI, and the corresponding standard deviation. We also report the retrieved fill factor for four locations within our ROI, while the HCRF spectra for these four individual pixels are shown in Figure 4.13.

Figure 4.15: (a) the average single scattering albedo for the ROI from the G-LiHT imagery, and the corresponding standard deviation across all the pixels; (b) the retrieved SSA for four locations within the ROI (the image-derived HCRF spectra for these pixels are shown in Figure 4.13). Figure from [52].
Figure 4.16: (a) The figure shows a pseudo-RGB image of the CONUS on 1st July, 2017 observed by the ABI multi-spectral imaging system. The ABI provides imagery at 16 different spectral bands (0.47\(\mu\)m-1.3\(\mu\)m) with a temporal frequency of 5 minutes. The image has a spatial resolution of 0.5-km. (b) The Algodones Dunes observed via the ABI imager. Figure from [52].

4.6 The Geostationary Operational Environmental Satellite (GOES)

4.6.1 GOES: Design & Instrumentation

The GOES satellite series are a collaborative venture between the National Aeronautics and Space Administration (NASA) and the National Oceanic and Atmospheric Administration (NOAA) [75]. The 16-channel Advanced Baseline Imager (ABI), the primary imaging system on the GOES-R series, is used for a variety of environmental applications relating to the weather, land, ocean, and the atmosphere [61].

The ABI is a multi-spectral imaging system, with 16 different spectral bands from the visible to the longwave infrared (0.47-13.3 \(\mu\)m) [61]. The spatial resolution of the system varies from 0.5 km to 2 km depending on the spectral band [61]. The imaging system has two different scanning modes, providing excellent coverage rate. It is capable of collecting a full disk (Western Hemisphere) image every 15 minutes,
images of the Continental United States (CONUS) every 5 minutes, and also a selectable 1000 km by 1000 km region every 30 s [61]. A pseudo-RGB image of the CONUS on 1st July, 2017 is shown in Figure 4.16. The ABI system also provides on-orbit calibration for all 16 bands, minimizing errors due to degradation over time.

### 4.6.2 Spectral Analysis & Fill Factor Retrieval

The analysis of the GOES imagery was performed on four bands from the visible to the near infra-red; band 1 (0.47-\(\mu m\)), band 2 (0.64-\(\mu m\)), band 3 (0.86-\(\mu m\)) and band 5 (1.6-\(\mu m\)). Band 2 has a spatial resolution of 0.5-km, while the remaining bands used in this study have a resolution of 1-km. The spatial resolution for bands 1, 3, and 5 was interpolated to 0.5-km. Figure 4.16 shows ABI imagery of the Algodones Dunes, a 23.5 km by 17.5 km region. Although the ABI instrument has the same view-geometry of the surface, as the solar position changes, the excellent temporal
Figure 4.18: Spectral libraries for a pixel from the GOES imagery. The spectral library in (a) is reflectance data from the morning and (b) is reflectance from the afternoon. The pixels for the spectral libraries overlap the ROI from the G-LiHT study. The reflectance is shown for 4 bands from the visible to the near infra-red. The colorbar corresponds to the phase angle of the pixel.

coverage of the system provides the necessary range of phase angles to perform the inversion. Figure 4.17 shows the variation of the phase angle from sunrise to sunset on July 1st, 2017. Since the phase angles are similar before and after noon, they act as the two sets of data required to perform the inversion in Equation 4.2. Figure 4.18 shows the spectral reflectance data from the morning and the afternoon at (32° 54’ 59” N, 115° 6’ 51” W), which overlaps the ROI from the G-LiHT study detailed in section 4.5.

Figure 4.19 shows a map of the retrieved fill factor obtained from the GOES imagery through the inversion of the modified Hapke model. There is not a large variance in the retrieved fill factor across the dunes from the GOES imagery. This is possibly due to the fact that GOES-R ABI imagery has a GSD of 0.5 km. The low spatial resolution of the system averages a substantial region on the ground, consisting of different materials, which ultimately affects the retrieved fill factor. However, at this spatial resolution, qualitatively the distribution of the fill factor does highlight certain characteristics of the dunes. The fill factor generally increases with
height, and we observed this relationship when retrieved fill factor was compared against LiDAR elevation data collected by the G-LiHT sensor during the 2015 field campaign. The Figure 4.20 shows side-by-side images of the fill factor and DEM of the dunes. The spatial resolution of the fill factor image was interpolated from 0.5-km to 1-m to match the GSD captured by the LiDAR system. The sediment fill factor typically increases (decreasing porosity) with the height of the sediment medium [76]. The surface sediments compress the materials underneath, increasing the density with height [76]. Figure 4.20 shows that high retrieved fill factors correlate well with the peaks of the higher dunes observed in the middle of the desert. The edges of the desert, where there is more of a basin or depression, have lower fill factor values associated with lower density. The northeastern part of the desert in Figure 4.20, circled in black, consists mostly of rock formations and dense veg-
etation, an area for which our sediment retrieval model for the fill factor does not apply, and produced a high fill factor. As expected here our retrieval model has only a weak correlation with the LiDAR data.

Figure 4.20: (Left) LiDAR data collected by the NASA G-LiHT system during the 2015 field campaign, and (Right) the corresponding retrieved fill factor over the same region from the NOAA GOES imagery on July 1st, 2017. The northeastern part of the dunes is circled in black, where we have mostly vegetation and rock formation, an area where our retrieval model for the fill factor does not apply. Figure from [52].

4.7 Monitoring Large-Scale Changes in the Sand Dunes

The GOES imager is an ideal system for monitoring the Algodones Dunes. Its high temporal resolution can observe changes in the fill factor, and thus the bulk density, in response to meteorological phenomena on short time scales.

Wind-blown sands have formed the Algodones Dunes whose topography changes continuously due to the influence of local wind patterns [64]. Dunes are generally steeper in the windward side and shorter on the lee side [77, 78]. The common mechanism for the wind induced sand movement is saltation, in which the wind
carries aloft individual grains from the surface and eventually deposits them back on the surface [77, 79]. The movement of particles within the dunes generally depends on particle characteristics (grain size, shape and density) and the wind speed [79]. Saltation occurs for particles of size approximately 70-500 µm, a range encompassed by typical grain size distributions observed in the Algodones Dunes in previous studies [3, 78]. This wind induced sand movement takes place almost entirely within the top 0.5 m of the desert surface, with 90% of the movement happening within 2.5 cm [77]. For fine-grained particles, the minimum velocity required for the movement of sand is approximately 5 m/s at 1 m above the surface [77]. A relationship between wind speed and grain size in which saltation occurs is described in further detail by [80]. The high rate of image acquisition by GOES along with the inversion process detailed in this article can be used to monitor changes in the dunes caused by meteorological influences such as wind and precipitation.

Figure 4.21 illustrates the fill factor retrieved from GOES ABI cloud-free imagery of the Algodones Dunes during the period from July 1st to 28th, 2017. The Figure also displays the standard deviation over the month of July. We obtained meteorological data from the Global Historical Climatology Network (GHCN) [81]. The database provides historical weather data from numerous stations around the globe. The average daily wind speed (AWND), maximum temperature (TMAX), and minimum temperature (TMIN) for each day are also shown in Figure 4.21. The meteorological data were recorded by the Marine Corps Air Station (MCAS) in Yuma, Arizona. Our retrieved fill factor from the GOES imagery of Algodones varies from day-to-day due to the process of saltation induced by the prevailing wind. It should be noted that wind pattern is not the only factor influencing the retrieved fill factor for a particular day. For example, the wind conditions are similar for July 2nd and the 15th, however, the fill factor is drastically different for these two days due to changing wind patterns leading up to that day as well as other environmental factors. The largest change in the retrieved fill factor occurs in the center of the Dunes as illustrated by the standard deviation in Figure 4.21. This region generally consists of active dunes with medium to fine sands, and the topography is susceptible to the prevailing wind. Winds have less impact on the northern
Figure 4.21: The retrieved fill factor of the Algodones Dunes from July 1st to 28th, 2017. The figure also displays the standard deviation in the fill factor over the month period. The average daily wind speed (AWND) in meter-per-second (m/s) and the maximum (TMAX) and minimum temperature (TMIN) in Fahrenheit (F) for each day are reported for each acquisition. Figure from [52].
end of the dune system, and to a lesser extent also the southern end. The presence of vegetation and rock formations within these regions of the Dunes stabilizes the sediments, minimizing the influence of winds on the topography.

4.8 Conclusion and summary

Physical properties of sediments such as density, grain size and surface roughness influence the angular dependence of the spectral signature of sediments. Models based on radiative transfer equations, such as the one developed by Hapke, can relate the angular dependence of the reflectance to these geophysical variables. This chapter focused on extracting geophysical parameters, fill factor (decreasing porosity) and the single scattering albedo, through the inversion of a modified Hapke model of airborne and space-borne imagery. The area of study was the Algodones Dunes located in Southern California. The Algodones Dunes System is considered a potentially desirable site for the vicarious calibration of space-borne imaging sensors, and the study detailed in this work provides a better understanding of the physical characteristics of the sediment surface.

We validated the inversion methodology by performing controlled laboratory measurements on sediment samples from the Algodones Dunes. We used GRIT-T to measure hyperspectral BCRF of these samples, and we found a good correlation between the retrieved fill factor and the measured density in the present laboratory experiments, corroborating experiments done in previous work [3]. After validating the inversion methodology, we demonstrated the retrieval of the fill factor from angular dependent reflectance data derived from airborne and satellite imagery time series.

We applied the inversion methodology to airborne hyperspectral imagery collected by the NASA G-LiHT system during the 2015 Algodones Dunes field campaign [59, 3]. The significant overlap between the G-LiHT flight lines during the campaign provided imagery with multiple geometries over the same region on the ground. In total, there were 16 different view geometries over the same 102 m by
109 m region used in this study. The retrieved fill factor and SSA provided a better understanding of the variability of the terrain.

We also retrieved the fill factor from NOAA GOES ABI imagery. The inversion used four bands from the visible to the near infra-red. The high temporal coverage of the system provided the necessary range of phase angles to perform the inversion. There was not a large variance in the retrieved fill factor due the low spatial resolution (0.5-km) of the GOES system. The low spatial resolution of the system averages a significant portion of the surface, smoothing variations in the retrieved fill factor. However, qualitatively the retrieved fill factor still highlighted some characteristics of the dune. The fill factor generally increased with height, and this correlation was clearly visible when compared to LiDAR data from the Dunes. We also used the high temporal resolution of the GOES imager to monitor changes in the dunes associated with meteorological phenomena. In this study specifically, we observed changes in the fill factor or density as a function of the intensity of the prevailing winds. The density of the dunes seems to vary day-to-day, due to the process of saltation induced by the winds. Prevailing winds had the greatest impact on the center of the Dunes system; there the predominant sediment has medium to fine sands, which are most susceptible to the winds. The presence of vegetation in the northern end of the Dunes, and to an extent the southern end, mitigates the effects of the winds, and these trends appear in our retrieved fill factor.
Chapter 5

Inter-calibration Studies

5.1 Introduction

The calibration of space-borne sensors is critical to ensure continuity and accuracy in long-term studies of geophysical parameters [82]. Over the past 40 years, there have been several Earth Observing (EO) systems launched to measure changes in Earth’s surface and atmosphere [83]. Space-borne sensors are continuously in development to ensure long-term studies of geophysical parameters, but inherent temporal gaps reduce the ability to monitor changes in the Earth’s environment. Landsat-8 represents the latest space-borne satellite from the Landsat Data Continuity Mission (LDCM) [84]. Landsat-8 has a spatial resolution of 30 m, which was designed to support most environmental studies. However, Landsat–8 provides global coverage every 16 days and, on average, has 35% of its images plagued by cloud cover [83, 85]. This inherent temporal gap limits the ability to study fine-scale changes in the Earth’s surface, and highlights the utility of inter-calibration [83]. Since inter-calibration can combine measurements from two different sensors, this technique can be leveraged to improve spatial, spectral, and temporal coverage [83].

Our area of study is again the Algodones Dunes System located in Southern California. The Algodones site was chosen due to its potential to be used for vicarious calibration of different NASA satellite systems. The dunes system exhibits very
similar characteristics to the well-known pseudo-invariant calibration site (PICS) Libya-4 [65, 59]. Due to its accessibility, it is challenging to obtain ground-truth measurements for characterization of the landscape from PICS such as Libya-4, which is located in the Sahara Desert of North Africa. Alternatively, the Algodones Dunes System, located 2 hours from San Diego in the United States, makes it significantly easier to perform the necessary field campaigns to characterize its terrain for the purpose of absolute calibration [65, 59]. The model based studies performed here were designed to support a primary mission of the Algodones Dunes campaign to provide an insight into uncertainties that need to be accounted for when performing inter-calibration.

The Digital Imaging and Remote Sensing Image Generation (DIRSIG) tool is a physics-based synthetic image generation model developed by the Rochester Institute of Technology (RIT) [10], which can be used to perform various inter-calibration studies. The advantage of using a simulation and modeling software such as DIRSIG is that it provides the ability to vary parameters that affect the inter-calibration process independently from one another. Although DIRSIG can model different spectral response functions, methods to correct for these differences are available in the works by Chander et al. [86]. This study specifically investigates the lesser known effects of differing view-geometries (sensor view and illumination angles) and time-of-collect on inter-calibration. The simulations described were conducted to provide an understanding on how pseudo-invariant sites such as the Algodones Dunes can be used for inter-calibration of satellite sensors, and to help define the key factors that need to be considered.

The ability of DIRSIG to simulate space-borne instruments was verified in this work by simulating the Aqua-MODIS & Terra-MODIS sensors over the Algodones Dunes. The at-sensor radiance measurement of the simulations were compared to data collected by the actual sensors over the dunes system. The validation study utilizes band 1 (0.620-0.670 µm), band 4 (0.545-0.565 µm), and band 3 (0.459-0.479 µm) of the MODIS instrument.

The verification of the model was followed by an evaluation of DIRSIG to support inter-calibration between sensors. The information provided by the MODIS sensor
was used to simulate Landsat-8 data. Band 2 (0.452-0.512 $\mu$m), band 3 (0.533-0.590 $\mu$m) and band 4 (0.636-0.673 $\mu$m) of Landsat-8 were simulated using DIRSIG and compared to cloud-free data collected by the actual sensor.

To support future NASA missions, we evaluate the potential of using International Space Station (ISS)-based imaging platforms for inter-calibration. Specifically, an evaluation of the Solar, Lunar for Absolute Reflectance Imaging Spectroradiometer (SOLARIS) \[87, 88\] sensor for calibrating other space-borne sensors such as MODIS and Landsat was conducted. SOLARIS is the reflected solar (RS) instrument of the Climate Absolute Radiance and Refractivity Observatory (CLARREO) mission \[87, 88, 89\]. The objective of the SOLARIS sensor is to develop and inspect calibration techniques, establish methods to obtain SI-traceability, and estimate reflectance from measurements of the sun and the scene \[87\]. The mission plan is to have the SOLARIS sensor placed on the ISS platform to investigate techniques and benefits for obtaining highly accurate measurements before placing high budget satellites into service \[87\]. As a platform, the ISS has become an attractive option to perform inter-calibration studies, as the long service life of the ISS along with the presence of a human crew and various equipment provides the possibility of performing various studies, which are not feasible with space-borne satellites \[90\].

The ISS inter-calibration studies presented here utilize the Aqua-MODIS instrument as a test sensor. There are numerous parameters that potentially need to be considered to perform an accurate inter-calibration between sensors (e.g., view geometry of the sensors, time-of-collect, differences in spectral response functions, BRDF of the material). These studies focused on assessing the impact of differing view-geometries and time-of-collect on the inter-calibration process. Specifically, the development of a simulated landscape, and a forward modeling approach was utilized to assess the sensitivity of the inter-calibration of Aqua-MODIS with SOLARIS on these two parameters.
CHAPTER 5. INTER-CALIBRATION STUDIES

5.2 Synthetic Landscape Development and Inter-Calibration

This section introduces the methodology used to create a synthetic landscape in DIRSIG (section 5.2.1). The process used to verify the DIRSIG software by simulating MODIS is detailed in Section 5.2.3, followed by an inter-calibration study of Landsat-8 using Aqua-MODIS.

5.2.1 Synthetic Landscape Development

To leverage data collected from the ground-truth campaign of the Algodones Dunes during 2015, DIRSIG was used to study factors that need to be considered when performing inter-calibration over pseudo-invariant sites such as Algodones. The region used to perform the inter-calibration introduced in this work is a 5 km x 5
km area with the center pixel located at 32°53'06" N and 115°00'57" W. Leveraging the airborne and in-situ measurements taken during the field campaign, DIRSIG was used to develop a synthetic, but realistic, landscape of Algodones. NASA Goddard’s LiDAR, Hyperspectral, and Thermal (G-LiHT) sensor was extensively used to image the Algodones Dunes [60]. The Goniometer of the Rochester Institute of Technology (GRIT) was also used to collect ground-truth data over the scene of interest [3, 91, 59]. Details of these instruments can be found in previous chapters. Figure 5.1(left) shows the region within Algodones used to create the simulated scene, while Figure 5.1(right) shows the GRIT instrument taking measurements on the ground with the NASA G-LiHT flying overhead during the 2015 field campaign.

The synthetic scene of Algodones was created using the “Scene Construction Tool” built into DIRSIG [92]. This tool ingests various forms of image data to describe the terrain. Figure 5.2 shows the different sources of data/inputs required by the DIRSIG tool to describe the simulated landscape. High-resolution imagery
Figure 5.3: A nadir-looking image of the Algodones Dunes at a GSD of 10 m (left) and the subsequent average radiance of the scene in the VNIR (right). Figure from [9].

by the National Agricultural Imagery Program (NAIP) dataset was used to classify the landscape and to describe its texture [93]. The 2 m digital elevation model provided by G-LiHT was used to facetize the geometric properties of the terrain. Hyperspectral data collected by GRIT during the field campaign was used to assign spectral features to each of the classes (defined by the NAIP data) within the synthetic landscape. The BRDF properties were described from the MODIS BRDF product [94], which uses the Ross-Li model [95, 96, 97, 98]. It should be noted that this is not the most appropriate model to describe the BRDF properties for sand as this kernel based model does not adequately capture the hot spot (or the backscatter direction) [99]. Future work will focus on incorporating actual BRDF measurements from the Algodones campaign into DIRSIG.

The DIRSIG simulation environment provides users with the ability to create sensor models at various focal lengths, sensor geometries, spectral responses, platform motions, and to view through various atmospheres. This allows the creation of any airborne or space-borne sensors to facilitate inter-calibration studies. Figure
5.3 shows a nadir-looking image of the Algodones scene that was developed with the “Scene Construction Tool”, and the subsequent TOA radiance for an arbitrary pixel when imaging with a hyperspectral sensor model. The Algodones Dunes was imaged at a ground sample distance (GSD) of 10 m using a VNIR hyperspectral sensor (101 bands) over the 0.4 $\mu$m-1.00 $\mu$m spectral range.

### 5.2.2 MODIS BRDF Product

The MODIS BRDF product is derived from a semi-empirical kernel driven, linear BRDF model (Ross-Li). The model is expressed as a sum of linear combination of two kernels (isotropic scattering and volumetric scattering) with weighting parameters, and a uniform isotropic term that describes the BRDF of materials:

$$
 r(\theta_s, \theta_v, \phi, \lambda) = f_{ISO}(\lambda) + f_{VOL}(\lambda)K_{VOL}(\theta_s, \theta_v, \phi) + f_{GEO}(\lambda)K_{GEO}(\theta_s, \theta_v, \phi) 
$$

where $\theta_s$, $\theta_v$ & $\phi$ are the solar zenith, sensor zenith, and the relative azimuth angles respectively. $K_{VOL}(\theta_s, \theta_v, \phi)$ is the RossThick kernel representing the volumetric scattering [95], while $K_{GEO}(\theta_s, \theta_v, \phi)$ is the LiSparse kernel representing geometric scattering [96]. $f_{ISO}$, $f_{VOL}$, and $f_{GEO}$ are the weigting parameters for the isotropic, volumetric, and geometric scattering respectively.

The weighting parameters are derived using model inversion with values that best fit the data. The MODIS BRDF/Albedo Model Parameters product (MCD43A1) provides the weighting parameters for the Ross-Li model to calculate the BRDF of the scene. The product is generated from atmospherically corrected, cloud free data measured over a 16-day period using both Aqua and Terra. The weighting parameters to calculate the BRDF over the region of interest in Algodones over four years (2012–2015) for the RGB bands of MODIS are shown in Figure 5.4. The parameter values were averaged over the four year span, and used in the DIRSIG simulation to estimate the BRDF of the scene. The isotropic, volumetric, and geometric parameter values used in DIRSIG are summarized in Table 5.1.
Figure 5.4: The isotropic, volumetric, and geometric weighting parameters derived from the MODIS BRDF product for the RGB bands over our region of interest in the Algodones dunes. The weighting parameters were averaged over a four years span (2012–2015), and these averages were used to calculate the BRDF of the synthetic landscape in DIRSIG.

Table 5.1: The isotropic, volumetric, and geometric parameter values used to compute the BRDF of the Algodones scene within the DIRSIG simulation.

<table>
<thead>
<tr>
<th>Weighting Parameters</th>
<th>Band 3 (0.459–0.479 µm)</th>
<th>Band 4 (0.545–0.565 µm)</th>
<th>Band 3 (0.620–0.670 µm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Isotropic Scattering</td>
<td>0.1662</td>
<td>0.2690</td>
<td>0.3817</td>
</tr>
<tr>
<td>Volumetric Scattering</td>
<td>0.0550</td>
<td>0.1042</td>
<td>0.1229</td>
</tr>
<tr>
<td>Geometric Scattering</td>
<td>0.0000</td>
<td>0.0061</td>
<td>0.0083</td>
</tr>
</tbody>
</table>

5.2.3  DIRSIG Verification

DIRSIG’s potential to be used for inter-calibration studies was demonstrated by generating a synthetic Algodones scene using different spaceborne satellite systems
CHAPTER 5. INTER-CALIBRATION STUDIES

Figure 5.5: (i) Aqua-MODIS with sensor azimuth and zenith of 188.58° & 31.64° respectively imaging the Algodones Dunes simulated over 2015 at visibilities ranging from 20 km to 50 km. (ii) The figure shows the best possible match of the simulated data with real measurements by the Aqua-MODIS. These measurements were observed at a visibility of 41 km. Figure from [9].

and comparing the TOA radiance to actual sensor data. The ability of DIRSIG to estimate/model TOA radiance of space-borne sensors is dependent on an accurate representation of the scene and the atmosphere. Recall that the material properties of the scene were measured during the field-campaign so only a characterization of the atmospheric conditions is required to simulate the TOA radiance.

DIRSIG employs the radiative transfer algorithm MODerate spectral resolution atmospheric TRANsmittance model [100], or MODTRAN, to simulate atmospheric conditions. In this verification study, atmospheric conditions were estimated for a
Table 5.2: The table lists the different sensor view-geometries of Terra-MODIS, Aqua-MODIS, and Landsat-8 being simulated in DIRSIG. The MODIS sensors are simulated from 2012-2015, while Landsat-8 is simulated from 2013-2017. These simulated measurements were then compared to measurements taken by the real sensors over the Algodones Dunes. Table from [9].

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Sensor View-Geometry</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sensor Azimuth (θ)</td>
<td>Sensor Zenith (φ)</td>
<td></td>
</tr>
<tr>
<td>Terra-MODIS</td>
<td>352.7°</td>
<td>39.8°</td>
<td></td>
</tr>
<tr>
<td></td>
<td>351.5°</td>
<td>30.3°</td>
<td></td>
</tr>
<tr>
<td></td>
<td>347.9°</td>
<td>7.3°</td>
<td></td>
</tr>
<tr>
<td></td>
<td>167.8°</td>
<td>5.3°</td>
<td></td>
</tr>
<tr>
<td>Aqua-MODIS</td>
<td>13.9°</td>
<td>3.5°</td>
<td></td>
</tr>
<tr>
<td></td>
<td>188.9°</td>
<td>9.0°</td>
<td></td>
</tr>
<tr>
<td></td>
<td>188.9°</td>
<td>31.6°</td>
<td></td>
</tr>
<tr>
<td></td>
<td>184.7°</td>
<td>59.4°</td>
<td></td>
</tr>
<tr>
<td>Landsat-8</td>
<td>352.0°</td>
<td>15.0°</td>
<td></td>
</tr>
<tr>
<td></td>
<td>39.0°</td>
<td>15.0°</td>
<td></td>
</tr>
</tbody>
</table>

fixed Aqua-MODIS geometry (θ = 188.58° & φ = 31.64°) using a standard mid-latitude summer profile and a desert aerosol for several visibilities, which was compiled into a look-up-table (LUT). Then, to characterize (or estimate) the atmospheric conditions of Algodones for DIRSIG, actual MODIS data was compared to the LUT over an entire year for visibilities ranging from 20 km to 50 km in 1 km increments. Note that the purpose of this study was to assess DIRSIG’s ability to model at-sensor satellite radiance. So, a rigorous characterization of the atmosphere was not performed.

The LUT is shown in Figure 5.5(i). The minimum percent difference between real and simulated data was used to estimate the atmospheric inputs that provided the best match. The minimum difference was observed at a visibility of 41 km. Figure 5.5(ii) shows the radiance measurement between the Aqua-MODIS and its simulation for the best fit. The Root Mean Square Error (RMSE) and percent difference (PD) for band 3, band 4, and band 1 were 12.23 $W m^{-2} \mu m^{-1} sr^{-1}$ (PD = 1.26%), 9.19 $W m^{-2} \mu m^{-1} sr^{-1}$ (PD = 5.14%), and 14.70 $W m^{-2} \mu m^{-1} sr^{-1}$ (PD =
8.81\%) respectively. The observed residuals are reasonable considering the use of Ross-Li and the manner in which the atmosphere was estimated.

With an estimate of the atmosphere in place, the TOA radiance for two spaceborne sensors was simulated: Aqua-MODIS & Terra-MODIS. Specifically, bands 1, 4, and 3 of the MODIS sensors were simulated and compared to real cloud-free data. The MODIS sensors were simulated for four different view-geometries from 2012-2015, see Table 5.2.

Figure 5.6: The sub-figures show the mean radiance calculated over the scene of interest in the Algodones Dunes using the Terra-MODIS sensor from 2012-2015, which were compared to measurements simulated by DIRSIG. The radiance measurements were compared for the RGB bands of MODIS for four different sensor positions. The view-geometries being simulated for the MODIS sensor are illustrated in Table 5.2. Figure from [9].
Figure 5.6 compares the average radiance of the scene between the actual and simulated Terra-MODIS for band 3, band 4 and band 1 (the RGB bands) of MODIS. The results for four different view-geometries of Aqua-MODIS are shown in Figure 5.7. The RMSE and percent difference between the simulated and original data are summarized in Table 5.3. DIRSIG primarily captures the at-sensor variability for all the simulated view-geometries of Terra and Aqua. An exception to this can be seen in Figure 5.7, where the predicted radiance is significantly higher for a particular sensor geometry ($\theta = 184.73^\circ$, $\phi = 59.35^\circ$) of Aqua-MODIS. Considering that this is the longest slant path, this is likely due to the manner in which the atmosphere was estimated. The percent difference error was also significantly higher (greater than 50%) for a few particular days. By inspection it was determined that the TOA radiance from these datasets was affected by the presence of cloud within the scene, which was not modeled in DIRSIG. Most of the deviation between the simulated and original data occurred during the middle of the year, where the sun is typically at higher elevation. This is likely due to the limitation of the Ross-Li model to account for the hot spot effect. The hot spot or the opposition effect results in a sharp increase in reflectance in the backscatter direction [99, 101]. The original MODIS data has higher radiance during the middle of the year due to the hot spot effect, which the model does not capture with the Ross-Li input. Overall, the percent differences are within a reasonable range for data to support the sensitivity studies presented in Section 5.3. However, future work will focus on driving down these errors to support inter-calibration studies (presented next) by better characterizing the atmosphere and the BRDF of the Algodones Dunes.

5.2.4 Inter-Calibration Study with Landsat-8

The two MODIS sensors in Section 5.2.3 were used to verify the DIRSIG model’s capability to adequately simulate imagery of the Algodones Dunes System. The feasibility of DIRSIG to perform inter-calibration studies between two sensors is evaluated here by simulating Landsat-8 using the aforementioned estimates of the material properties and the atmosphere from the MODIS sensor. Bands 2, 3 and 4 of
Landsat-8 were simulated and compared to real cloud-free data over the Algodones Dunes. Landsat-8 was simulated for two view-geometries from 2013-2017 (the sensor angles are reported in Table 5.2).

Figure 5.8 compares the average at-sensor radiance between the Landsat-8 sensor and the simulation for two view-geometries for band 2, band 3, and band 4. The RMSEs and percent differences are summarized in Table 5.3. There is, again, good agreement between the original and simulated data. Some of the high percent differences are due to the presence of clouds in the Landsat imagery, while other errors can be attributed to the estimates of the atmospheric and BRDF inputs in the DIRSIG model.

Table 5.3: Table summarizing the Root Mean Square Error (RMSE) and percent difference (PD) with the DIRSIG simulations. Table from [9].

<table>
<thead>
<tr>
<th>Sensor View Geometry</th>
<th>RMSE (W/m²·μm⁻¹·sr⁻¹)</th>
<th>PD (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Band 3 (0.459-0.479 μm)</td>
<td>Band 4 (0.545-0.565 μm)</td>
</tr>
<tr>
<td><strong>Terra-MODIS</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>θ = 352.7°, φ = 39.81°</td>
<td>7.66 [4.94]</td>
<td>2.33 [0.01]</td>
</tr>
<tr>
<td>θ = 351.5°, φ = 30.28°</td>
<td>10.98 [7.71]</td>
<td>3.32 [0.87]</td>
</tr>
<tr>
<td>θ = 347.9°, φ = 7.26°</td>
<td>8.57 [5.38]</td>
<td>4.76 [2.63]</td>
</tr>
<tr>
<td>θ = 167.79°, φ = 5.3°</td>
<td>4.89 [0.50]</td>
<td>8.27 [7.02]</td>
</tr>
<tr>
<td><strong>Aqua-MODIS</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>θ = 13.91°, φ = 3.53°</td>
<td>5.85 [0.84]</td>
<td>8.42 [7.09]</td>
</tr>
<tr>
<td>θ = 188.58°, φ = 31.64°</td>
<td>6.52 [0.25]</td>
<td>6.14 [3.99]</td>
</tr>
<tr>
<td>θ = 184.73°, φ = 59.35°</td>
<td>21.91 [16.58]</td>
<td>27.86 [22.32]</td>
</tr>
</tbody>
</table>

|                      | Band 2 (0.450-0.510 μm) | Band 3 (0.530-0.590 μm) | Band 4 (0.640-0.670 μm) |
|----------------------|                        |        |                        |
| **Landsat-8**        |                        |        |                        |
| θ = 352.0°, φ = 15.0° | 7.21 [5.31]             | 12.98 [11.10]            | 7.11 [4.58] |
| θ = 39.0°, φ = 15.0°  | 6.94 [1.60]             | 10.30 [8.11]             | 6.02 [2.31] |

This study was designed to assess the feasibility of using DIRSIG as a transfer mechanism to inter-calibrate one sensor with another. While the absolute errors are quite high to justify performing inter-calibration of Landsat-8 with MODIS-Aqua as described here, future work will assess the sensitivity of the atmospheric and BRDF inputs in inter-calibration accuracy.
5.3 Inter-Calibration Studies Using the ISS

The focus of the March 2015 campaign was to evaluate the potential of pseudo-invariant sites such as the Algodones Dunes to support inter-calibration studies of the CLARREO Pathfinder mission, specifically for the SOLARIS sensor. This section discusses methodologies that focus on assessing the potential to use instruments on-board the ISS to calibrate other space-borne satellites. The Aqua-MODIS sensor was used as a test case in this work. The inter-calibration study assesses the sensitivity of collection time (Section 5.3.1) and view geometry (Section 5.3.2) on inter-calibration. Section 5.3.3, explores whether the changing orbit of the ISS can cause any issues with inter-calibration.

5.3.1 Temporal Study

Due to the nature of the inter-calibration process, there will always be a temporal offset between sensors. To assess the impact of temporal offset on inter-calibration accuracy, an Aqua-MODIS image was simulated for June 14, 2014 at 20:40 UTC over the Algodones Dunes using DIRSIG (note that this date/time represents an actual MODIS overpass). Next, the synthetic Algodones Dunes landscape was imaged from 13:40 to 04:10 UTC (sunrise to sunset) using DIRSIG. The difference in radiance between each simulated time and the nominal time was calculated to assess the impact of temporal offset of image acquisition on at-sensor radiance, which can be used to set the requirements for a temporal constraint for inter-calibration opportunities.

The percent difference in the at-sensor radiance measurement between the nominal and test collection time for band 1, band 4, and band 3 of MODIS is shown in Figure 5.9. The general trend in the plot indicates that the percent difference naturally increases with elapsed time from the nominal collect. However, there seems to be a small window of time, approximately ±1 hour of the original flight, where the percent difference is approximately 5% or less for all three bands. Note that this time window is dependent on the amount of inter-calibration accuracy required by
the user’s application. This ±1 hour time frame can potentially be used as a temporal constraint for inter-calibration opportunities of the Aqua-MODIS with sensors on-board the ISS, while imaging the dunes system. The Systems Tool Kit (STK) from Analytical Graphics, Inc. (AGI) was used to track the orbit of the ISS, and find inter-calibration opportunities over the 36-day period (May 29, 2014 - July 3, 2014) based on the temporal constraint. The Aqua-MODIS sensor typically images the Algodones Dunes between 20:00 UTC-21:35 UTC every 1-2 days, and based on the ±1-hour time constraint there were several days where inter-calibration studies could be performed over the time period. Figure 5.10 shows the ISS groundtrack with the inter-calibration opportunities over the 36-day period.

5.3.2 View-Geometry Study

The view-geometry of a sensor has a significant effect on the at-sensor radiance measurements. The ISS and the Aqua platforms are in dramatically different orbits, and the likelihood of SOLARIS & MODIS having the same view-geometries is low. Note that SOLARIS does have a 3-axis gimble to minimize view-angle differences, but they will still exist operationally [88]. To quantify the impact of view-geometry on the inter-calibration accuracy, DIRSIG was used to simulate the Algodones Dunes at various geometries over a hemisphere ($\theta : 0^\circ - 360^\circ$ & $\phi : 0^\circ - 80^\circ$). The different view-geometries used to image the Algodones Dunes for the Aqua-MODIS sensor are shown in Figure 5.11.

The percent difference in radiance of each view geometry from the nominal MODIS view was calculated for band 1, band 3 and band 4 for DOY165 (June 14, 2014), DOY169 (June 18, 2014), DOY174 (June 23, 2014) and DOY178 (June 27, 2014), where DOY is day of the year. The percent differences are represented as polar plots in Figure 5.12. The nominal MODIS view is shown in red, while the orbit of the ISS looking at the scene of interest within the Algodones Dunes is represented by the white curves within the polar plots.

The maximum difference due to the sensor position is approximately 10%, with no error when they have the same view-geometry. Like the temporal study, sensor
geometry constraints can be placed based on the user’s application. There are a few different inter-calibration opportunities for a sensor on-board the ISS (white-curve) on each of the days shown in Figure 5.12, where difference due to view-geometry is low (e.g., less than 1%) enough that it would not have had a significant effect on the calibration procedure. For example, in DOY169 there seems to be approximately 12 calibration opportunities between the sensor on-board the ISS and Aqua-MODIS sensor. The percent difference is less than 1% at those 12 different view-geometries (white-curve), indicating that this was a potentially good opportunity to perform inter-calibration between the SOLARIS and Aqua-MODIS sensor. DOY174 represents a poor case for inter-calibration, as the sensor on-board the ISS would have been in positions where the percent difference was well over 8% in band 3 of MODIS.

5.3.3 The Changing ISS Orbit

The inter-calibration opportunities in the two different studies were predicted based on dates in 2014, where both the orbits of ISS and Aqua-MODIS were known. Although, the orbit of Aqua-MODIS remains constant at an altitude of 705 km, the same cannot be said about the ISS [102, 103]. The ISS resides in a lower earth orbit, and experiences constant aerodynamic drag from the atmosphere [103, 104]. The orbit of the ISS is constantly decaying due to microgravity, and requires periodic reboost to maintain the correct altitude [103, 104]. The reboosting maneuver is typically performed using thruster firings by the attached Progress M spacecraft, which makes frequent trips to resupply the space station [104]. The altitude profile of the ISS in 2016 over the Algodones Dunes, measured using the STK software, is shown in Figure 5.13. The change in altitude of the ISS can be seen over the 1-year period; the negative slope is due to the orbital decay caused by the aerodynamic drag while the sharp positive slopes are a result of the reboosting maneuvers. However, the ISS height changes only 12 km over the 1-year period, and the effect it has on the view-geometry of a sensor, such as MODIS, is almost negligible. For all the view-geometries of both Aqua- & Terra-MODIS, the biggest change in sensor zenith was $1^\circ$ due to change in height of the ISS. A change in sensor zenith of $1^\circ$ effects the
TOA radiance by approximately $2 \text{ Wm}^{-2}\mu\text{m}^{-1}\text{sr}^{-1}$, which is quite negligible. So, the unpredictable nature of the ISS orbit should not influence inter-calibration.

### 5.4 Summary and Conclusion

The objective of this work was to develop a simulated environment to support inter-calibration studies for the Algodones Dunes System. The first part of the work focused on the feasibility of the DIRSIG software to simulate space-borne sensors. DIRSIG was used to simulate TOA radiance of the Algodones Dunes using Aqua-MODIS, Terra-MODIS, and Landsat-8. The TOA radiance was reported for the RGB bands of the sensors. Comparisons between simulated and original data for the three different sensors show good agreement, illustrating the potential utility of DIRSIG to serve as an inter-calibration transfer mechanism between two instruments. Future work will focus on improving simulations by replacing the Ross-Li BRDF model with the radiative transfer equations developed by Hapke [5]. Hapke’s model has been widely used to estimate the BRDF of materials, especially for granular sediments. The BRDF model can take into account single scattering, multiple scattering events, as well as the opposition effects, which are the shadow hiding opposition effect (SHOE) and the coherent backscatter opposition effect (CBOE). This would immensely improve DIRSIG’s ability to simulate airborne and space-borne satellites.

This work assessed some of the limiting factors in the inter-calibration process. The chapter investigated how differences in view-geometries (sensor view and illumination angles) and time-of-collect can affect inter-calibration with an ISS-based platform such as SOLARIS. In this specific study, it was demonstrated that a $\pm 1$ hour window from the nominal collect resulted in less than 5% differences for all three bands. This $\pm 1$ hour time frame can potentially be used as an initial temporal constraint for finding calibration opportunities between Aqua-MODIS and sensors on-board the ISS. Once a temporal constraint is determined, a view-geometry constraint can be placed to minimize view angle effects. In the simulations presented
here, the maximum difference due to the sensor position was approximately 10%. Within the four different days used in the study, there were multiple calibration opportunities between a sensor on the ISS and Aqua-MODIS where view-geometry had less than 1% impact on the TOA radiance. Considering the versatility of the proposed SOLARIS gimble, these days represent adequate opportunities to perform inter-calibration. The study also explored the challenges that may arise from the ISS being present in a lower earth orbit. However, the change in the ISS orbit is not significant enough to have much of an influence on the inter-calibration process.
Figure 5.7: The sub-figures show the mean radiance calculated over the scene of interest in the Algodones Dunes using the Aqua-MODIS sensor from 2012-2015, which were compared to measurements simulated by DIRSIG. The radiance measurements were compared for the RGB bands of MODIS for four different sensor positions. The view-geometries being simulated for the MODIS sensor are illustrated in Table 5.2. Figure from [9].
Figure 5.8: The sub-figures show the mean radiance calculated over the scene of interest in the Algodones Dunes using the Landsat-8 sensor from 2013-2017, which were compared to measurements simulated by DIRSIG. The radiance measurements were compared for the RGB bands of Landsat for its two different looks of the dunes system. Figure from [9].
Figure 5.9: Percent difference in the observed at-sensor radiance to the original MODIS-flight from sunrise to sunset. The percent difference is shown for band 1, 3 & 4 of MODIS. The percent difference is relatively low ±1 hour of the initial flight time.
Figure 5.10: Inter-calibration opportunities of Aqua-MODIS using a sensor, on board the ISS, over a 36-day period in June of 2014 based on the time-constraint.
Figure 5.11: DIRSIG is used to image synthetically the Algodones Dunes at various different view-geometries for the Aqua-MODIS sensor. This was used to study the effect view-geometry can have on the inter-calibration process. Figure from [9].
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Figure 5.12: The polar-plot illustrates the percent difference in the view-geometry of the MODIS sensor in band 3, 4 and 1 for four different days in June 2014 (DOY165, DOY169, DOY174 and DOY178). Figure from [9].
Figure 5.13: The mean height (km) of the ISS in 2016 over the Algodones Dunes. The changes in height are due to the orbital decay of the space station and subsequent reboost to maintain the orbit. Figure from [9].
Chapter 6

Soil Moisture Characterization

This chapter focuses on characterizing soil moisture content (SMC) using the radiative transfer model (detailed in section 2.6) MARMIT. The model is validated under controlled conditions of our laboratory using the goniometer system, GRIT-T. The lab studies explore the implications of both directionality and wavelength in retrieving SMC from the radiative transfer model. The lab study was followed by applying the physics based model in mapping soil moisture content from remotely sensed data collected during a 2018 field campaign at Hog Island, a barrier island off the coast of the Delmarva Peninsula, Virginia.

6.1 MARMIT model: Inversion methodology

The MARMIT model, introduced in [46], is a recent improvement to the Bach model [20] that takes into account the transmittance of light across the liquid-air layer. The total reflectance of the wet soil, according to the MARMIT, is expressed in equation 2.59. The inversion methodology involves the acquisition of hyperspectral reflectance data at different sensor geometries, and minimize the residual between the estimated and measured total reflectance of the wet soil. The minimization involves a two-parameter search over the thickness of the water level, $L [m]$, and the efficiency term, $\epsilon$, using the gradient based Nelder–Mead simplex method.
In [46], the measured soil moisture content (SMC) is compared with the mean water thickness (mean light path) defined as $\phi = L \times \epsilon$. The SMC is statistically related to the mean water thickness using a logistics function,

$$ SMC = \frac{K}{1 + \alpha e^{\psi \phi}} \quad (6.1) $$

where K is the maximum value of the logistic function, $\psi$ is the steepness of the curve, and $\alpha$ is a translational factor along the x-axis.

The calculation of the reflection for wet soil using the MARMIT model requires
the spectral index of refraction for water, which is taken from Segelstein (1981) [105]. The spectral index of refraction for water is shown in Figure 6.1. We also need the spectral absorption coefficient of water, which is taken from the works by Pope & Fry (1997) [106] and Kou et al. (1993) [107]. The spectral absorption coefficient of water is show in Figure 6.2. These values for the water absorption coefficients and refractive index are available online: https://omlc.org/spectra/water/abs/.
6.2 Laboratory Experiments

Our laboratory experiments included BCRF measurements of four different sediment samples. The four samples are from distinctly different soil types, where the sediment varies in its physical characteristics such as mineralogy, salinity, texture, organic matter content and roughness. The samples were acquired from the Algodones Dunes in California, a lakebed region in Northwest Nevada, and Hog Island in the Delmarva Peninsula of Virginia. Figure 6.3 shows the regions where we collected the soil sample for our laboratory studies. The Algodones sediment sample (ALG) is typically composed of quartz, feldspar, rock fragment and an assortment of heavy minerals. The Nevada sample (NEV) is mostly composed of clay and is made up of silicon, aluminum, and oxygen. Clay is the smallest soil particle, and typically has a very high capacity to hold water. One of the sediment samples from Hog Island is from a salt-panne (HOGP) environment and soil from this region can be considered to be a loam, consisting of mostly clay, silt and sand. The other sample from the island is taken from the beach shore (HOGB), and is very similar in composition to the ALG desert sediment. The experiments will involve manipulating the soil moisture content of the samples, and examining how it affects the observed BCRF.

Each of the four samples was initially dried over a 24 hour period at 110° C using a Humboldt oven (Figure 3.5f) to remove the presence of any moisture from the sediment. We want to make certain that all samples in our experiments have approximately the same initial dry density, which was achieved by the process of pluviation. The drop height of the sediment within the pluviation apparatus is correlated with the relative density of the sediment. Thus, by ensuring we have the same drop height for all our samples, we can achieve approximately the same initial dry density of the sample.

The four samples then underwent BCRF measurements using GRIT-T (Figure 3.2). The BCRF pattern used in our experiment is shown in Figure 6.4. We picked a very sparse scan pattern for our experiment, a step size of 20 deg in zenith and 36 deg in azimuth, since we want our measurements to take no longer than ten minutes to minimize the potential for evaporation.
Figure 6.3: The soil samples used in this study was collected from four distinctly different regions across the United States: the Algodones Dunes in California, a lakebed region in Northwest Nevada, and two samples from Hog Island in the Delmarva Peninsula of Virginia.

Figure 6.4: The BRDF scan pattern used in the moisture experiment.
The BCRF measurements for the dry samples were followed by introduction of water into the sample. This was accomplished by using a sprinkle infiltrometer (Figure 3.5d). The sprinkle infiltrometer is a rainfall simulator [108], which introduces moisture into the sample at a wide range of predetermined rates. The apparatus wets the soil in a more natural manner and removes the possibility of soil slaking due to the introduction of water. The instrument also creates a realistic boundary condition for the soil layer, which includes the effect due to roughness of the soil sample that can greatly influence the infiltration process [108]. A schematic sketch of our lab setup using the infiltrometer is shown in Figure 6.5.

Figure 6.5: A schematic illustration of the sprinkle infiltrometer.
The method for using the infiltrometer consists of the following steps:

1. Remove the rubber stopper and the air entry tube, and pour deionized water into the apparatus.

2. Re-insert the rubber stopper and air-entry tube firmly into the vessel, and ensure they are air-tight.

3. Open the pinch clamp to introduce air pressure into the device. The air pressure forces water through the capillary tubes, and removes any air from them.

4. Close the pinch clamp, and the infiltrometer is now ready to be used.

5. Measure the initial height of the water column inside the apparatus \( H_1 \).

6. The sprinkle infiltrometer is then placed above our sediment sample.

7. Open the pinch clamp, and let water rain onto the sediment sample. The water is added into the soil until it is deemed near saturation.

8. At the end of the measurement period, determine the final height of the water column inside the apparatus \( H_2 \) and the time at which it is taken.

The simulated rainfall rate can be determined using

\[
r = \frac{H_2 - H_1}{T_f}
\]  
(6.2)

We can also change the rate of our simulated rainfall by sliding the air-entry tube up or down for higher or lower rates respectively. The soil moisture content is then expressed as a weight percentage \( \text{SMC}_g \):

\[
\text{SMC}_g = \frac{M_w - M_d}{M_d}
\]  
(6.3)

where \( M_w \) is the mass of the wet soil sample and \( M_d \) is the mass of the dry sample.
Figure 6.6: (left) Site Map of the Delmarva Peninsula, VA along with the barrier islands part of the VCR/LTER, with Hog Island shown in red. (Right) Our study site during the 2018 field campaign along the shoreline on the southern tip of Hog Island. The figure shows in situ measurements that were conducted during the field survey in 2018.

The saturated soil sample then underwent BCRF measurements using GRIT-T. The BCRF measurements were done every few minutes as the sample slowly air-dried, changing its SMC. We achieved approximately 20 BCRF measurements for different levels of SMC. This data was the basis for the retrieval of SMC from inversion of the MARMIT model detailed in section 6.1.

6.3 Field Experiments

The laboratory studies were followed by applying the MARMIT model to extract soil moisture content from remotely sensed data collected during a 2018 field campaign. The field campaign was conducted at Hog Island (37° 25’ 5.91” N, 75° 41’ 36.71” W), a barrier island off the coast of Delmarva Peninsula, Virginia (Figure 6.6). The island is part of the Virginia Coast Reserve/Long Term Ecological Research (VCR/LTER) site, which has been involved in extensive ecological and geological
studies [109, 110, 111, 112]. Hog Island is a shallow coastal bay, 14 km off the mainland, and approximately 10 km long and 2.5 km in width.

Figure 6.7: (left) RGB image of the coastal shoreline collected by the VNIR sensor at an altitude of 50 m. (Right) Image of the coastal shoreline collected by the SWIR sensor at an altitude of 100 m.
Table 6.1: The SMC data collected during the 2018 field survey. † represents data points where we also collected BRDF measurements with GRIT-T.

<table>
<thead>
<tr>
<th>Sample Name</th>
<th>Soil Moisture Content (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1</td>
<td>5.19</td>
</tr>
<tr>
<td>B2</td>
<td>15.85</td>
</tr>
<tr>
<td>B3</td>
<td>18.28</td>
</tr>
<tr>
<td>B4</td>
<td>18.37</td>
</tr>
<tr>
<td>B5</td>
<td>8.80</td>
</tr>
<tr>
<td>B6</td>
<td>17.93</td>
</tr>
<tr>
<td>B7</td>
<td>19.73</td>
</tr>
<tr>
<td>B8</td>
<td>22.96</td>
</tr>
<tr>
<td>B9</td>
<td>15.02</td>
</tr>
<tr>
<td>B11</td>
<td>17.81</td>
</tr>
<tr>
<td>B12</td>
<td>3.00</td>
</tr>
<tr>
<td>B13</td>
<td>14.68</td>
</tr>
<tr>
<td>B14</td>
<td>20.07</td>
</tr>
<tr>
<td>B15</td>
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<tr>
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</tr>
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<td>B17</td>
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<tr>
<td>G2†</td>
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</tr>
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<td>G3†</td>
<td>18.15</td>
</tr>
<tr>
<td>G4†</td>
<td>18.98</td>
</tr>
</tbody>
</table>

A major field campaign was conducted in the summer of 2018 to characterize and map the salt marsh ecosystem in southern Hog Island. The focus of this study took place along the shoreline on the southern tip of the island, also shown in Figure 6.6. The region of interest (ROI) of our study was imaged using two different Unmanned Aerial System (UAS) based hyperspectral imaging (HSI) sensors. One of the sensors was a Headwall Nano-Hyperspec, which is a pushbroom system providing spectral measurements from 400 to 1000 nm with 270 spectral bands and 640 across-track spatial pixel. The coastal zone was also imaged using a Headwall Hyperspec SWIR sensor, which is another pushbroom system providing spectral measurements from 900 to 2500 nm with 267 spectral bands and 384 across-track spatial pixels. Example images collected by the VNIR & SWIR sensor over our ROI are shown in Figure 6.7. We also collected extensive ground-reference data over our ROI, among them
being soil moisture content (SMC) as well as BRDF data using our goniometer. The SMC data collected during the 2018 field survey is shown in Table 6.1.

6.4 Results

6.4.1 Spectral Analysis

Figure 6.8 shows the evolution of the soil spectra as a function of SMC for the four different soil datasets. For all soil samples, the reflectance is highest when completely dry, with the reflectance increasing with wavelength from visible to the infrared part of the electromagnetic spectrum. As the SMC increases, we notice a decrease in reflectance across all wavelengths, with the drop in reflectance being more evident in the infrared. The change in moisture content is most pronounced at the two major water absorptions bands at 1440 nm and 1930 nm. We also observe weak water absorption features at 970 nm and 1160 nm for some of the spectra, this is prominently visible at the high SMC reflectance spectra for the HOGB sediment sample (Figure 6.8d). The change in band depth is more pronounced in the SWIR and clearly nonlinear compared to the visible part of the spectrum. However, from our experiments, we notice that the reflectance does not always decrease with an increase in water content. For example, the NEV soil does not follow this trend for some of the low SMC spectra. The spectra for 6-8% SMC is higher than the reflectance at SMC values of 2-4%, which is not consistent with the other soils. The rate of change in reflectance is different for each of the sediment samples as well. We see a big drop in reflectance for the HOGP (Figure 6.8c) and HOGB (Figure 6.8d) sample. The different rates of change in reflectance as a function of SMC were partially influenced by the time in between each measurements. Although, we hoped to reach complete saturation for all four sediment samples, the HOGB was the only soil sample that achieved this goal. This level of saturation was evident with complete absorption or almost zero reflectance in the SWIR at the high SMC values. The complete absorption of the spectra is only evident at the strong absorptions features (1440 nm & 1930 nm) for the other three datasets. The strong change in
absorption in the SWIR bands as a function of SMC suggest that this wavelength region will be most effective for the characterization of water content using the MARMIT model.

Figure 6.8: The change in spectral reflectance with changing SMC from air-dry to saturated. The GRIT-T instrument measures reflectance from the visible to the short-wave infrared (350-2500 nm) over the complete hemisphere. In this figure, we only show the reflectance at a sensor zenith of 0 deg and azimuth of 36 deg. The colorbar corresponds to the percentage soil moisture content. The spectra are plotted for four different sediment samples: (a) ALG, (b) NEV, (c) HOGP and (d) HOGB.

Physical properties of the sediment, water content included, are not only depen-
Figure 6.9: The RGB images of the four soil samples in two different moisture states (air-dry and saturated) and their corresponding BRDF plots at wavelengths 986 nm and 2150 nm. The first row shows the RGB image of the ALG air-dry sample followed by the BRDF plots at wavelengths 986 nm and 2150 nm, and then the RGB image of the saturated sample with its corresponding BRDFs. The second row shows the same figures for the NEV soil sample, followed by the HOGP soil in third and HOGB sample in the fourth row.
Figure 6.10: The calibration step relating the SMC to the mean water thickness ($\phi$) for (a) ALG, (b) NEV, (c) HOGP and (d) HOGB datasets.

dependent on the wavelength but also on the view- and sensor-geometry. Figure 6.9 below shows the BRDF plots for the four different soil samples. The BRDF is shown for two moisture states (saturated and air-dry) and at two different wavelengths (986 nm and 2150 nm). Alongside the BRDF plots, the figure also displays the RGB images of the sample. The first row shows the RGB image of the ALG air-dry sample followed by the BRDF plots at wavelengths 986 nm and 2150 nm, and then the RGB image of the saturated sample with its corresponding BRDFs. The second row shows the same figures for the NEV soil sample, followed by the HOGP soil in
third and HOGB sample in the fourth row. The sediment samples get darker with the presence of water. This can be seen visually from the RGB images and results in a drop in reflectance, which is observed both in the BRDF plots and the spectra shown in Figure 6.8. For all dry sediments, we observe a strong backscattering lobe for both BRDF plots. We also notice a forward scattering lobe for the ALG and HOGB sample. The forward scattering lobe for the dry sample is not present for the NEV and HOGP sample, which are mostly composed of clay and have finer particles. As expected, there is a big drop in reflectance as the soil gets “wetter”, and we also observe a significant change in the BRDF for the saturated samples. An optically smooth surface generally reflects specularly, for example, when the surface is covered by a thin film of liquid. This phenomena is reflected in our BRDF plots, with a strong forward scattering lobe in the saturated sample. The surface for the NEV soil becomes rougher with the presence of water, and it is not as specular as the other soil surfaces, which is why it does not have a prominent forward scattering lobe. The forward scattering becomes less noticeable as the samples slowly air-dry. We see less of the backscattering lobe for the saturated ALG, HOGP and HOGB soils. We also observe a significant drop in the reflectance in the saturated samples from 986 nm to 2150 nm compared to the dry soils.

### 6.4.2 SMC Retrieval using MARMIT

#### 6.4.2.1 Lab Study

The SMC is estimated by relating it to the mean water thickness using a logistic function (equation 6.1). Bablet et. al [46] explains it is not possible to determine a unique relationship between mean water thickness and SMC that is valid for all types of sediment. The variation in the sediment characteristic as well the methodology to collect the data (e.g. the sediment wetting and drying protocol) has a significant influence on the relationship between mean water thickness and SMC. As a result, the inversion was done separately for each sediment sample, with a unique logistic function relating the SMC to the mean water thickness. Figure 6.10 shows the S-shaped curve for each of the four different soils. The logistic functions are plotted for
the wavelength where we obtained the best fit for each of the different soils. The best fit was observed at wavelengths 2082 nm, 1320 nm, 1550 nm and 1572 nm for the ALG, NEV, HOGP and HOGB soil respectively. For these wavelengths, the accuracy of the retrieval was very high ($R^2 > 0.92$). There were several wavelengths where the $R^2$ was greater than 0.9 in the SWIR. However, the accuracy to retrieve SMC was very poor in the VIS-NIR wavelength range. Figure 6.11 shows the normalized root mean square error (NRMSE) for each sediment sample for the complete wavelength range (400-2500 nm) and the sensor azimuth of GRIT-T. We only saw a minuscule variation in the retrieval accuracy across view-geometry. Interestingly, the NRMSE varied more with sensor azimuth compared to sensor zenith. The NRMSE plots show that the accuracy in retrieving SMC using the MARMIT model seemed to depend more on the wavelength compared to the directionality of the reflectance. A plot of the measured SMC versus the estimated SMC for all sediment samples from the lab and field study (section 6.4.2.2) is shown in Figure 6.12 ($R^2 = 0.97$). The errorbar in the estimated SMC values from the lab studies represent the deviation in the retrieved SMC due to sensor zenith and azimuth. Having validated the inversion methodology in a set of controlled laboratory experiments, we now turn our attention to the retrieval of the SMC from data collected by an UAS-based HSI system.
Figure 6.11: The NRMSE obtained with MARMIT for the retrieval of SMC for a) ALG, (b) NEV, (c) HOGP and (d) HOGB datasets. The colorbar represents the NRMSE.
6.4.2.2 Field Study

We collected hyperspectral data along the shoreline on the southern tip of Hog island using a UAS-based imaging platforms during a 2018 field campaign. HSI was collected using both a sensor in the VNIR and SWIR from the UAS platform. However, based from our lab experiments, we decided to use only the SWIR data to perform the inversion of the MARMIT model to retrieve SMC. The moisture data we collected during the 2018 field survey is shown in Table 6.1. The logistic function relating SMC to mean water thickness is shown in Figure 6.13. The best fit was
observed at wavelength 2077 nm with a $R^2$ value of 0.92, which was similar to the beach data from the lab study (Figure 6.10d). The NRMSE for the SWIR data, without the atmospheric bands, from the UAS is shown in Figure 6.13. Similar to our observations from the lab, there are several wavelengths in the 1000-2500 nm range where the NRMSE is minute and can be used to retrieve SMC with relative accuracy. The derived logistic function using the ground-reference points, $SMC = 20.9/(1 + 9.5\exp(3.2\phi))$, was then used to map SMC across the complete ROI of our study from the beach. A mosaic image of the imagery collected by the UAS and corresponding derived SMC map is shown in Figure 6.14. The SMC map was derived using the 2077 nm band, which gave us the best fit for the logistic function. From visual inspection during the 2018 field survey and even from the SWIR data shown in Figure 6.14, the sediment close to the shoreline had a higher water content, followed by a region of low, high and again low SMC as you move away from the shoreline. Figure 6.14 shows that the retrieved SMC from inversion of MARMIT was capable of mapping these different sediment moisture regions across the beach with high accuracy.
Figure 6.14: (left) A mosaic image, at wavelength 2077 nm, of the data collected by the SWIR HSI sensor on the UAS platform. (right) The SMC map derived from the SWIR UAS imagery. The colorbar corresponds to the SMC percentage.
6.5 Conclusion and Summary

This chapter focused on the retrieval of the soil moisture content through the inversion of the physics based model MARMIT from five different soil datasets. Four of these sediment samples involved the validation of the MARMIT model under controlled laboratory conditions. The four samples are from distinctly different soil types, where the sediment varies in its physical characteristics such as mineralogy, salinity, texture, organic matter content and roughness. The laboratory experiments involved understanding the effect wavelength and directionality of the reflectance had on the retrieval of SMC. The SMC was retrieved with relative accuracy for all four sediment samples using MARMIT. The SMC was retrieved independently for each sediment sample and on a per wavelength basis. The best result was obtained at a different wavelength for each of the four soil datasets, with the R² value greater than 0.92. There were numerous wavelengths in the SWIR where the SMC was retrieved with high accuracy. However, the NRMSE was significantly higher in the VIS-NIR part of the spectrum. Although, the shape of the BRDF for sediments varied substantially with the presence of water, the inversion methodology to retrieve SMC was not affected by the directionality of the reflectance. The validation studies from the lab experiments were followed by the characterization of SMC from data collected by an UAS-based HSI sensor. The area of study was the shoreline on the southern tip of Hog island. The SMC was retrieved, similar to the lab experiments, with high accuracy and R² value of 0.92. The MARMIT model provided us a way to map moisture content near the shoreline of Hog Island with data collected from a UAS mounted HSI sensor. Future studies should focus on extending the retrieval of SMC using MARMIT over a variety of soil types with several different physical properties (roughness, grain size, texture, etc.), and demonstrate the fidelity of this model to characterize SMC from other remote sensing platforms.
Chapter 7

Sediment Fill Factor Retrieval II

This chapter will be a continuation of the sediment fill factor and single scattering albedo (SSA) retrieval by inversion of the modified Hapke model we detailed in chapter 4. The area of study in our previous experiments was the Algodones Dunes located in Southern California. In our upcoming experiments, we will extend our retrieval methodology of the sediment fill factor in a completely different physical environment - a salt marsh ecosystem.

We conducted growing season field campaigns in the back-barrier salt marshes on Hog Island, a well-studied barrier island that is part of the Virginia Coast Reserve. In these studies, we collected data using a high-efficiency hyperspectral imaging (HSI) sensor mounted on a telescopic mast. We also collected extensive ground-reference data to validate our retrieval methodology from hyperspectral imagery captured by the imaging system.

7.1 Instrument Calibration

The ground-based Headwall VNIR system [56] was characterized in-house using the LabSphere Heilos integrating sphere. Although, the Headwall system was initially calibrated by the vendor, we had noticed artifacts from their radiometrically calibrated images (Figure 7.1). As a result, we performed our own calibration of the
Figure 7.1: The radiance image produced from Headwall’s calibration, where artifacts, due to vignetting, are clearly visible along the edge pixels; showing the need to perform our own in-house calibration of the system.

The instrument was calibrated for a series of integration times (2.5 ms to 4.5 ms at 0.5 ms intervals), which were used in our field experiments in 2017 and 2018. The calibration setup is shown in Figure 7.2. The HSI instrument was placed in front of the exit port of the integrating sphere. The HSI sensor was imaged at 10 different illumination conditions, from no light to full daylight levels, for each of the system integration times. The two xenon lamps were used as the light source to provide constant illumination onto the HSI sensor. For each illumination and system integration time, the HSI sensor was set to acquire a total of 480 scans, which resulted in a $1600 \times 480 \times 371$ data cube. An example image cube from the
calibration is shown in Figure 7.3, where error due to vignetting can be seen quite clearly along the edge pixels. This is reiterated in the signal-to-noise ratio (SNR) plot across all the 1600 pixels at a wavelength of 601 nm in Figure 7.4. At the same time, the calibrated ocean-optics VNIR spectrometer within the Helios system was used to measure the radiance over the same conditions. The spectra across the different illumination conditions and exposure times is shown in Figure 7.5. We averaged the 480 scans of the HSI sensor, and calculated the gain and offset for each 1600 across track pixel and 371 wavelength to convert raw DN to radiance. For sensors with linear response, the relation would take the following form:

\[ L_i(\lambda) = DN_i(\lambda) \times g_i(\lambda) + b_i(\lambda) \]  

(7.1)

where \( L \) [\( Wm^2sr^{-1}\mu m^{-1} \)] is the output radiance of the HSI sensor, \( DN \) is the raw digital number, \( g \) [counts \( W^{-1}m^2sr\mu m \)] is the sensor gain, \( b \) [counts] is the bias of
Figure 7.3: The 1600×480×371 raw DN data cube acquired during the calibration of the HSI system. This specific image was collected at an integration time of 4 ms and at full daylight levels.

the sensor, and $i$ represents the across-track pixel.

Figure 7.4: The calculated SNR for the image cube shown in Figure 7.3 at a wavelength of 601 nm.
Figure 7.5: The spectra from the ocean-optics VNIR spectrometer within the Helios system across all illumination conditions and exposure time. We collected radiance spectra at 10 different illumination conditions, from no light to full daylight levels, for each of the exposure times.
The placement of Spectralon® panels within the scene enabled the conversion of the imagery into surface reflectance. The radiance/reflectance image produced from our own in-house calibration is shown in Figure 7.6. There are no more artifacts, due to vignetting, present in our radiometrically calibrated images. The figure also shows the resulting radiance and reflectance spectra from our data products. We also performed GPS surveys using the Garmin RTK GPS TRM55971 of fiducials within the scene, which allowed us to geo-register the images. This enabled us to calculate the solar and sensor geometries of the HSI images captured by the ground-based system.

Figure 7.6: The radiometrically corrected image produced from our own in-house calibration, and the resulting radiance (left) & reflectance (right) spectra from our data products.

### 7.2 Field Survey

The ROI of this study is a salt panne environment, which is a water retaining depression typically located within brackish marshes. The area of study is shown in Figure 7.7. During the 2018 field survey, we collected extensive ground reference
Figure 7.7: (left) Site Map of the Delmarva Peninsula, VA along with the barrier islands part of the VCR/LTER, with Hog Island shown in red. (Right) Our salt panne study site during the 2018 field campaign on the southern part of Hog Island. The figure shows the \textit{in situ} measurements that was conducted during the field survey in 2018; P1–17 are the field survey points and HSI1–4 are the position of the mast-based HSI system.

data, bulk density among others, and overlapping hyperspectral imagery from a ground-based HSI system. The ground-based system, which is described in section 3.2, is a Headwall VNIR Micro-hyperspec High Efficiency E-series sensor. This data set was used in a rigorous verification of the initial results that we have obtained from our study in chapter 4. The bulk density measurements along with the SMC collected during the field campaign are shown in Table 7.1. The ground–based system was imaged at four different locations around the salt panne, and at five different heights (2 m to 6 m at 1 m increments). The RGB images of the salt panne from the HSI system are shown in Figure 7.8. The hyperspectral imagery captured had a ground sampling distance (GSD) anywhere between 0.5 to 20 cm.
Table 7.1: The moisture content and bulk density data collected during the 2018 field survey.

<table>
<thead>
<tr>
<th>Sample Name</th>
<th>Moisture Content (%)</th>
<th>bulk density (g/cm$^3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>20.343</td>
<td>0.536</td>
</tr>
<tr>
<td>P2</td>
<td>20.789</td>
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<td>P5</td>
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<tr>
<td>P6</td>
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</tr>
<tr>
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<td>P15</td>
<td>19.303</td>
<td>0.516</td>
</tr>
</tbody>
</table>

### 7.3 Results

#### 7.3.1 Spectral Analysis

Figure 7.9 illustrates the spectral library and polar plots for four different locations around the salt panne. The spectral library plots the reflectance in the visible and near-infrared (400–1000 nm) wavelength region for different solar & view-geometries imaged with our mast-based HSI system. The spectral libraries for the clay-based sediment are consistent with observations from our previous studies, with the reflectance increasing with wavelength in the VIS–NIR region of the electromagnetic spectrum. The overall amplitude/magnitude of the reflectance values are slightly lower than our previous experiments (chapter 4) due to the high presence of water in our area of study, the salt panne. The high water content within the ROI is illustrated in the SMC values shown in Table 7.1, with the average SMC being approximately 20%. The scattering of the target pixels is evident in both the forward
and backscattering directions, with the phase angle varying from 30 deg to 130 deg. This range of phase angles was evident for all pixels within our ROI.

Figure 7.8: RGB images of the salt panne collected by the Headwall Micro-hyperspec sensor, the ground-based system, at four different locations and at five different heights. The locations of the HSI system around the panne are shown in Figure 7.7.

Figure 7.9 also shows the corresponding polar plots at wavelengths 807 nm and 551 nm respectively. The plots are a composite of 10-14 different looks from the HSI sensor. Although, the salt-panne was imaged at 20 different positions, however, the ground-reference points were not in view for all 20 different HSI images. The sensor-zenith angles are all greater than 70 deg for the different looks due to the
Figure 7.9: The image-derived spectral reflectance and HCRF polar plots at wavelengths 807 nm & 551 respectively. The spectral library and polar plots are shown for four different locations around the panne: (a) P2, (b) P5, (c) P7 and (d) P8. The HSI sensor provides hyperspectral reflectance from 400 nm - 1000 nm over 371 bands. The colorbar in the spectral library corresponds to the phase angle. The polar plots show how the solar and sensor geometries are distinctly different for each individual pixel, leading to unique HCRFs.
unique setup of the mast-based HSI system. The high sensor zenith angle is in stark contrast to traditional airborne and space-borne platforms, which typically collect data at nadir looking directions. The HCRF for pixels within the salt-panne are fairly different from each other, which is illustrated in both the spectral library and polar plots in Figure 7.9. This demonstrates the influence of the view-geometry as well as the geophysical properties of the sediment on the reflectance.

7.3.2 Inversion Retrieval

The set of images collected from the HSI system was then used to derive the fill factor and SSA by inversion of the Hapke model detailed in chapter 4. The range of phase angles for each pixel within the salt panne provided us with satisfactory information about the scene to perform inversion of the Hapke model. In the inversion procedure, we assumed that neighboring/adjacent pixels had the same geophysical properties. Since the HSI system provided imagery at very high spatial resolutions (0.5 to 20 cm), it was a reasonable assumption for the inversion process. As a result, the spectra from adjacent pixels served as the two input data sets for inversion using Equation 4.2. Figure 7.10 shows the retrieved fill factor versus the measured bulk density for the 12 different ground reference points across the salt panne. The final fill factor was an average of the fill factors obtained at each wavelength by the inversion process, since density is invariant to wavelength. The inversion of the Hapke model show moderately good correlation between the retrieved fill factor and measured density, with a $R^2$ value of the 0.82. The $R^2$ value was calculated by ignoring the last two density points (0.549 & 0.551 g/cm$^3$). The low values in fill factor at those two high densities can be attributed to the onset of coherent effects within the regolith where the model is no longer valid. The coherent effect arises when the separation between sediment particles are on the size of the wavelength, which occurs when particles are closely packed. The fill factor values in general were also higher to what we have observed from our previous studies in a desert environment (the Algodones Dunes). Figure 7.10 also displays the averaged SSA (shown in red) for all twelve ground points, and standard deviation across the density
Figure 7.10: (left) The average retrieved fill factor from inversion of the modified Hapke model versus the measured density ($R^2$ value of 0.82). (right) The average retrieved SSA. Estimates from all wavelengths is shown in gray. The SSA is generally dependent on the optical properties of the medium. The derived SSA values from the panne were significantly lower than those that we have seen in our previous studies (Figure 4.8). Both the high values of the fill factor and low value of the SSA can be attributed to the high presence of water within the salt panne.

The validation of the inversion methodology across the ground reference points was followed by mapping the fill factor across a large section of the panne. The presence of fiducials within the salt panne enabled the georegistration of the HSI images using a third–order polynomial equation. The instrument design and collection method of the system produced varying GSD for each along-track pixel captured. As the line scanning unit was swept vertically across a scene, pixels capturing the foreground (bottom of image) had smaller GSD (0.5 cm) than those capturing information in the background (top of image), where GSD was 20 cm. The HSI images were resampled to the same GSD of 10 cm using cubic interpolation. The overlap area from the HSI images was a 30 m by 30 m region in the middle of the salt panne, which is shown in Figure 7.11. The retrieved fill factor over the 30 m by 30 m is also shown in Figure 7.11. The fill factor values over the ROI, similar to Figure 7.10,
Figure 7.11: (left) RGB image and (right) retrieved fill factor derived from the 30 m by 30 m region of the salt panne, using the ground-based HSI system from 20 different view and illumination geometries.

were high due the presence of moisture.

7.4 Summary and Conclusion

This chapter focused on the extraction of geophysical parameters, fill factor (decreasing porosity) and the single scattering albedo, through the inversion of a modified Hapke model from imagery collected using a mast-based HSI system. The area of study, for this chapter, was a salt panne environment located in Hog Island, Virginia. In chapter 4, this inversion methodology to retrieve fill factor was applied to imagery collected from a desert environment, the Algodones Dunes. Salt panne and the dunes are two exceedingly different environments. The dunes consisted of soil mainly composed of quartz, feldsar and rock fragments. On the other hand, the sediments within the panne consists of mostly clay, silt and sand. The grain size distribution of the desert soil was considerably larger than those from the panne.
The amount of moisture was drastically higher in the panne compared to the dunes. The desert soil had next to no moisture, while the SMC for the salt panne was on average 20%. The smaller grain size distribution alongside the high presence of moisture lead to the sediments being more compact, resulting in a low porosity or high fill factor. The high SMC values are also reflected in the low retrieved SSA for the sediments. The retrieved fill factor from our results in Figure 7.10 increases with density, except for the two highest density points, where we see the retrieved fill factor value drop drastically. This phenomena arises due to the effects of coherency. Radiative transfer models, such as the one developed by Hapke, typically predicts a correlation between reflectance and density for a single sediment particle, provided the material does not exhibit any coherent effects. We start to see the effects of coherency when the separation between particles and wavelength are similar in size. This correlation between the density and reflectance ceases to exist at the onset of coherent effects. We observe the effects of the coherency at high density, where sediments are more closely packed, and the group of particles start acting as a single particle resulting in lower fill factor values.

We found a good correlation between the retrieved fill factor from the HSI imagery and the measured bulk density from the field, corroborating validation studies from previous experiments in chapter 4. These validation studies in our previous experiments where done by performing controlled laboratory measurements and not under field conditions. The experiments detailed in this chapter validate that this inversion methodology using Hapke’s radiative transfer model can be applied, with confidence, to retrieve the fill factor from angular dependent data derived from remotely sensed HSI imagery.
Bibliography


[95] J. K. Ross, “The radiation regime and architecture of plant stands (the hague: Dr. w. junk),” 1981.


